Real-time Locating Systems for indoor applications
the methodological customization approach

Bartosz Jachimczyk
Emerging wireless technologies increase the potential and effectiveness of wireless Real-time Locating Systems (RTLSs), which precisely localize the position, and identify things and people in real time. Among many applications, RTLSs are widely used in the industrial sector for indoor logistics and safety applications. However, signal interferences, which affect the system’s performance, are a serious issue of all indoor RTLS applications. Among others, the interferences are caused by the changeable working environment, the geometry and structure of the space, furnishing, and other obstacles. A customization of the RTLS’s architecture and localization algorithm may provide a way to overcome the interference problem and then enhance the systems’ performance.

The objective of this thesis is to develop and implement customization methods, which enhance system performance in the changeable working environment without compromising the functional and non-functional requirements defined by future users and stakeholders. The customized solution is to be based on the comprehensive methodological analysis of the system’s technical and environmental constraints, along with the requirements specified by the application field. The customization process covers the selection, adjustment and adaptation of the wireless technologies and methods in order to enhance the location system’s performance, in terms of accuracy and precision without compromising its simplicity and price.

In this research, wireless technologies of Radio Frequency Identification (RFID) and Ultra-wideband (UWB) are applied. The related indoor localization methods, such as, ranging techniques based on Received Signal Strength (RSS) and Angle of Arrival (AoA), are a thesis focus. Moreover, estimation methods like Fingerprinting and Angulation are used.
One of the proposed customization methods of RFID-based 3D RTLS, refers to the heuristic analysis-based optimization of a number and configuration of readers. For the same type of system, an alternative way of performance improvement is a customization of localization algorithm, explicitly the Neural Network-based estimation algorithm and its structural features and training methods.

Also in this thesis, performance improvement methods of the AoA-based RTLS operating in an UWB technology are proposed. The proposed customization of this system type is based on the uncertainty pattern defined by a statistical uncertainty model, which maps the localization uncertainty in terms of precision in the 2D workspace. The model depicts how the localization uncertainty depends on an arrangement of Location Sensors and workspace geometry. Another proposed customization method is realized by defining and implementing correction vectors for different working environments, which enhance the system’s performance in terms of its accuracy.

This thesis consists of two parts. Part I, Prolegomena, presents the overview of applied theories and research methods. This part aims to illustrate the links between the articles constituting the second part of the dissertation. Part II, Papers consists of five reformatted papers already published in peer reviewed journals and conferences.

Keywords: Accuracy and Precision; Angle of Arrival; Fingerprinting Method; Indoor Localization; Indoor Positioning System; Multi-Sensor System; Neural Network; Radio Frequency Identification - RFID; Real Time Locating System; Received Signal Strength; RFID Network Planning; Scene Analysis; Sensors Arrangement; System Customization; Uncertainty; Uncertainty Map; User Driven Design.
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Abbreviations

AoA Angle of Arrival
GDB Gradient Descent Backpropagation
GNSS Global Navigation Satellite System
GPS Global Positioning System
HF High Frequency
IMU Inertial Measurement Unit
IPS Indoor Positioning System
KNN K Nearest Neighbours
LDPLM Log-Distance Path Loss Model
LF Low Frequency
LMB Lavenberg-Marquardt Backpropagation
LoS Line of Sight
LS Location Sensor
NLoS Non-Line of Sight
NN Neural Network
QoE Quality of Experience
RFID Radio Frequency Identification
RPO Readers Planning Optimization
RSS Received Signal Strength
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<tr>
<td>RSSI</td>
<td>Received Signal Strength Indicator</td>
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<td>RTLS</td>
<td>Real-time Locating System</td>
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<td>SA-NN</td>
<td>Scene Analysis-Neural Network</td>
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<td>SEM</td>
<td>Standard Error of the Mean</td>
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<td>TDoA</td>
<td>Time Difference of Arrival</td>
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<td>ToA</td>
<td>Time of Arrival</td>
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<td>UDD</td>
<td>User Driven Design</td>
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<td>UHF</td>
<td>Ultra-High Frequency</td>
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<td>UWB</td>
<td>Ultra-wideband</td>
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<td>VLR</td>
<td>Variable Learning Rate Backpropagation</td>
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<td>WLAN</td>
<td>Wireless Local Area Network</td>
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List of Appended Papers

This thesis is based on the following research papers, which are referred in the text by Roman numerals:


Other publications related to the subject of the thesis produced during the doctoral studies:


Part I
1 Introduction

1.1 Background and motivation

Emerging wireless technologies increase the potential and effectiveness for localization of persons and objects. These technologies operate on radio waves, optical and acoustic signals, and magnetic fields. Depending on the application character or stakeholder’s need, a combination of wireless technologies and a suitable localization algorithm meet the requirements.

The outdoor positioning systems and Indoor Positioning Systems (IPSs), which have an ability to locate an item’s position in a defined space at a real time, or close to it, are classified as Real-Time Locating System (RTLS) [1].

In general, there are two main kinds of outdoor RTLSs:

- Global Navigation Satellite System (GNSS), which provides the location and time anywhere on the Earth when at least four specialized satellites operate in the Line of Sight (LoS);
- Cellular Networks are able to localize mobile phones and mobile devices via multi-lateration of radio signals among several cell towers of the network.

The global coverage and sensible localization quality allow those technologies to outperform other outdoor solutions. However, due to non-LoS conditions, interferences and signal attenuation caused by construction elements of buildings, a signal’s instability caused by movement of people, doors and other objects e.g. furniture and high demand of accuracy and precision, neither the worldwide localization standard called Global Positioning System (GPS), an representative of the GNSSs, nor Cellular Networks positioning systems are applicable to localize objects indoor [2].
Thus, for the indoor localization purpose, RTLSs do not specify any exclusive technology nor corresponding solutions. However, there are some predominating technologies and signals, which are applied in a RTLS’s physical layer:

- Optical systems;
- Infrared systems;
- Acoustic systems;
- Magnetic systems;
- Radio wave based systems including Wireless Local Area Network (WLAN), RFID, UWB, ZigBee, and Bluetooth;
- Inertial Navigation Systems.

Currently, due to their reliability and robustness, RTLSs based on radio wave technology are the most popular solutions for indoor localization.

Depending on the application character and corresponding requirements, to solve their specific localization issues, the RTLS architecture may be designed according to one of indoor localization categories: [3]:

- **Presence based localization** – when the location system detects whether a tag is present in a given area;
- **Room level localization** – when the tag location is returned as present in a specific room;
- **Sub-room level localization** – where the tag location is returned as present in a specific part of a room;
- **Choke points localization** - in this category the tag location is returned by specific choke points such as doors, etc. The system determines whether the tag is present inside or outside specific areas or whether it is entering or leaving a permitted area;
- **Association** - the tag location is returned as proximity with respect to another tag;
- **Precise localization** – in this category, the tag’s location is pinpointed precisely, with exact location coordinates (absolute or relative) on the map or plan of the building. Because it may be extrapolated to other localization categories and due to wide scope of its applications, the precise location is the main interest of this thesis.

It can be observed that due to their increasing capabilities and enhancing performance, the indoor RTLSs have gained growing attention in many sectors. Among others, RTLSs may be applied as localization and tracking tools in complex Enterprise Management Systems in large industrial and logistics fields, for instance container terminals [4], distribution centres and high-storage warehouses [5].
Besides that, indoor RTLSs have been widely used for safety at construction sites [6], [7], in healthcare for monitoring and tracking people and goods [8], [9], [10] and in agriculture for animals’ monitoring [11]. Additionally, the new trends such as IoT or Industry 4.0 create yet unknown opportunities for RTLS vendors. The innovative start-ups, market competitiveness, high return on investment and regulatory compliance across industries are the factors driving the growth of the RTLS market. The RTLS market is expected to grow from USD 3.19 billion in 2018 to USD 8.79 billion by 2023, at a compound annual growth rate of 22.5% between 2018 and 2023 [12].

1.2 Thesis objectives and scope

The objective of this thesis is the methodological customization of indoor Real-time Locating Systems. The customization here is understood as a specific user-centred design method, which intends to adapt and/or adjust the system to meet functional and non-functional requirements in the changeable working environment including its size, shape, and both fixed and movable contents. Customization covers the selection, adjustment and adaptation of wireless technologies and methods in order to enhance the location system’s performance in terms of accuracy and precision. It also concerns method simplifications aimed for real time performance improvement and system price reduction.

The customized solutions are based on the predefined design methodology represented by a 3D layer cake diagram illustrated in Figure 1.1. The design consists of the two stage methodological analysis and customized solution synthesis. At the first analytical stage is an analysis of application requirements, depicted by two shades of blue in the layer cake, which includes the comprehensive methodological analysis of users’ and stakeholders’ functional and non-functional requirements and environmental constraints. The results of this stage constitute the frame within application fields, where logistics and safety applications are the focus of this thesis. Well-defined constraints and requirements would facilitate a selection of the best-suited architecture of the multisensory RTLS’s-based solution. The second analytical stage consists of a technology-oriented comparative analysis of available RTLS wireless technologies, which are depicted by two shades of green in the layer cake. In this thesis, Ultra-wideband (UWB) and Radio Frequency Identification (RFID) wireless technologies are in solution focus. Furthermore, in the second analytical phase, the two localization steps, explicitly the ranging technique and estimation method have the purpose to determine the RTLS architecture. At last, the two stage analysis results are used to synthesize a solution illustrated by the yellow layer. The solution applies the customization method for the customization base i.e. elementary RTLS solution corresponding to the determined RTLS architecture from the analytical phase. The customization base
may also be treated as an RTLS solution universally offered on the market. The synthesis leads to the customized solution as a basic RTLS architecture with an applied customization method, which is illustrated by the orange top layer on the diagram.

![Diagram of design methodology of RTLS customized solution.](image)

The performance enhancement in terms of localization accuracy and precision, along with method simplification, are the goal of the RTLS customization. Concerning the goal, both performance criteria are approached using analytical and/or heuristic methodology, which are in the scope of this thesis. Whereas, it depends on the technology whether a standard RTLS solution is customized heuristically or analytically.

The proposed customization applies hardware- and software-oriented methods and tools. The hardware approach covers customization of:

- the system’s architecture in terms of LSs deployment and a number of active LSs;
measurement methods such as Angle of Arrival (AoA), Received Signal Strength (RSS), which among others affect a selection of applied antenna, whereas, the software approach concerns customization of:

- Neural Network (NN) structure customization in Scene Analysis-Neural Network (SA-NN) estimation method;
- applying an uncertainty pattern in the form of an AoA localization uncertainty map;
- correction vectors method for different working environments.

The customization methods and tools listed here are applied to enhance the RTLS performance in a specific but changeable indoor working environment to meet specific functional and non-functional requirements.

### 1.3 Thesis outline

This thesis consists of two parts. Part I, Prolegomena, presents the technical background, an overview of applied theories and research methods related to RTLS and its customization. This part aims to understand the links among the papers constituting Part II, Papers, which consists of the five reformatted papers published in peer reviewed journals and at conference transactions. All the papers concern RTLS customization methods within RFID and UWB wireless technologies, which use localization techniques and methods, i.e. ranging and estimation.

RTLS customization methods presented in Papers II-V, along with Paper I referring to preliminary research on the RTLS customization, were carried out according to the design methodology depicted in Figure 1.1. The overview of the five included papers is presented in Table 1.1, and covers: dedicated indoor applications, used wireless technologies and localization manners, and applied ways of customization. The listed issues correspond to methodological stages illustrated by the 3D diagram layers in Figure 1.1. Moreover, Table 1.1 presents what the estimated contribution of each paper to the thesis is in terms of RTLS customization.

Paper I refers to the localization quality of the RFID-based RTLS in an indoor heterogeneous and noisy environment. To enhance the system’s performance, a hybrid solution consisting of the fingerprinting-based estimation method called Scene Analysis and NN is proposed. The suggested Scene Analysis-Neural Network system is designed, implemented and examined. The solution aims on robustness and localization accuracy of RSS measurements affected by environmental interferences. The proposed SA-NN system was a steppingstone to
further research concerning RTLS customization methods, which were developed in Paper II and Paper III.

Table 1.1. An overview of approaches of the papers included in the thesis related to: indoor applications, wireless technologies and localization manners, ways of customization and their contribution in the thesis.

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<td>Dedicated indoor applications</td>
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The research presented in Paper II concerns customization of the RTLS to a defined indoor environment, explicitly finding an optimal number and configuration of readers in RFID based 3D RTLS. The heuristic analysis of all possible arrangements for a varying number of readers is used to determine the minimal number of sensors and their optimal deployment for a desired localization accuracy. The analysis is based on evaluation of modelled virtual- and real-systems.
Paper III proposes a new way of performance improvement by customization of SA-NN estimation algorithm for varying environmental conditions. The localization quality is to be further enhanced by a customization of NN structural features, such as a number of neurons and a type of transfer function in a hidden layer along with type of transfer function in the output layer, as well as the training method. Efficiency of the customized SA-NN system is validated by different simulations and verified by physical experiments.

Paper IV and Paper V deal with a customized performance improvement of the AoA-based RTLS operating in an UWB technology. Paper IV shows how the uncertainty of estimated localization depends on the LS arrangement and the workspace geometry. Moreover, a statistical uncertainty model mapping the localization uncertainty in terms of precision in the 2D workspace is defined as an uncertainty pattern and then used for customization of the RTLS. A simulation-based evaluation of the implemented customized RTLS validates the analytical model applied to the fingerprinting map. The performance of the models is verified by results of physical experiments.

Paper V shows the possible RTLS enhancement approach based on an analytical model, which facilitates customization of the AoA ranging technique in varying 3D environments. This model aims to extend and enhance the uncertainty model proposed in Paper IV. The analytical model is then validated by the simulation results and verified by experimental ones. The proposed RTLS customization method is facilitated by defining and implementing the correction vectors for different working environments to improve the system’s performance in terms of its accuracy. To prove the accuracy enhancement, the proposed customization of the system for a given working environment is verified by physical experiment.

The main contributions of this dissertation cover three areas:

1. Localization algorithms:
   - implementation of the radio wave propagation model, namely Log-Distance Path Loss Model (LDPLM), for Received Signal Strength Indicator (RSSI)-based SA-NN system [I];
   - modelling and implementation of a new SA-NN RTLS based on the RSSI fingerprinting technique [I];
   - customization of estimation algorithm of the SA-NN system based on a heuristic analysis and experimental verification of the NN structural features and training methods affecting the localization accuracy [III];
modelling and implementation of new 2D and 3D ranging techniques based on AoA measurements [IV], [V];
modelling and implementation of a new 2D AoA-based fingerprinting technique for customization of the UWB-based RTLS [IV];
modelling of the 3D angular-based localization algorithm composed of AoA ranging and extrapolation techniques. The proposed novel algorithm was implemented and evaluated on UWB-based RTLS [V];
the new innovative customization method based on a correction vector was modelled, implemented and evaluated. This method is used to customize the UWB-based RTLS [V].

2. Customization of RTLS architecture:

optimization of the RFID-based SA-NN system by using Readers Planning Optimization (RPO) in terms of trade-off between number of LSs, their deployment and desired accuracy and price [II];
defining how the localization uncertainty depends on the size and shape of the workspace coming from analysis of the UWB-based RTLS’s performance in terms of localization precision in 2D [IV];
establishing how the 3D localization precision of the UWB-based RTLS’s depends on an arrangement of LSs in the workspace [V].

3. Localization uncertainty models:

development of a new statistical uncertainty model of the fingerprinting 2D localization method. The proposed model defines the localization uncertainty of the AoA in terms of precision within the workspace. The model was implemented, evaluated and verified by the UWB-based RTLS [IV];
development of a new analytical geometrical uncertainty model concerning precision and accuracy of the AoA localization method in a 3D indoor space. The model was implemented, evaluated and verified by the UWB-based RTLS [V].

All proposed techniques and methods were validated by simulation tests and verified by physical experiments carried out within corresponding indoor environments.

The focus of Chapter 1 of Part I Prolegomena is on an overview of the thesis, explicitly its background, objectives, scope and content (thesis outline). Chapter 2 describes the research methodology applied for systematic
customization of an indoor RTLS. Chapter 3 presents application requirements, which define the initial design constraints and requirements, based on the User Driven Design (UDD) process. Chapter 4 provides a technology-oriented comparative analysis of possible RTLS technologies and common radio-wave based solutions. Moreover, in this chapter the localization algorithm components such as ranging techniques and estimation methods are described. Chapter 5 defines the principal customization criteria and then overviews the proposed RTLS customization methods. A brief summary of the included papers, conclusion of the thesis, and future works are given in Chapter 6.
2 Research Methods

This thesis applies both theoretical and experimental research methods to solve problems in a field of engineering science, which the classical methodological model is illustrated in Figure 2.1. It starts with an initial stage when the problem is identified based on a specific human’s need. Then the problem is reworded into a research question, and then the hypothetical solution is proposed. The initial stage is followed by solution development phase, which consists of modelling and implementation. Mathematical and computer models along with analyses of simulations and measurement data are used to synthesize the solution. The final stage of the research is a validation and verification of both solution and its implementation. The verified solution should be transformed into a product, which fulfils the initial needs [13].

The quantitative analysis, based on statistical and numerical methods using simulations and computational techniques, is essential for the solution synthesis. Nevertheless, measurements and experiments are crucial to verify the theoretical models and simulation results. Furthermore, in experimental sciences such as engineering, heuristic models are often sufficient for solving the research problem. Then the measurement and experimental methods are used in the synthesis phase. Such an approach refers to the New Experimentalists’ concept of ‘experiment’s own life’ [13].

It is worth noticing that both human needs and the developed engineering product are closely bound to an application field, since the new product is going to fulfil the needs within the application field. However, the research design may have a wider scope and could be implemented into several products and application fields. In the same way, any customized solution may be implemented into several applications fields.
The analytical and heuristic research methods applied for methodological customization of an indoor RTLS are complementary in a sense that when analytical methods fail or became incommensurate to solve the problem, the heuristic method is used efficiently to find a solution.

### 2.1 Problem identification and definition, hypothesizing a solution

The solutions reported in the included papers [I-V] were developed in line with the classical engineering research methodology, with an initial stage of problem identification and definition followed by research questions and suitable hypotheses [7], [8]. The identified problem defines a human’s needs and is based on personal experience and various forms of gathered information. The research questions and hypotheses concern the expected relationship or difference between independent variables, where those variables need to be defined in measurable terms to quantitatively prove the solution [15], [16].

Figure 2.1. Methodological model of engineering science [14].
The fundamental research problems concerned in all papers [I-V] included in the thesis are related to the effects of the working environment and the system’s structure on the system’s performance. The geometry and structure of an indoor workspace, furnishing, and other obstacles affect the localization process when different features of radio signals are applied. Therefore, to reduce the impact of these interferences and then to improve the localization performance, the RTLS’s algorithms need to be customized for the specific operating environment. Furthermore, the system’s structure, such as a calibration point, number and type of sensors or their deployment, is closely related to the geometry and structure of an indoor workspace, and therefore, it must be customized for the actual working environment.

Performance enhancement of indoor RTLSs, which is the issue of the enclosed papers [I-V], is understood in terms of the localization uncertainty expressed by precision and accuracy. However, each paper proposes a different way of customizing, inter alia by adjustment of RTLS structure or customization of localization methods.

Paper I, by referring to the problem of insufficient 3D IPS’s performance in terms of precision and accuracy, answers the question how a system consisting of an algorithm combining the Scene Analysis technique, along with an Artificial Neural Network can improve the localization quality compared to known Scene Analysis algorithms.

Paper II deals the problem of IPS performance introduced in Paper I, from a perspective of cost-efficient architecture, which depends on a number of readers, their deployment, used antennas, wiring etc. This paper shows how the system’s performance depends on its configuration and what the trade-off is between the IPS performance quality and its price.

Paper III approaches the problem of performance improvement of the SA-NN localization algorithm by customizing NN. The studied issue is a customization of NN structural features and training methods to enhance the system performance. The customized NN structural features are: number of neurons and type of transfer function in hidden layer along with a type of transfer function in an output layer and training methods. The heuristic customization is based on inferences from simulation and experimental results.

Paper IV deals with an indoor RTLS, which is based on the AoA ranging technique. It applies the fingerprinting technique using the uncertainty pattern created by the new precision model. The main answered question is how a 2D uncertainty map established on the localization precision model of AoA-based system can be used to customize the RTLS in order to improve its performance.
The auxiliary solved problem was how to combine a geometrical AoA approach with a measurement statistical approach into the system precision model.

Paper V extends the scope of Paper IV into the 3D environment and furthermore, adds the accuracy, to the previously used precision, as the performance measure. The accuracy is defined here as a difference between the true value and the mean of a measurement set. The objective of the paper is to find out how to customize the system for varying working environments by applying a specific correction vector to improve the system’s performance in terms of its accuracy. The customization vector is estimated based on a developed uncertainty model of accuracy and precision of AoA localization in 3D.

As it was mentioned, in principle all papers focus on the same customization problem. However, the applied technologies, working environment and some other conditions vary, which require different methodological approaches.

2.2 Solution development

In all included papers [I-V], the solution development consists of modelling and implementation. Modelling here is interpreted as a mathematical or logical representation of a system, phenomenon or process. In principle, the models are formulated by mathematical equations or algorithms, which are a basis for simulations understood as virtual implementations. The simulation results of virtually implemented models are used to analyse and/or anticipate the system’s or process’s behaviours under various conditions. Related phenomena are also observed or analysed using physical implementations of the models.

Research problems may be approached using theory or heuristics, depending on the character of investigated phenomena. Due to the complexity and particularly intricate character of radio-wave based indoor localization, the heuristic approach is commonly used for analysis. In papers [II], [III], [V], the heuristic analysis is applied to compare the performance of virtual and real RTLSs. Whereas in Papers [I], [IV], [V], statistical theories are applied for the uncertainty model and to customize RTLSs.

The presented works [I-V] deal with the RTLS customization meant as an adjustment and adaptation of localization methods to the particular environment or application field, to enhance the location system’s performance. For this purpose, the models and software implementation of RSS-based [I-III] and AoA-based [IV-V] localization algorithms are initially established. Moreover, in papers [IV-V], the analytical models of AoA localization uncertainty are introduced. All implemented models are evaluated under different scenarios to show how the environmental and structural features influence the system’s performance.
In Paper I, a radio wave propagation phenomenon and the RFID system combining Scene Analysis with the NN technique are modelled. Based on the theoretical algorithmic models, software and hardware implementations are realized. The models developed in Paper II along with their heuristic evaluations are used to find, at which readers’ configuration assures a trade-off between the desired localization accuracy and system’s cost. In Paper III, based on the models from Paper I, the SA-NN model is examined to experimentally define how the training methods and NN structural features affect system performance.

Paper IV and V deal with the UWB RTLS and AoA based ranging techniques. In the first of these two papers, the fingerprinting technique is used for modelling an indoor environment for a RTLS workspace. The method comprises the ranging techniques and the model of uncertainty, in terms of the precision pattern of the AoA based ranging technique. The proposed solution was implemented in the Matlab environment and simulated for varying indoor test environments.

Paper V introduces a holistic approach to RTLS uncertainty in terms of accuracy and precision, therefore the geometrical model of the AoA localization method in 3D is defined. The analytical model is implemented in the Matlab environment and used to show how different system’s features influence its performance. Furthermore, the extrapolation angular-based 3D localization algorithm, estimating the tag’s location using azimuth and elevation angle measurement of a pair of LSs, is modelled and implemented.

The modelled and virtually implemented solutions needed to be verified to prove their usefulness and advantages.

2.3 Validation and verification methods

Verification is the experimental process of proving that the solution proposed in the development phase meets the initial specified technical requirements. Thus, validation is the simulation process of evaluating whether the solution fulfils stakeholders’ or future user’s operational needs and that the model implementation fairly complies with the developer’s conceptual description and specification [17], [18]. In both verification and validation, various analytical activities are carried out such as model inspections, along with the comparative and statistical analysis, e.g. analyses of the system’s robustness and performance.

To verify the proposed engineering solutions, it is necessary to apply tough experimental test scenarios. In all the included papers [I-V], the performed simulations and virtual experimental results are verified by relevant physical
experiments. The functionality and quality assessments suitable for each solution are applied.

The verification of the solution proposed in Paper I is based on the comparison of simulation results with the results from the physical SA-NN system measurements. Since the applied virtual and real test environments match each other, it is concluded that the propagation model is a suitable representation of indoor radio wave propagation phenomena. Moreover, to prove the advantage of the proposed solution, performance of the SA-NN system was compared with results from other reported Scene Analysis applications.

Paper II focuses on an investigation of virtual and real systems to find out which configuration assures the trade-off between a desired localization performance and the system’s cost. The conclusion comes from a comparative evaluation of localization quality inferenced from virtual and physical experiment results. The results indicate a clear correlation between a number and placement of active readers and localization performances.

Verification of the proposed customization of NN structural features and training methods presented in Paper III is done by a comparative analysis of simulation and physical experiment results. The results confirmed the supposed effects of NN’s structural features and training function on RTLS performance.

In Paper IV, the simulation results are verified by real test measurements, to prove the quality of the proposed AoA statistical geometrical uncertainty model. Moreover, the matching ratio between the proposed analytical uncertainty model and the experimental results of the localization standard error was quantitatively estimated. The expected interferences from indoor obstacles, and an impact of the calibration point placement were also examined.

In Paper V, the proposed uncertainty model is quantitatively verified by estimating the matching ratio of the simulation and experimental results. The matching ratio confirms that the analytical model fits reality with a high probability level. The experimental results prove that the global correction vector is the suitable customization method to reduce localization-offset error.
3 Application Requirements

The customization of RTLS is understood here as an approach of the specific user-centred design method, which intends to adapt and adjust the system to meet functional and non-functional requirements under the particular environmental constraints. The designer customizes the product in respect to the users’ desires, rather than forcing them to change their behaviour and environment to accommodate the product [19]. The designer needs to focus on users’ satisfaction, ensuring their safety as well as matching their abilities and preferences. Therefore, the user-oriented design considers the ease of use, ergonomics and reliability along with efficiency in terms of simplicity and price.

The users’ desires and stakeholder’s functional and non-functional requirements, along with environmental constraints, constitute the elementary design frame within an application field, as shown in Figure 3.1. The well-defined design frame, in terms of requirements and constraints, enables the correct selection and then suitable adaptation and adjustment of the applied technologies and methods. Since the application requirements define the initial needs to enable customization, a comprehensive and systematic application analysis is axiomatic, from the stakeholder’s and user’s perspectives along with the designer’s vision.
Figure 3.1. Application requirements and constraints as a design frame of developed solution.

The design initial constraints and requirements, which have to be considered in the UDD-process, are classified and described in the following sections. While the fundamental design aspects, common for all RTLS indoor applications, are described in the following sections. The examples of distinctive aspects of the specific location-aware applications, such as logistics and safety, are specified and described in the further subchapters.

3.1 Users’ requirements

Beyond the technical issues, the designers of user-centred solutions in application fields such as assistance or safety, need to bear in mind the users as individuals [20]. Designers have to include the users’ perspective into the design and development process in order to accomplish a satisfying system [19]. The designer must cooperate not only with the stakeholders but also with the future users to understand their perspective. Such approach is the foundation of the applied research.

The goal of the initial interplay among the stakeholder, designers and users is to complete the detailed information about the system context-of-use, which is a base of the UDD [19]. The users’ characteristics and tasks along with operating environment including its technical, physical and organizational aspects, need to be indicated and discussed. The user’s experience is a respectable source of such information.
Based on the identified system’s context-of-use and preliminary list of users, the user types can be classified. It is necessary to define the user categories with respect to functional and non-functional aspects. For each identified type or group of users, it is necessary to define the user’s interface features. The possible human-machine interfaces such as text-based, audio or graphical displays need to be related to the usability point of view [3], [19], [21].

Nevertheless, even the user driven design of RTLS may affect the user’s environment or habits. These effects should be minimised and acceptable for the users. A customization of the RTLS may entail a possible rearrangement of the system’s components, which may require changes in the working environment [II]. The calibration procedure is an example of an instant, which may need an users’ involvement and therefore should be reasonably justified [IV].

Wearing the location device or tag should be easy to handle by users and as unnoticeable as possible. Thus, their shape, size, weight or colour play a significant role. In the case of radio devices, the way one wears them affects the system’s efficiency and robustness. Moreover, if any problematic situation occurs, users’ support must be considered. Furthermore, it is necessary that the RTLS’s calibration and maintenance be simple, possible even for a non-professional by following required, relevant, and clear user instructions [3], [22], [23]. The user-oriented designed RTLS should inspire a positive emotional response from the users [24].

### 3.2 Stakeholder’s requirements

The customization by user-oriented design also requires comprehensive analysis of stakeholder’s needs and vision. Therefore, an analysis of stakeholder’s requirements, which can be either functional or non-functional, is needed in the initial stage of the design. The provided functional requirements define main functionalities of the system to establish objectives of system development. Non-functional requirements define the performance and quality criteria along with factors of system operation and investment cost. The functional requirements influence system architecture, services used, protocols etc. Both, functional and non-functional requirements are directly related to an application and work environment.

To distinguish between the fundamental design aspects, which are common for all RTLS indoor applications, and these aspects, specific for the location-aware application, the application field has to be defined. The types of location-aware indoor applications, which are in focus of the research dealing with customization of RTLS, are:
• person safety applications such as patients monitoring and tracking, workers’ protection;
• logistics applications such as equipment localization monitoring, control equipment distribution;
• security application such as personnel monitoring in restricted areas, equipment protection; unauthorized access detection.

Since the distinctive functional requirements are necessary to characterize the application frame, in this thesis the logistics-related relevant functional requirements are used as a case study. The logistics applications involve management of activities, which facilitate the movement within and coordination of the supply chain. RTLSs are one of the key logistics tools currently used by companies and institutions to acquire logistics information to accomplish the specified location-oriented functionalities.

The examples of places where RTLSs are applied are warehouses and storages, where the systems facilitate the movement of goods through the logistics chain-by-chain visibility. This is the basic logistics functional requirement for monitoring of an asset at a possible facility location representing the workspace. This is also the key aspect of modern agile logistics defined as the ability of an organization to respond rapidly to changes in demand, both in terms of volume and variety [25].

To fulfil the location functional requirements, the designer needs to consider the tag’s mobility in terms of speed, the size of the workspace, the scalability in terms of maximum number of users or assets, and the density of tags in a specific zone. These parameters are necessary to design system dynamics and eventually to adjust the sampling rate to manage the functionality.

The fundamental requirement from stakeholder’s perspective are the system’s reliability and incessancy. To ensure this, the middleware architecture and dedicated procedures need to routinely maintain and consider situations such as a lack of Internet connection, hardware failure and others random faulty situations.

Except the basic RTLS’s logistics-oriented functional requirements, such as visibility and continuous operation, the stakeholder needs to define the non-functional requirements. These constitute the system’s performance criteria and therefore need to be analysed and considered in the design process [3], [26], [27]:

• Compatibility and interoperability with third-party logistics software understood as an ability for information exchange with others parts of management system such as the warehouse management system,
transportation management system, event management system, ordered management system and enterprise resource planning system;

- **Low latency** defined as the delay, at which the requested information is available to the user;
- **Information security and confidentiality** mean that the system could not become accessible for unauthorized processes, systems or individuals. The terms of collection and use of personal information have to be consistent with the privacy policy;
- **Tamper resistance** against the potential users’ malicious actions both on hardware and software.

These logistics-oriented functional and non-functional requirements, commonly defined by the stakeholder, frame the operability and performance criteria of the designed RTLS.

### 3.3 Environmental constraints

Radio-wave based technologies are highly affected by environmental conditions, especially radio-based indoor RTLSs. Therefore, the selection from a set of possible wireless techniques and methods is based on their robustness of environmental effects. RTLS customization for a specific environment means to reduce environmental effects on the system’s performance in a way that the system meets the application requirements, then the environmental analysis defining constraints needs to be carried out and the environmental characteristics should beforehand be identified and mapped.

A significant impact on RTLS performance is caused by workspace layout, such as a building structure, furnishings and other equipment. There exist application workspaces, which not only consist of furnishing and other obstacles, but things that move in the space. Furthermore, the heterogeneous walls include windows, doors, etc. The building materials that are used can also be multifarious. Especially, the metal structures highly influence the localization quality of radio wave-based RTLSs, due to interferences in signal propagation causing signal reflections and dumping. Indoor environment characteristics are the important causes of interferences and therefore impose specific constraints and restrictions [IV].

To select and then customize the RTLS wireless techniques and methods, identification and justification of all possible environmental constraints are required, and should be included in the design process. The following environmental aspects need to be considered:
- System’s working conditions e.g. humidity, pressure, temperature, vibrations, dust etc. [3];
- The presence of people in terms of their density and mobility [28], [29];
- Variability and changeability of the environment arrangement [3], [30];
- Environment dynamics and interactions of moving persons and vehicles [3], [30];
- Cleaning restrictions, important in some applications e.g. medical [10].

The listed environmental aspects affect the selection of wireless technologies and localization techniques and may disqualify some of them [3], [31]. The discussed environmental aspects frame particular constraints in system’s adjustment and adaptation. Therefore, the environmental analysis, which plays a crucial role in the RTLS customization, needs to be carried out in detail.

### 3.4 Summary

The fusion of the stakeholder’s needs and vision with the users’ requirements, along with the environmental constraints, is necessary to accomplish the functionalities without compromising other requirements. The fusion result is the design guideline for RTLS architecture including middleware and software. An example of the logistics-related application requirements and constraints are summarized in Table 3.1. The analysis of the table content helps to specify possible wireless techniques and methods and to frame the design and development criteria, which influence the system’s architecture, its components and services. If the stakeholder’s and user’s functional and non-functional requirements represent the vision of the developed system, then the environmental analysis contributes to the reduction of environmental effects on the location system’s performance.
Table 3.1. Logistic-related application requirements and constraints.

<table>
<thead>
<tr>
<th>Requirement/constraint</th>
<th>User’s</th>
<th>Environmental</th>
<th>Stakeholder’s</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Functional</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Information about system context-of-use e.g. users’ characteristics, tasks, operating environment;</td>
<td>• Working conditions;</td>
<td>• Visibility;</td>
<td></td>
</tr>
<tr>
<td>• Affecting user habits;</td>
<td>• Presence of people;</td>
<td>• Continuous operation;</td>
<td></td>
</tr>
<tr>
<td>• Calibration and maintenance;</td>
<td>• Variability and changeability of the environment arrangement;</td>
<td></td>
<td></td>
</tr>
<tr>
<td>• Placement of the location devices;</td>
<td>• Environment dynamic;</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Non-functional</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>• User categories;</td>
<td>• Cleaning restrictions;</td>
<td>• Compatibility and interoperability;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Building and construction materials;</td>
<td>• Low latency;</td>
<td></td>
</tr>
<tr>
<td></td>
<td>• Workspace layout;</td>
<td>• Confidentiality;</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Tamper resistance;</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Investment cost;</td>
<td></td>
</tr>
</tbody>
</table>
4 Technological Analysis

Since the goal of customization is an enhancement of RTLS’s performance by selection, adjustment and adaptation of the wireless technologies and methods to the specific environment, there is a need for technical analysis of the possible system’s technologies, methods and algorithms. The technical analysis should be preceded by an application analysis providing an application overview, and concerned with the stakeholder’s needs, as well as the users’ requirements and environmental constraints.

The following chapter includes a technology-oriented comparative analysis of possible RTLS technologies. Moreover, the common radio-wave based RTLSs, its architecture and constraints are presented. Furthermore, the parts of localization algorithms, which are ranging techniques and estimation methods are described. In the last section, several RTLS solutions are technologically characterized and compared to each other in order to provide a scope of possible and available RTLS solutions.

4.1 Differentiation of RTLS technologies

The wireless nature of RTLS technology is fundamental for a mobile localization. The specific indoor environment and related constraints affecting wireless techniques are substantial for a selection of wireless techniques and therefore challenging for a designer. Furthermore, the system customization, which depends on an exclusive technique, meant as an adjustment of RTLS architecture and/or adaptation of localization methods, must be accomplished to gain its capacities.

There is a set of factors, which differentiate the wireless technologies, such as: power requirements; indoor or outdoor applicability or else both indoor and outdoor; tag’s form, coverage area; environment character; existing infrastructure and location model. RTLSs do not specify any exclusive technology, however, due
to their features there are some predominating technologies, which are applied in a RTLS’s physical layer such as, [30], [32], [33]:

- Optical;
- Infrared;
- Acoustic;
- Magnetic;
- Radio wave including Wireless Local Area Network (WLAN), RFID, UWB, ZigBee, and Bluetooth;
- GNSS;
- Inertial Navigation Systems.

The listed wireless technologies are dedicated to different applications to solve their specific localization issues. Each of these wireless technologies uses a dedicated location model and can vary in coverage and accuracy depending on a type of medium used as electromagnetic-, optical- or mechanical-waves. Although, nowadays radio wave technology is the most popular solution for both indoor and outdoor.

The technologies can be classified due to their coverage and localization accuracy as it is presented in Figure 4.1. The biggest coverage is observed for GNSS and cellular networks, which are preferable in outdoor applications. Due to the reliability and robustness, for indoor applications more desirable are UWB, RFID and WLAN technologies. Because of their ability for high coverage with relatively good accuracy, those technologies are widely applied in different sectors. And though vision, acoustic and magnetic technologies are characterized by better accuracy, they are less popular mostly because of their high environmental requirements.
There exist also hybrid solutions, which combine two or more wireless technologies to enhance the versatility and performance of RTLS, [31], [32], [34]. Such solutions show good system’s robustness and applicability for both indoor and outdoor localization. However, these hybrid localization systems are more complex and therefore relatively expensive.

Due to the focus of the thesis on indoor applications, the commonly used RFID and UWB radio-wave based solutions are analysed in detail in this section. Both wireless technologies, can be characterized by specific technological constraints, which are described in the following section.

### 4.1.1 RFID characteristics

RFID-based localization systems are specified by the three main components: readers, deployed antennas and tags. The distance between an antenna and single tag is estimated from ranging calculations based on measured signals, such as RSS, Time of Arrival (ToA), and AoA. The RSS-based solutions are the most commonly used in the RTLS system, due to their simplicity and low price. RFID-based localization systems using ToA or AoA ranging techniques are more complex and accurate, however these systems’ prices are higher.

There are two types of RFID technologies such as passive and active. The passive one applies tags, which are not equipped with a source of power and are
therefore smaller and of shorter range compare to active ones. The size of a passive tag may vary and should correspond to the asset’s size. Due to their low prices, passive tags are commonly applicable as smart labels in supply chain management or access control.

The radio wave frequency determines an operation range of passive RFID systems and there are three used main frequency bands [31]:

- **Low Frequency** (LF) 125 kHz – 134 kHz – a short range up to 10 cm, less affected by metal or water, applied for animal identification;
- **High Frequency** (HF) 13.56 MHz - an operating range from 1cm up to 1m, used in access control and security applications;
- **Ultra-High Frequency** (UHF) 868 MHz – 965 MHz - an operating range up to 6 m. It is used in industrial and medical applications for tracking and identification of persons and goods.

Despite the used radio frequency band, the operating range depends on environmental conditions. Moreover, passive RFID systems operating on higher bands cope worse with obstacles as in water or metal.

Battery powered active RFID tags have a longer range, but they are more expensive compared to passive ones. The power source assures a long range up to 100 m and allows a use of internal memory, which dedicates them for more sophisticated applications such as tracking, i.e. cargo assets of high worth, machinery, etc. Depending on environmental conditions, the tag’s housing should be specified, which affects the cost. Maintenance of active RFID technology requires a periodic battery replacement, generating an additional cost. Depending on usability and operating frequency, a battery lifetime varies from 5 to 10 years [35].

Available active RFID systems operate in two main frequencies, 433 MHz or 915 MHz. While a lower frequency operates better with assets made of metal or water, the higher band assures a longer operating range. Since the data transfer rate depends on the transmission frequency, this aspect should also be considered by a designer for applications applying many tags.

### 4.1.2 UWB characteristics

UWB-based RTLSs are similar to RFID-based with such difference that they use ultra-wideband signals, which occupies a very wide frequency band and exceeds 500 MHz. The ultra-wideband technology is based on pulse transmission, therefore, UWB-based systems operate at very low power levels.
UWB technology is widely applicable for indoor localization applications and the used frequency range is from 3.1 GHz to 10.6 GHz for unlicensed users, in most of countries including USA and Europe, see Figure 4.2. The high bandwidth results in high data transfer rate and high robustness, even in a multipath environment with obstacles. The high bandwidth can be also advantageous in providing high resilience to fading, interference resistance and greater accuracy of ranging and geolocation. UWB technology has high penetration ability through obstacles such walls, wood and clothing, nevertheless liquids and metal materials cause still interferences. The UWB-based RTLSs are attractive for certain applications due to their approach to spectrum sharing in environments where fixed band services already exist. Therefore, UWB systems are less susceptible to interference from other RF systems [36], [37], [38].

![Radio spectrum of wireless technologies used for indoor localization](image)

Due to its properties, the UWB-based RTLSs operate in large area. The distance between tags and antennas is determined based on measured features of UWB pulses with a defined update rate, which depends on the number of tags in the system. The distance is calculated using time or angle-based ranging techniques. Unlike RFID systems, signal power, RSS, may be used by the UWB-based RTLSs for data filtration [V]. RTLSs based on ToA or Time Difference of Arrival (TDoA) measurements require additional connections, which are required to synchronize the LSs.
Generally, there are many advantages over other radio-wave based solutions associated with UWB-based RTLS. It is crucial for RTLS that, the UWB systems assure excellent localization performance and good interference resistance in challenging environments compared to conventional RFID systems [38]. However, the technological complexity significantly affects the cost of UWB components.

4.2 RTLS architecture and constraints

Nowadays, most of indoor RTLSs are based on radio-wave technologies, largely due to their superior performance. The radio-wave based RTLS’s architecture consists of hardware and software used to determine the real time position of assets or resources quipped with a device operating within the system [39]. It is possible to distinguish three main components of the system, see Figure 4.3:

- **Tags** – mobile devices operating within a used location technology and are built in or attached to an asset as a person or object;
- **Location Sensors** – devices mounted in fixed known positions, which receive radio wave or acoustic signals (wireless media) from the tags and then communicate with them. The Location Sensors are also called Readers;
- **Location engine** – the software, which uses information from the LSs to estimate location of the tag.

Apart from those three components, depending on the system’s application, the RTLS may consist of middleware, which provides services to third-party software applications. The application software may also be considered as a part of RTLS. With RTLS middleware, it can pull together performance functionalities defined by the user such as web services [3].
The technology-related constraints, common for every radio-wave based solution, which need to be considered by designers are [2], [3]:

- *Tags’ density* – the maximum number of tags, which can be used in a specified area, ensuring the system proper performance and real-time ability;
- *Response time of the tag* – the time needed to get tag’s response signal after a request, which is crucial for real-time ability;
- *Wiring harness in the workspace* – installation of wires and cables through the wall;
- *Readers - antennas* specified by their characteristics and type;
- *Energy sources and a way of use* – determining battery life in tags and availability;
- *Spatial scalability* – defining the system’s coverage area;
- *Cost* – comprehensive expenses of hardware, software and their installations, licences, trainings, maintenance procedure, troubleshooting and support.

Possible radio-wave RTLS technologies are assessed mainly based on functional and non-functional requirements, along with environmental constraints defined in UDD. The assessment is performed based on presented technological aspects, where some may be classified as Key Performance Indicators that help quantitatively differentiate technologies in the technological synthesis.
4.3 Localization Algorithm

Each RTLS consists of a localization algorithm composed of two components: ranging technique and estimation methods. The ranging technique is used to establish the tag’s position by measured distances from the tag to each LS placed at known fixed positions. The results are used by an estimation method to determine the tag’s coordinates. In this section, common ranging techniques and estimation methods for indoor localization are presented [IV].

4.3.1 Ranging techniques

A type of ranging technique is related to the distance finding system and mainly depends on features of the measured signal such as Received Signal Strength, Time of Arrival, Time Difference of Arrival or Angle of Arrival [40]. These techniques are based on measurements carried out by the LSs equipped with antennas to measure properties of signals emitted by the tag [IV].

The radio wave indoor multipath propagation strongly depends on the environmental structures and mobility, which particularly affects the reliability of RSS-based wireless solutions. Therefore, these solutions are less qualified for safety applications. However, due to their simplicity they are commonly used in other application fields.

The time-based ranging techniques apply the measurement of the propagation time for the RF signal. Generally, there are two time-based ranging techniques ToA and TDoA. The applicability of ToA- and TDoA-based localization systems is limited due to their hardware requirements. To synchronize all devices, these techniques require an accurate clock system consisting of the start-stop timer or time-to-digital converter with high resolution. These requirements increase the system’s price [41].

The Angle of Arrival ranging technique measures the RF signal’s direction of propagation by finding the angle of incidence on an antenna array. It is done by measuring the TDoA at elements of the sensor’s array. A disadvantage of the method is that in NLoS conditions, when the AoA signal is faded, the performance of an AoA-based localization system decreases significantly [IV]. However, the AoA-based RTLSs are more reliable than RSS-based and more cost-friendly compared to time-measurement-based.
4.3.2 Position estimation methods for indoor application

The measures acquired by different ranging techniques are processed by estimation algorithms. The algorithms estimate the tag’s position based on measures established by the ranging technique and known fixed LSs’ placements. Depending on the ranging technique, the following algorithms can be used:

- Lateration method;
- Angulation method;
- Fingerprinting method;
- Proximity method;
- Dead reckoning (inertial) method.

The Lateration methods, which are based on the ranging technique of RSS or ToA/TDoA, determine the tag’s position in 2D or 3D and apply the distance measurements from the tag to LSs with their reference coordinates. The lateration algorithm applies a geometric method to estimate intersection points of geometric figures representing distances from each LS to the tag. Depending on the number of LSs, it might be distinguished as trilateration or multi-lateration, where the former one is based on distances from three LSs [37].

The Angulation method is a geometric approach, which applies AoA measures. The position is estimated based on angles between LS-asset direction lines and reference line defined by angles of incidence [42].

The Fingerprinting method is known as a scene analysis technique and can be applied to any ranging technique. This is a two-phase method based on matching the measurement data with a beforehand-established map pattern. To estimate the asset’s position, a suitable deterministic classification method e.g. NN, K-Nearest Neighbour or Support Vector Machine applied to classify measured fingerprint data on the established pattern [IV]. The fingerprinting techniques are usually applied for radio-wave based IPSs, but they can be also applied in acoustic systems [43], [44].

The Proximity method is the simplest positioning technique, which approximates a position of an asset by its presence in a specific area. The workspace is divided into cells defined by the grid of antennas deployed in the whole working space, usually on the floor. This estimation algorithm determines the position based on association with the transceiver position whence the strongest signal is received. The positioning accuracy depends on the transceivers deployment density [45], [46] and is usually used for 2D positioning in robotic and mobile vehicle tracking applications [I]. The proximity technique is commonly applied for RFID technology.
The *Dead reckoning* method comes from maritime navigation, is a process of estimating a current tag’s position in 2D based on the previously estimated positions, measured speed, elapsed time and way (course) direction. For this solution, the localization uncertainty cumulatively increases with time, therefore it requires a periodical system’s recalibration. Nowadays, in indoor applications, this method is usually associated with Pedestrian Dead Reckoning, which estimates the position of persons wearing Inertial Measurement Units (IMUs) [47] or handled computers [48].

### 4.4 Summary

The analysis of RTLS technologies concerns main technological aspects, and it needs to be carried out during the design process. These technological constraints combined with the application requirements and constraints determine the possible relevant technologies, techniques and methods.

To quantitatively justify usefulness of different RTLSs, they are summarized in Table 4.1. Apart from well-known radio wave-based RTLSs like RADAR or Horus, there are some commercial systems offered in the market. Each solution is characterized by a kind of wireless technology, used localization methods in terms of ranging technique and estimation method, localization performance in terms of accuracy and precision, operated space dimension and price.

As it is shown, the UWB-based RTLSs demonstrate many advantages over other radio-wave based solutions. The crucial aspect is the best localization performance. For all presented solutions, the accuracy is less than 0.3 m together with high precision. Moreover, UWB-based solutions may localize objects both in 2D and 3D. However, the technological complexity causes the cost of UWB solutions to be higher than other radio wave-based RTLSs.

Systems based on WLAN and active RFID technology reach accuracy in the range from 1 m to 5 m. Passive RFID applying the proximity estimation method may achieve accuracy up to 0.5 m, which results from the dense grid of tags deployed in the workspace.

Usually, RTLS ranging techniques are based on wireless technologies. In practice, WLAN, RFID and Bluetooth solutions estimate a tag’s position based on RSS measurements. In the case of UWB solutions, TDoA and AoA signal features are used to determine a tag’s coordinates.
Table 4.1. Comparison of indoor RTLS solutions.

<table>
<thead>
<tr>
<th>RTLS</th>
<th>Wireless technique</th>
<th>Ranging technique</th>
<th>Estimation method</th>
<th>Accuracy</th>
<th>Precision</th>
<th>Space Dimension</th>
<th>Cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>RADAR [49]</td>
<td>WLAN</td>
<td>RSS</td>
<td>KNN</td>
<td>3-5 m</td>
<td>50% within 2.5 m and 90% within 5.9 m</td>
<td>2D/3D</td>
<td>Low</td>
</tr>
<tr>
<td>Horus [50]</td>
<td>WLAN</td>
<td>RSS</td>
<td>Fingerprinting</td>
<td>2 m</td>
<td>90% within 2.1 m</td>
<td>2D</td>
<td>Low</td>
</tr>
<tr>
<td>Ekhau [31], [51]</td>
<td>WLAN</td>
<td>RSS</td>
<td>Probabilistic method</td>
<td>1 m</td>
<td>50% within 2 m</td>
<td>2D</td>
<td>Low</td>
</tr>
<tr>
<td>Ubisense [31], [52]</td>
<td>UWB</td>
<td>TDoA + AoA</td>
<td>Least square</td>
<td>0.15 m</td>
<td>99% within 0.6 m</td>
<td>2D/3D</td>
<td>High</td>
</tr>
<tr>
<td>Dart [31], [53]</td>
<td>UWB</td>
<td>TDoA</td>
<td>-</td>
<td>&lt; 0.3 m</td>
<td>50% within 0.15 m</td>
<td>2D/3D</td>
<td>Medium</td>
</tr>
<tr>
<td>Zebra [31]</td>
<td>UWB</td>
<td>TDoA</td>
<td>-</td>
<td>&lt; 0.3 m</td>
<td>-</td>
<td>2D/3D</td>
<td>High</td>
</tr>
<tr>
<td>Landmarc [54]</td>
<td>Active RFID</td>
<td>RSS</td>
<td>KNN</td>
<td>&lt; 2 m</td>
<td>50% within 1 m</td>
<td>2D</td>
<td>Low</td>
</tr>
<tr>
<td>WhereNet [31], [55]</td>
<td>Active RFID</td>
<td>TDoA</td>
<td>Trilateration</td>
<td>2-3 m</td>
<td>50% within 3 m</td>
<td>2D/3D</td>
<td>Low</td>
</tr>
<tr>
<td>NaviFloor [2], [56]</td>
<td>Passive RFID</td>
<td>RSS</td>
<td>Proximity</td>
<td>0.5 m</td>
<td>-</td>
<td>2D</td>
<td>Low</td>
</tr>
<tr>
<td>Zonith [2], [57]</td>
<td>Bluetooth</td>
<td>RSS</td>
<td>Proximity</td>
<td>room</td>
<td>-</td>
<td>2D</td>
<td>Low</td>
</tr>
</tbody>
</table>
5 Customized Solution Design and Validation

The customization of RTLS is understood here as a specific user-centred design method, which intends to adapt and adjust the system to certain changeable environmental constraints to ensure the functional and non-functional requirements. The process is based on comprehensive methodological analysis of the application requirements and possible technologies. This analysis must precede the synthesis part representing the customization method applied for the customization base. The expediency of the customized solution is validated by simulations and verified by physical experiments carried out within the corresponding indoor environment. The test results define the customization quality.

Possible approaches, domains and aspects of the customization process are illustrated in Figure 5.1. The customization enhances a standard RTLS solution by applying software and hardware methods, preceded by either heuristic [II, III, V] or analytical [IV, V] analyses. The chosen way depends mostly on the types of applied wireless technologies and the localization algorithm. Moreover, defined application requirements i.e. functional and non-functional requirements along with environmental constraints, are analysed and the results constitute the frame within application fields. Thus, the trade-off between the specific environmental requirements and performance quality define the customization objective function. Within the frame of the defined technologies and used customization tools, the required system’s performance in terms of accuracy and precision should be achieved without compromising the system simplicity and cost. The customization methods described in this chapter are generic and may be conveyed onto other localization systems.
The principal customization criteria represented by environmental requirements and the trade-off of performance quality vs. simplicity vs. cost are defined in the first subsection of this chapter. In following sections, the main contributions of this thesis, are the proposed RTLS customization methods including sensor planning optimization [II], a fingerprinting approach [IV], an application of correction vector [V] and a NN customization [III] are described. Additionally, for each customization method, the validation and verification methods and results are discussed [I-V].
5.1 Analysis

5.1.1 Performance criteria

To specify the localization performance criteria, one needs to define a measurement, which according to The Joint Committee for Guides in Metrology is “the process of determining the value of the measurand, that is, the value of a quantity to be measured. The measurement quality is described in terms of uncertainty, which characterizes the dispersion of the result that could be attributed to the measurand” [58]. Therefore, the localization performance quality is understood as the localization uncertainty in terms of precision and accuracy where the simplified interpretation of 3D localization quality in terms of accuracy and precision measures for \( i \)-th tag’s position as illustrated in Figure 5.2 [31].

![Figure 5.2. Illustration of 3D localization accuracy and precision for \( i \)-th tag’s position.](image)

The accuracy measure, \( \Delta_i \) represents the distance between the true position \( P_i \) and the location estimate \( \hat{P}_i \) obtained from the RTLS. Whereas, the precision is illustrated by the sphere with the estimate’s standard error \( \sigma_i \) as a radius. The sphere is centered in the estimated position \( \hat{P}_i \) and includes respectively 68% of \( N \) measured localization samples. Both localization uncertainty measures, accuracy and precision, characterize a dispersion of measured results from the tag’s true
In the following sections, the localization performance is modelled in a static mode using the two measures: accuracy and precision [59].

Expediency of the customized solution needs to be evaluated, based on suitable performance measures, defined in advance. The quality of the developed solution may be assessed based on either subjective or objective quality indicators. The subjective measures can be gained from a survey of individual users applying Quality of Experience (QoE) tools. The QoE is used to evaluate the subjectively perceived uncertainty and response time. However, there are also objective experimental measures such as localization accuracy and precision, along with system sensitivity and response time. All included papers [I-V] challenge the objective measures of localization quality in terms of accuracy and precision, which are used to evaluate and verify the customized solutions.

5.1.1.1 **Accuracy**

The localization accuracy expresses the system capability to obtain the true value of a item’s position in 3D [58]. Then, the accuracy component \( \Delta x_i \) of the \( x \) coordinate estimated for the point \( P_i \) located in the test environment, can be expressed as:

\[
\Delta x_i = \overline{x}_i - x_i,
\]

(5.1)

where variables of \( P_i(x_i, y_i, z_i) \) respectively refer to the true localization coordinates at \( i \)-th position of the tag, whereas variables of \( \overline{P}_i(\overline{x}_i, \overline{y}_i, \overline{z}_i) \) refer to the mean of \( N \)-th times measured localization coordinates at \( i \)-th tag’s position. If the remaining two accuracy components \( \Delta y_i \) and \( \Delta z_i \), of \( y \) and \( z \) coordinates respectively are specified analogically to (5.1), then the localization accuracy \( \Delta_i \) at \( i \)-th tag’s position can be shown as:

\[
\Delta_i = \sqrt{\Delta x_i^2 + \Delta y_i^2 + \Delta z_i^2}.
\]

(5.2)

5.1.1.2 **Precision**

The second uncertainty measure - localization precision describes the measurement’s repeatability and is based on an estimate of the mean standard error \( \overline{\sigma} \) of the mean localization uncertainty. A low value of the standard error means high precision and vice versa. For the \( i \)-th tag’s position, which is estimated from \( N \) measurements, a Standard Error of the Mean (SEM) \( \overline{\sigma}_x \) of the component \( x \), can be expressed in relation to its variance as:
\[
\bar{\sigma}_{x_i} = \sqrt{\frac{\sigma^2_{x_i}}{N}}
\]

where \(\bar{\sigma}_{x_i}\) and \(\sigma^2_{x_i}\) are SEM and variance respectively of the \(x\) component at \(i\)-th tag’s position.

The remaining two SEMs \(\bar{\sigma}_{y_i}\) and \(\bar{\sigma}_{z_i}\) of \(y\) and \(z\) coordinates respectively are defined analogically. Then the corresponding SEM \(\bar{\sigma}_i\) of the localization estimate of \(i\)-th tag’s position, which is the measure of precision, can be calculated as follows [V]:

\[
\bar{\sigma}_i = \sqrt{\bar{\sigma}_{x_i}^2 + \bar{\sigma}_{y_i}^2 + \bar{\sigma}_{z_i}^2}.
\]

### 5.1.2 Environmental criteria

The indoor workspace’s characteristics such as its geometry, building structure, furnishing and other equipment directly impact the RTLS performance. Moreover, some application workspaces consist not only of fastened furnishing and obstacles, but also the objects, which move in the space. Furthermore, usually the heterogeneous walls include windows, doors, ventilation, etc., and used multifarious building materials, especially metal elements highly influence the localization quality of radio wave-based RTLSs due to their interferences with signal. These indoor environmental characteristics impose specific constraints and restrictions. The relationships between the indoor environmental characteristics and RTLS’s performance are essential customization aspects. Environmental criteria could be tackled analytically, however due to their complexity, usually a heuristic approach distinctive for each workspace is required.

Moreover, due to interferences and reflections phenomena, space geometry and sensor arrangement are crucial factors affecting the wireless indoor localization. Regardless an analytical optimisation of the sensor arrangement, and arrangement customization, based on heuristic analysis, is required, because of the system’s complexity.

RSS-based RTLSs, is especially sensitive to changes in the workspace. The radio propagation model, which defines the signal path loss in an indoor environment, needs to be customized according to the dynamic changes to approximate indoor radio wave properties [I-III].
RTLSs, which apply a measure of AoA or ToA/TDoA signal characteristics, require establishment of a calibration point to perform a distinctive calibration procedure. The calibration point is usually located in the centre of the workspace. The calibration point is to be set in the LoS of all LSs, possibly centrally in the workspace, as it is shown in Figure 5.3 [IV - V]. Some complex environments with many LSs require several calibration points. Regardless of how complex the environment is, in each workspace the unique origin of the coordinate system needs to be specified. Usually it is one of corners of the workspace.

![Figure 5.3. Workspace model representing indoor environment [IV].](image)

5.2 Solution Synthesis

The solution synthesis concerns an implementation of the most suitable possible software-oriented customization methods. The applied technologies and used methods of the location engine determine the customization approach. Analytical modelling of the implementation tools is the preferable customization method. However, for some techniques, when the analytical approach is not possible, then the heuristic approach is the only way of customization. In this thesis both approaches are applied, the analytical one is applied for UWB-based RTLSs whereas the heuristic one is used to RFID-based RTLSs.

5.2.1 Sensors Planning Optimization

An example of RTLS customization is a Readers Planning Optimization applying a heuristic approach, which is described in [II]. In this paper, the RFID SA-NN 3D indoor positioning system, which was proposed in [I], is customized
by finding an optimal number and configuration of readers. The customized solution aims to assure a desired 3D localization quality for a minimal number of readers without compromising costs. To find the most suitable arrangement of the RTLS, we apply a heuristic approach using the SA-NN model [I] tested under various conditions. The investigation is based on the simulated indoor environment model, which consists of eight RFID readers located in all corners of the cuboidal area, see Figure 5.4. The indoor environment model was related to the workspace of the physical experiment.

![Figure 5.4. Room model with possible readers deployment [II].](image)

Based on the indoor environment model [II], the RPO problem considers the following aspects:

- A number of active readers from three to eight;
- A number of possible configurations of readers;
- Cost-effectiveness.

The analysis of all possible arrangements for a different number and configurations of readers helps to determine their optimal deployment. It defines a minimal number of readers for a desired localization accuracy.
5.2.2 Fingerprinting technique approach

Another way of RTLS software customization, which also concerns LSs arrangement of UWB-based RTLS is the fingerprinting technique presented in [IV]. The analytical customization method applying this technique is based on defined uncertainty pattern in the form of an AoA localization uncertainty map. The uncertainty map is established using a statistical approach to the AoA localization precision of each pair of location sensors, geometry of indoor space, and RTLS arrangement. The fingerprinting technique is founded on the comparison of measurements with the analytical pattern. The method’s algorithm is illustrated in Figure 5.5.

![Algorithm of RTLS AoA fingerprinting method](image)

Figure 5.5. Algorithm of RTLS AoA fingerprinting method [IV].

The basal offline analytical phase consists of environmental and fingerprint assays. The environmental part applies the parametric data, such as a shape and size of the workspace, a deployment of sensors, and a location of the calibration tag, etc. These parameters are used to define environmental characteristics needed in the further steps. The workspace model is employed to the fingerprint analysis, where an uncertainty map is derived from the offline ranging technique and the localization uncertainty distribution model.

Then, the workspace model and uncertainty map from offline phase are implemented into the online synthesis, which applies the AoA online ranging technique to estimate the tag’s positions in relation to all pairs of location sensors.
The estimation algorithm is used to determine the final tag’s position from a set of considered locations.

One of the main contributions of this solution is a definition of the uncertainty pattern in the form of an AoA localization fingerprint map, which maps zones by indicating the preferable pairs of LSs of least uncertainty. The uncertainty map is calculated using the AoA statistical geometrical model proposed in [IV]. An example fingerprint map presented in Figure 5.6 is depicted by a grid of markers, corresponding to the preferable pairs of LSs for which the localization standard error is smallest. Neighbouring markers indicating the same pair of LSs form the homogenous groups, which map zones with preferable pairs of LSs.

![Figure 5.6. Simulated uncertainty map. Colour markers correspond to the preferable pairs of LSs for which the AoA uncertainty is smallest at the grid point.](image)

### 5.2.3 Correction Vector approach

An alternative RTLS customization method is based on the RTLS’s performance assessment using the analytical uncertainty model of AoA localization in a 3D indoor space. The proposed uncertainty model comprises two localization performance measures: accuracy and precision. This approach facilitates the system customization by defining and implementing the correction vectors adjusted to different working environments in order to improve the system’s accuracy. Using a geometrical approach for a specified RTLS architecture and working indoor environment, the models of localization measurement accuracy
and precision are defined, whereas the accuracy is treated as an offset error. The approach is presented in detail in the paper [V].

An effect of the localization offset error can be reduced by a correction vector, which is to be estimated heuristically in accordance to the system’s architecture and test environment. For a certain pair of LSs in a given environment, the correction vector may be estimated based on measurements from \( K \) tags, while each measurement is sampled \( N \) times at \( M \) locations. Then, the \( x \) component of the correction vector, \( k\mathbf{v}_x \), may be calculated from:

\[
kv_x = \frac{1}{K \cdot M \cdot N} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \Delta x_{k,n,m},
\]

where \( \Delta x_{k,m,n} \) is the difference between the true localization and the \( n \)-th measurement at \( m \)-th localization of \( k \)-th tag. The remaining two correction vector components \( k\mathbf{v}_y \) and \( k\mathbf{v}_z \), of \( y \) and \( z \) coordinates respectively can be calculated analogically to (5.5). Then the correction vector \( \mathbf{k}\mathbf{v} \), specific for the localization system in the test environment, can be expressed as:

\[
\mathbf{k}\mathbf{v} = \begin{bmatrix} kv_x \\ kv_y \\ kv_z \end{bmatrix}.
\]

5.2.4 NN structure customization approach

Since NN is the core of the SA-NN algorithm introduced in [I], then to improve a system’s performance its structure and training method must be customized to the operating environment. Because of a lack of analytical methods for customizing NN structures, a heuristic approach is proposed [III]. The heuristic analysis is carried out based on a series of simulations, where the various NN architectures are tested in different environmental conditions.

In [III], NN structural features within SA-NN can be customized to improve the system performance. In a given working environment are the size and type of transfer function of a hidden layer, and the transfer function of an output layer. The considerable size of a hidden layer varies from 5 to 50 neurons. For the evaluated NN structure with one hidden layer, there is a possible combination of two transfer functions from the following set of transfer functions of the hidden and output layers:
• Linear;
• Symmetric saturating linear;
• Hyperbolic tangent sigmoid.

To find the most suitable training method for the feedforward SA-NN based system, three backpropagation methods were analysed: Gradient Descent Backpropagation, (GDB), Lavenberg-Marquardt Backpropagation method (LMB) and Variable Learning Rate Backpropagation algorithm (VLR). All considered methods are suitable for this particular case, however estimation quality is the main distinguishing feature.

5.3 Validation and Verification

The developed customization methods needed to be evaluated and examined in a dedicated way. Therefore, each of the developed solutions was validated by simulation results and empirically verified by physical experiments carried out in corresponding indoor environments.

5.3.1 Sensors Planning Optimization

To examine how the system configuration affects the localization accuracy, virtual validation and experimental verification of the customized solution using the SA-NN system were applied. The experiment was carried out in a cuboidal room of the same dimensions of 5.13 m × 4.5 m × 2 m as the virtual one, equipped with basic office furniture [I]. To evaluate the localization quality, the experiment was performed for 20 randomly selected positions of the target tag.

The verification experiments show a correlation between a number of active readers and estimated localization accuracy. In [II], there proved a relationship between mean localization uncertainty and a number of used RFID readers for the best scenarios of three chosen test cases: eight, six and four active readers. Experimental and simulation results for four and eight active readers differ slightly, whereas in the case of eight readers, the experimental results show 4.5% better localization uncertainty than for four readers.

The results confirm that there is also a strong correlation between the arrangement of used RFID readers and localization accuracy. The results confirm that the experimental findings match the relationship among different configurations’ performances from the simulations. There is a clear correlation between virtual and physical experimental results for four active RFID readers. The
best, medium, and worst localization accuracies of the examined configurations in simulation and physical experiment match each other.

The analysis proves for both simulation and experimental results that the system consisting of four active readers, mounted near the ceiling or near the floor are the optimal solution to a given problem.

### 5.3.2 Fingerprinting technique approach

The implemented solution of the fingerprinting technique is validated by simulations using three different test scenarios for three test environments representing modelled indoor environments of different geometries. In each test environment, LSs were located in workspace upper corners. The validation was done by estimating the localization uncertainty distribution of the workspace for each pair of LSs. Examples of uncertainty distributions for one pair of LSs in three different environments are presented in Figure 5.5.

![Figure 5.5](image-url)

**Figure 5.5.** Example uncertainty distributions for one pair of location sensors in three test environments [IV].
Then the uncertainty distributions and relevant AoA fingerprint maps for six combinations of LS pairs were compared to prove that size of the workspace affects the uncertainty map layout as it is visible in Figure 5.6.

![Fingerprint maps](image)

(a) (b) (c)

Figure 5.6. Fingerprint (uncertainty) maps for three test environments [IV].

The customization based on the fingerprint method was also verified by physical experiments. The physical experiments were performed in the workspace corresponding to one of the test environments. The workspace consists of two large windows, the entrance door and a wardrobe as shown in Figure 5.3. Analogously to the simulation test, four LSs were installed in the corners on the ceiling. The results of experimental and simulation fingerprint maps are shown in Figure 5.7. From the comparison of these two uncertainty maps one can conclude that the analytical method based on the AoA statistical geometrical model matches the AoA uncertainty distribution in an indoor space [IV].
5.3.3 Correction Vector approach

The relevance of the Correction Vector approach was verified by physical experiments for two pairs of LSs. The performance of the AoA-based 3D localization method was verified by comparison to RTLS’s commercial algorithm results treated as a reference.

The verification experiments provided the tags’ location estimates using the AoA-based localization algorithm at 36 spatial reference location samples in the test environment represented by a lecture hall with a size of 11.0 m × 10.0 m × 7.0 m for two AB and AD LS pairs. The average offset error of x, y and z components and the resultant average offset error of the location system in the tested environment were found using (5.5) and (5.6). The correction effect was justified by comparison of the new estimated localizations with the reference RTLS’s localization results. The reference results were obtained using the commercial hybrid algorithm provided by Ubisense, which estimated the tag’s location based on TDoA measurements from four LSs [60].

The cumulative distribution functions of the average offset errors of the AoA-based localization method before and after correction, along with the reference method results for all considered spatial location samples, are presented in Figure 5.8. The presented distribution functions proved that the correction vector reduces the average offset error.
5.3.4 NN structure customization approach

The proposed heuristic approach is validated based on a series of simulations where various NN architectures are tested for different environmental conditions. Then the approach was verified experimentally.

To analyse an effect of NN customization on a localization performance, different NN structures and various training methods were implemented in a Matlab model and then simulated. Simulations have been performed in different indoor operating environments representing a medium size room without obstacles and a large living space with many obstacles. Simulations were carried out for each training method and each combination of NN structural features. The localization coordinates were estimated from contaminated RSS. Since the heuristic model was based on experimental results, all readers’ propagation characteristics were included in the model. The used radio wave propagation characteristics depicted environmental interferences and noise, which affect quality of the transmitted signal. Each simulation applied a Log-Distance Path Loss model, defined in [I], as the radio wave propagation model.
The results of the best customized NN system for each training method for one test environment, were verified by comparison with data from the physical experiment using four RFID readers located in all ceiling corners of the cuboid. The experiment was performed for 20 randomly selected positions of the target tag.

The results of simulations and experiments prove that NN structural features and training methods strongly influence the system’s accuracy and precision. From the results one can see that the experimental system performed worse than the simulated one, especially in terms of accuracy. Also, the number of neurons especially in the hidden layer can cause a big difference in the system’s accuracy and precision, and therefore needs to be closely considered with the customization.
6 Summary

6.1 Overview of the Papers

In this chapter, the five papers included in the thesis are summarised. Each paper consists of a description of the research objectives and used methods with main contributions. Moreover, validation and verification methods are presented and their results are discussed. Generally, all the papers concern RTLS customization methods, both analytical and heuristic, aimed for system’s performance improvement. But each method presented in the papers deepen different aspects of RTLS, which are system’s architecture, measurement methods or estimation methods.

6.1.1 Paper I - Performance Analysis of an RFID-based 3D Indoor Positioning System Combining Scene Analysis and Neural Network Methods

Paper I refers to the quality problem of the RTLS in an indoor heterogeneous and contaminated environment. To enhance the system’s performance, a hybrid solution consisting of the fingerprinting-based estimation method called Scene Analysis combined with NN is proposed. The suggested SA-NN system is designed, implemented and examined. The solution aims on enhancement of system robustness and localization accuracy of RSS measurements affected by environmental interferences.

The objective of this paper was to propose the RFID-based RTLS, which would improve the performance in terms of accuracy of the target’s localization in a 3D indoor space compared with previously reported fingerprinting techniques. Apart from the new hybrid localization algorithm, the Log-Distance Path Loss Model was proposed for modelling the RSS based distance measurement in strongly contaminated indoor environments.
To prove the research hypotheses, the simulation model and the physical experiment stand were designed and implemented, then the dedicated tests were carried out. The test results were compared to the results of widely used solutions. The LDPLM based simulation results along with these of physical experiments validates that the proposed positioning system improves the localization accuracy of an RFID tag compared with previously reported Scene Analysis-based solutions.

The proposed hybrid SA-NN system established a fundament for our further research concerning customization methods of indoor RTLS working in strongly contaminated environments.

6.1.2 Paper II - Hybrid Scene Analysis-Neural Network System for 3D Indoor Positioning

The research presented in Paper II refers to the readers’ arrangement, which affects the RTLS performance. Readers’ deployment modelling and heuristic analysis were required to make system customization possible in terms of a trade-off between the performance and costs. The customization of the RTLS for the defined indoor environment, leads to an optimal readers arrangement in RFID based 3D RTLS.

The aim of this research was to customize the RTLS to the settled indoor environment in terms of an optimal number and configuration of readers. The RFID based 3D RTLS developed in [I] was used as a case study. The heuristic analysis of all possible arrangements for a different number of readers determined the minimal number of sensors and their optimal deployment for a desired localization accuracy.

In this publication, the customization is done heuristically based on an investigation of virtual and real systems to find out which solution is the most suitable for desired localization accuracy and costs. The presented analysis results show that the RFID-based RTLS, consisting of four active readers mounted in the ceiling corners provides the optimal cost-effective solution.

6.1.3 Paper III - Performance Improvement of NN Based RTLS by Customization of NN Structure – Heuristic Approach

This paper aims on performance improvement of the hybrid SA-NN indoor localization algorithm applied on RTLS introduced in [I]. This paper proposes a new way to customize the SA-NN estimation algorithm for different environmental conditions. The localization quality is enhanced by adjustment of NN structural features and training methods applying a heuristic approach.
The objective of this paper was to find out how the NN-based estimation algorithm can be adjusted to improve its localization performance in terms of accuracy and precision. It was assumed that system performance could be improved by customization of NN structural features such as the number of neurons, a type of transfer function in the hidden layer and a type of transfer function in output layer and training methods.

To prove the research hypothesis, efficiency of the proposed customization was validated by different simulations where various NN structural features and training methods were tested for different environmental conditions. Then, the approach was verified by physical experiments. Both simulation and experimental results were analysed to customize NN structural features and training methods for a settled indoor environment.

The results of simulations and experiments prove that NN structural features and training methods strongly influence system’s performance in different test environments and therefore need to be closely considered with the customization.

6.1.4 Paper IV - Using the Fingerprinting Method to Customize RTLS Based on the AoA Ranging Technique

This research paper deals with a performance enhancement of AoA-based RTLS operating with UWB technology. It was shown how the localization uncertainty depends on the arrangement of Location Sensors and on the workspace geometry. Moreover, a new statistical uncertainty model mapping the localization uncertainty, in terms of precision and accuracy in the 2D workspace, was defined and then applied to customize the indoor RTLS.

The main objectives of this paper were to develop an analytical method to customize RTLSs, in order to improve the localization performance in terms of precision. The proposed method is based on the AoA ranging technique and fingerprinting method along with an analytically defined uncertainty model applied to the localization uncertainty fingerprinting map. The presented solution includes the following crucial concerns: geometry of the indoor space, RTLS arrangement, and a statistical approach to localization precision of location using an AoA signal.

The implemented solution of the fingerprinting technique was validated by a set of simulations using different scenarios for varying test environments. Estimations of the localization uncertainty distribution of the workspace for each pair of LSs were analysed. Customization of RTLS based on the fingerprint method was also verified by physical experiments performed in the workspace corresponding to one of the simulated environments.
The simulation and physical experiment results were in line with each other, which confirms that the analytically established fingerprint map is a valid representation of RTLS’ performance in terms of precision. Therefore, the proposed analytical uncertainty model is a suitable tool to customize RTLS. Furthermore, the research shows an effect of the workspace geometry and workspace layout onto the RTLS’ performance.

6.1.5 Paper V - Customization of UWB 3D-RTLS Based on the New Uncertainty Model of the AoA Ranging Technique

This paper deals with the RTLS performance enhancement applying the measurement analytical model to facilitate customization of the AoA ranging technique in varying 3D environments. The model extends and enhances the uncertainty model proposed in Paper IV. The implemented RTLS customization method was facilitated by defined and implemented correction vectors adjusted to the working environment, which improve the system’s performance in terms of its accuracy.

The research focuses on the new geometrical (analytical) uncertainty model of AoA localization in a 3D indoor space, which comprises the two performance measures of accuracy and precision. The purpose of model was to customize the system configuration by defining and implementing the correction vectors for varying working environment to improve the system’s performance in terms of its accuracy. Additionally, the angular-based 3D localization algorithm estimating the tag’s position in 3D from azimuth and elevation angle measures, is introduced.

The proposed model was validated and verified by simulated and experimental results. The advantages of the method were verified by comparing them with a reference commercial RTLS localization engine.

The research confirms that the analytical uncertainty model is the valid representation of RTLS’ localization uncertainty, in terms of accuracy and precision, and can be used for system customization. The simulation results in a 3D indoor space show how the localization uncertainty, in terms of precision, depends on the LS’s configuration in the workspace. Moreover, the research proves that the correction vector can be used to reduce localization offset error caused by variety of the system’s architecture and calibration process, and by the tags’ and working environments’ heterogeneity. The enhanced performance of AoA-based UWB-based RTLS challenges the performance of the reference hybrid TDoA methods supported by AoA technology. Whereas, the proposed method excels above the reference in terms of simplicity and price.
6.2 Conclusions

The presented thesis focuses on RTLSs and their methodological customization in the specific indoor environment. The proposed algorithmic customization approaches consist of subsequent methodological analysis for application and technological requirements to synthesize a customized solution.

The thesis proves that the system customization by methodological selection, adjustment and adaptation enhances the location system’s performance in terms of accuracy, precision and method simplification. The proposed methodological customizations applying the user-centred design method, intends to dynamically adapt and/or adjust the system to meet the functional and non-functional requirements in the changeable environment. The customization enhances RTLS solutions by applying software and hardware methods and tools, which may be either heuristic or analytical.

One of RTLS customization methods concerns localization algorithms, usually consisting of ranging techniques and estimation methods. The proposed localization algorithm-based customization is carried out by implementation of fingerprinting techniques based on common RSS measurements or more advanced AoA-based measurements. In both techniques, for both 2D and 3D cases, the RSS-based and AoA-based ranging techniques have been modelled and implemented.

The customization method using the AoA-based ranging technique concerning a fingerprinting technique is based on an analytically defined uncertainty model, which is used to map the localization uncertainty in terms of precision in the workspace. The analytically established fingerprint map shapes the RTLS’ performance and facilitates a customized solution, which increases localization performance in terms of precision.

RTLSs performance improvement method, deals with the localization algorithm based on AoA ranging technique with an extrapolation method which determines the localization estimate. Such system is customized by applying the correction vectors defined for a specific working environment. The proposed correction vector method significantly enhances the system’s performance in terms of its accuracy. The correction vector reduces localization offset error caused inter alia by heterogeneity of the system’s architecture, uncertainty of the calibration process, and changeable indoor environments.

The RTLS, based on NN estimation methods is customized by adjustment of the NN technique to improve its localization performance. The NN configuration represented by structural features such as the number of neurons, type of transfer
functions and training methods is customized heuristically, which improves system performance in terms of accuracy and precision.

The RTLS customization is also realized in the hardware domain understood as RTLS architecture. Readers Planning Optimization is applied to heuristically optimize a number and configuration of readers in a way, which compromises localization performance and the system’s cost.

The RTLS customization requires definition of localization uncertainty models. The proposed new statistical uncertainty model for the fingerprinting localization method in 2D meets the requirements. The proposed model, which defines the localization uncertainty of the AoA in terms of precision within the workspace, has been extended to a 3D indoor space.

All presented customization methods are generic and can be conveyed onto other applications and localization systems in various wireless technologies. However, the design process needs to be carried out according to the design approach consisting of methodological analysis and customized solution synthesis.

6.3 Future Research

A technological revolution in wireless technologies, sensing devices and computing leads to a paradigm shift in customization of products and services. Human individualism can be enhanced by tool individualization, not just in aesthetics aspects, possible in the past. Now we like to use tools and products designed and developed according to our desire and individual needs and tastes. Such future is possible in the near future [61], [62].

The advancement in technologies along with high availability and reduced cost of new technologies establishes new standards in modern engineering, such as Internet of Things, Machine Learning or Cloud Computing. Thanks to that, the increased technological capabilities along with availability of scientific results, especially in the engineering field, result in competitiveness of technological solutions offered by technological companies. Furthermore, by customization the high-tech solutions are adaptable to customer or application requirements and conditions. However, systematic and methodological way to customize a solution for the client needs to be developed. A user driven design approach is a possible tool to solve the problem.

One of the major research challenges in the thesis field of wireless indoor localization is modelling of radio wave propagation. Further development of universal or quasi-universal models reflecting the problem of radio wave propagation in an indoor space is still desirable. A reliable analytical model of radio
wave physics in the indoor space would enhance a design of indoor positioning for RSS-based localization systems.

The current state of the art indicates that the future research in indoor and outdoor RTLSs aims in improvement of system quality by developing new localization algorithms, implementing AI techniques, adaptation of predictive algorithms and creating hybrid solutions of various wireless techniques. I believe that such solutions would be applied inter alia in safety and logistics applications. Customization aimed for performance enhancement in the key zones of an indoor environment is particularly important for safety applications like kindergartens or monitoring of solitary and elderly people. Future research may also concern customization of localization systems to logistics applications and would be used to enhance warehouse operations and monitoring of asset flow by precise tracking.

Furthermore, prediction of human movement, activity and behaviour is one of the research challenges in the nearest future. Wireless localization systems, integrated data sources about users and finally prediction models and algorithms are future fields of researchers’ interests. These interests cover pattern recognition, classification methods and development of new AI methods.

Customization is a wide subject based on modern engineering, and becomes a popular approach in various applications. Emerging software solutions, web services and increased customer requirements enable web-services customization of web-based IT solutions. It becomes a standard approach to an extension or modification of software features to fit the user’s desire. The largest Internet based companies, such as Amazon, Google, Facebook, LinkedIn etc. acquire information about their users to customize the offered content. We will soon experience the fully customized Internet!

Another potential sector, where customization may play a key role is education. It is a matter of time until students will compose their own study plan in order to develop their preferable skills and gain knowledge not in a custom and classical scope, but individually, in a tailored way. Based on the data about student’s abilities and skills, AI algorithms can customize the study programs to increase education efficiency [63], [61], [64].

There are other possible application fields where customization will play a crucial role such as material engineering, nanotechnology, computer science, etc. which cannot be neglected.

Customization in relation to human kind is called personalization. Personalized medicine, for example is very active area of development [65]. It allows segmentation of large populations into groups based on their own characteristics, including genetic information, sex, age, and personal habits.
Targeted therapy for small groups of people or even individuals increases the treatment effectiveness. Therefore, personalized medicine research deals with the development of decision support systems and predictive diagnostics aimed for the tailored treatment [66].

This approach in medicine is strongly based on genetic analysis and profiling, which can be a next research milestone. Due to possibilities offered by genetic engineering already proven in agriculture and livestock, genetic customization may be also applied in future medicine. Genetic engineering, i.e. editing and customization, is a hot topic in modern science. However, society’s knowledge, awareness and levels of religiosity influence the public's views on genetic engineering. In this case, ethics plays a crucial role. Yuval Noah Harari wrote that, “the next big project of humankind will be to acquire for us the divine powers of creation and destruction, and upgrade Homo sapiens into Homo deus” [61].
References


Performance Analysis of an RFID-based 3D Indoor Positioning System Combining Scene Analysis and Neural Network Methods

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Performance Analysis of an RFID-Based 3D Indoor Positioning System Combining Scene Analysis and Neural Network Methods

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Abstract

The main purpose of this research is to improve localization accuracy of an active Radio Frequency Identification, RFID tag, in 3D indoor space. The paper presents a new RFID based 3D Indoor Positioning System which shows performance improvement. The proposed positioning system combines two methods: the Scene Analysis technique and Artificial Neural Network. The results of both simulation using Log-Distance Path Loss Model and physical experiments validate that the proposed positioning system improves the localization accuracy of an RFID tag compared with well-known Scene Analysis technique solutions.

Keywords: Indoor Positioning System; Neural Network; Radio Frequency Identification; Scene Analysis.
1. Introduction

For many years, short range wireless technologies have been used in various industrial and home applications including Indoor Positioning System (IPS) used to localize or track objects or people inside buildings. Many solutions have been based on Radio Frequency IDentification (RFID) technology. However, most of the RFID-based IPSs do not satisfy the target localization reliability and accuracy in 3D space. A design of robust and accurate system for 3D target localization is needful.

Scene Analysis (SA) which is one of fingerprinting techniques [1], [2] is based on comparison of actual measurements of Received Signal Strength (RSS) or Time of Arrival (ToA) with a pattern called a radio map, which is a set of measurements performed beforehand with tags placed at the points of given coordinates. Nevertheless, RFID transmitters and receivers which are able to measure ToA need to be precisely synchronized, which makes this application relatively expensive. Besides the fact that the RSS measurements are exposed to indoor environment interferences, this type of measurement is commonly used.

This paper proposes a new hybrid IPS combining SA with Artificial Neural Network (ANN). The hybrid system using RSS measurements affected by interferences in an indoor environment, may improve robustness and accuracy of target localization.

The presented results of simulations and physical experiments confirm the considerable advantages of the proposed solution compared with other reported solutions.

2. Survey of related works

Nowadays, indoor localization systems based on WIFI, Bluetooth, ultrasound, infrared or RFID standards are widely used [3] for the following purposes such as tracking [4], smart packaging [5], automated parking [6], [7] or biomedical monitoring [8], [9]. Especially due to its advantages, the RFID technology using different algorithms has been widely applied for target localization [4], [6], [7], [10].

Common algorithms used for 3D positioning in an indoor environment are triangulation and SA methods [3]. They apply RSS or ToA for distance
measurement [11]. The widespread proximity algorithm is used for 2D positioning in robotics and tracking applications [4].

One of the popular SA-based techniques of target localization is the RADAR method, which is a deterministic approach, and in addition to signal strength, uses a radio propagation model [12]. The Horus method applying a probabilistic technique, exploits the correlation among the collected RSS measurements to improve localization accuracy [13].

In [14], Miao et al. propose a hybrid Genetic Algorithm–Back Propagation Neural Network (GA-BP NN), algorithm for 2D RFID-based indoor positioning. Their results confirm that using the ANN can reduce problems caused by complexity and variation in the radio signal propagation in an indoor environment.

It was shown that the integration of the fingerprinting algorithm with Neural Network can enhance localization accuracy in an indoor environment [15]. The authors propose the ANN based pattern matching algorithm to estimate the positioning error, which is used to adjust primarily computed target coordinates.

3. Problem statement and main contribution

From the review of related works one can observe that RFID systems based on triangulation or SA techniques are used to localize a target in a 3D space. Taking into consideration the fact that triangulation has some drawbacks, e.g. missing an intersection, the alternative SA method may be worth further development. Applying the Scene Analysis can improve a target localization when the used RSS measurements are contaminated by indoor environment interferences.

Considering the stated performance problem of 3D IPS, the well-founded research inquiry leads to a question if the localization quality can be improved by a RFID system using the algorithm combining the Scene Analysis technique with Artificial Neural Network?

It seems to be justifiable to hypothesize that using a positioning system based on the RFID Scene Analysis technique combined with the Artificial Neural Network, improves accuracy of the 3D target localization in an indoor environment compared with reported Scene Analysis algorithms.

The main contribution of this paper is modelling of the RFID system combining the Scene Analysis with the NN technique and then implementing the model in Matlab to verify its performance. To validate the simulated results, the
physical system is used and suitable experiments are performed. Furthermore, the proposed system performance is referred to performance of reported solutions.

4. Modelling

A radio propagation model which defines the signal path loss in an indoor environment, is needed to model a virtual positioning system. The SA-NN IPS is modelled and analysed using a suitable block diagram.

4.1. Radio wave propagation model

The Friis transmission equation is useful to represent radio waves propagation between RFID readers and tags. In case of free space, the received signal power for a given transmitter-receiver distance \( d \) is defined by the Friis Free Space Propagation Model as:

\[
P_r(d) = \frac{P_t(d)}{L} \left( \frac{\lambda}{4\pi d} \right)^2
\]

where \( P_r, P_t \) represent the received power and the transmit power, respectively. \( G_r, G_t \) refer to a gain of the received antenna and transmitted antenna, respectively, \( \lambda \) is the wavelength, \( d \) is the distance between receiver and transmitter and \( L \) depicts the system losses.

For an isotropic antennas in (1) \( G_r=G_t=L=1 \), thus the path loss \( A \) defined as a dB ratio can be expressed by:

\[
A(d) = 10\log \left( \frac{P_r(d)}{P_t(d)} \right) = 20\log \left( \frac{\lambda}{4\pi d} \right)
\]

A surrounding environment, interferences and noise affect the quality of the used RSS. Therefore, the widely used Log-Distance Path Loss Model, LDPLM, defines a mean signal loss over an indoor distance \( d \) as [16]:
\[ PL(d) = A(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_\delta, \]  

where \( PL(d) \) is a path loss at transmitter-receiver distance \( d \), \( A(d_0) \) refers to the path loss (2) for reference distance \( d_0 \), \( n \) represents a propagation factor which for a free space environment equals \( n=2 \). The inferences are represented by \( X_\delta \), which depicts a log-normal Additive White Gaussian Noise, AWGN, a random variable with zero mean and standard deviation \( \sigma \).

### 4.2 Positioning system model

The system consists of a set of \( N \) RFID readers located in reference points and a tag in a specified position. The tag position is defined by a vector of tag’s RSSs received by the readers, where RSS depends on the distance between the tag and a reader.

The principle of the RFID based Scene Analysis technique is a comparison of the actual RSS measure with RSS pattern called also RSS map [1], [2]. The proposed model is divided into two stages: offline and online. During the first, offline stage, the map is established from RSSs measurements at points of given 3D coordinates. The map precision is limited by a number of points and by interferences of RSS measurements caused by the indoor environment. During the second, estimation online stage, the identified target coordinates are found by referring the actual RSS measurements to the previously created map.

The SA paradigm is similar to the ANN principle and therefore a possible hybrid SA-NN solution may gain from advantages of both methods. The block diagram of the proposed hybrid positioning system is shown in Fig. 1. The system algorithm begins with the offline phase, when RSS map and NN structure are established. Firstly, tag’s RSSs at \( k \) different known points are measured by each of \( N \) readers. A set of the sampling points creates a sampling grid in an indoor environment. The measurements create RSS sampling matrix \( \text{RSS}_s \) of the size \( k \times N \). The sampling matrix \( \text{RSS}_s \) along with a matrix of \( k \) corresponding tag’s coordinates \( (x_{si}, y_{si}, z_{si}) \), create the database called \( \text{RSS Map} \). The composed RSS Map is used as an input data of ANN training process determining the appropriate values of NN weights and biases.
The online estimation phase begins with measurements of $N$ RSS values of an identified tag placed at unknown position $(x_t, y_t, z_t)$. The RSS measurements from all $N$ readers create matrix $\text{RSS}_t$ which is used in the estimation process resulting in the estimate of target tag coordinates $(x_e, y_e, z_e)$.

5. Solution implementation

The implemented model includes software and hardware parts. The system consists of eight readers located in a test cubic room of the size $5.13 \times 4.50 \times 2$ m presented in Fig. 2.

![Block diagram SA-NN positioning system.](image)

Fig. 1. Block diagram SA-NN positioning system.
5.1 Software implementation

The proposed positioning system is implemented in MATLAB. The ANN system consists of three layers: the input layer, the hidden layer and the output layer. The input layer includes eight inputs corresponding to tag’s RSS received by each reader. The size of the second hidden layer was determined empirically by starting from a small number of neurons, gradually increasing up to the number of 23, at which the network performance did not show improvement anymore. The network output layer includes three neurons corresponding to the estimated tag’s 3D positioning coordinates. Activation functions used in the hidden layer are hyperbolic tangent sigmoid functions. Moreover, the linear function is used in the output layer.

Fig. 2. Room model with placement of readers and a tag.

The Neural Network training process is based on the back propagation function. To determine the best back propagation method, various functions were examined and the function that updates weight and bias values was chosen accordingly to the gradient descent momentum and adaptive learning rate. Mean Square Error, MSE, was used as the best performance function.
5.2 Hardware implementation

The tested real positioning system consists of eight RFID readers connected to a PC and one active tag. The Wavetrend L-RX-900 with AN100 linear polarized whip antenna served as a reader. The active tag was L-TG 501. The system carrier frequency was 433.92 MHz. The tag was mounted vertically to the tripod with adjustable height. All readers were arranged based on the heuristic knowledge.

5.3 Model integrity

The hardware implementation process began with the formation of a Received Signal Strength Indicator, RSSI map. The RSSI is a numeric parameter defined by the manufacturer, which indicates the power of a signal and is commonly used as a signal strength parameter in RFID or WIFI receivers [14]. However, the used RFID equipment does not provide a direct relationship between the relative RSSI and the corresponding absolute power of a signal. Since the virtual IPS model is based on RSS expressed in dBm, therefore the comparison of simulation and physical experiment performance uses different SA maps, which nevertheless does not limit the analysis generality.

6. Validation

The validation of the proposed solution is based on the comparison of the simulation results with the results from the physical system measurement. Moreover, performance of both the virtual and physical systems is collated with data from other reported Scene Analysis applications.

6.1 Physical experiment results

Our validation was performed in the cubic room of the size 5.13 m × 4.5 m × 2 m. The eight readers were installed in room corners, as presented in Fig. 2.

The offline learning phase of the experiment started with the placement of target tag at coordinates (0.5, 0.5, 0.5) m. The room was sampled with a 0.5 m step.
in all directions, and ended up at the coordinate (4.5, 4, 1.5) m, which resulted in 216 sample *RSSI Map*, used in SA-NN training process.

![Physical Experiment Uncertainty Distribution](image)

**Fig. 3.** Histogram of tag position estimation uncertainty of physical experiment.

The online estimation phase was performed for 20 randomly selected positions of the target tag. The uncertainty histogram of estimated positioning shown in Fig. 3, allows us to conclude about its normal distribution. The results presented in Table 1 indicate that the mean positioning uncertainty of hybrid SA-NN IPS system is 5.0 cm and the standard deviation is 20 cm.

### 6.2 Virtual experiment results

In all simulations, we used the value of propagation factor $n=2.79$. The standard deviation $\sigma=2.7$ of the log-normal AWGN $X_\delta$ (3) was applied in the virtual experiment offline phase. The used values are based on measurements reported in [16] for a similar indoor environment.

Our tested virtual system was based on the LDPLM (3) used to create a virtual RSS Map based on a grid of 0.5 m mesh with 550 samples.

The virtual experiment was performed for randomly generated 100 tag positions using the same LDPLM (3). To examine system robustness to noise, the simulations were performed for three AWGN levels with zero mean value and variance of $\sigma_1=1.7$, $\sigma_2=2.7$ and $\sigma_3=3.7$. The uncertainty histograms of estimated
virtual positioning shown in Fig. 4, allows us to conclude about their normal distribution. The simulation results shown in Table 1 indicate that the system’s mean positioning uncertainty is within the range of 2.8 cm for the lowest noise level up to 7.3 cm for the noisiest case. The standard deviation is quite consistent in the range between 20 cm and 23 cm.

![Simulation Experiment Uncertainty Distribution](image)

**Fig. 4.** Histogram of tag position estimation uncertainty from simulation.

### 6.3 Result analysis

To uniquely judge the quality of our solution, we apply the detection efficiency factor, treated as a ratio of a number of target localized with accuracy better than required 1 m to a number of all measures. The results presented in Table 1 show that the simulation localization efficiency varies just a little, between 86% and 90%. Then, the physical experiment detection rate is just slightly worse at the level of 85%.

The applied various levels of AWGN corresponding to different types of environment, are used to verify, if the assumed value of standard deviation $\sigma$ for log-normal random variable $X_\delta$ (3) is appropriate for the tested physical experiment. The figures in Table 1 show that results from simulations with the primarily assumed standard deviation $\sigma=2.7$ match the physical experiment results. For this noise level, the mean uncertainties are 3.3 cm and 5.0 cm for virtual and real experiments respectively, and standard deviation of 21 cm and 20 cm for simulation and physical experiment, respectively.
From the results in Table 1, we can also judge that the proposed system is robust for increasing noise level. Both the standard deviation of the position estimate uncertainty and the efficiency, almost do not change with an increasing noise level. It indicates high precision of the measurement method.

<table>
<thead>
<tr>
<th>SNR (simulations)</th>
<th>Mean uncertainty [cm]</th>
<th>STD [cm]</th>
<th>Efficiency</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$x$</td>
<td>$y$</td>
<td>$z$</td>
</tr>
<tr>
<td>$\sigma = 1.7$</td>
<td>-0.2</td>
<td>2.5</td>
<td>-1.3</td>
</tr>
<tr>
<td>$\sigma = 2.7$</td>
<td>-2.9</td>
<td>1.4</td>
<td>0.8</td>
</tr>
<tr>
<td>$\sigma = 3.7$</td>
<td>-5.0</td>
<td>4.0</td>
<td>3.0</td>
</tr>
<tr>
<td>Experiment</td>
<td>-1.6</td>
<td>-4.7</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 1. Experimental results of virtual and physical systems performance.

To further verify our proposal we compared its performance with reported results from other Scene Analysis applications, see Table 2. The Horus system designed for detection on the whole floor of the building, achieves positioning uncertainty of about 42 cm with standard deviation of 28 cm [13]. For similar detection area, as for Horus, the RADAR method average uncertainty was 400 cm with standard deviation of 326 cm [12]. Both, Horus and RADAR methods concern 2D positioning using the WLAN standard. Another RFID based Scene Analysis technique of 2D target localization is a method based on GA-BP Neural Network [14]. Its reported distance mean uncertainty was 8.1 cm with standard deviation of 210 cm. As compared to these reported results, the proposed SA-NN method designed for 3D single room localization, achieves the distance estimation mean uncertainty of 5.0 cm and standard deviation of 20 cm and shows the best positioning accuracy.

<table>
<thead>
<tr>
<th>Method</th>
<th>Technology</th>
<th>Area</th>
<th>Mean [cm]</th>
<th>STD [cm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>SA-NN</td>
<td>RFID</td>
<td>3D room</td>
<td>5.0</td>
<td>21</td>
</tr>
<tr>
<td>Horus</td>
<td>WLAN</td>
<td>2D floor</td>
<td>42</td>
<td>28</td>
</tr>
<tr>
<td>RADAR</td>
<td>WLAN</td>
<td>2D floor</td>
<td>400</td>
<td>326</td>
</tr>
<tr>
<td>GA-BP</td>
<td>RFID</td>
<td>2D room</td>
<td>8.1</td>
<td>210</td>
</tr>
</tbody>
</table>

Table 2. Performance comparison of different Scene Analysis applications.
7. Conclusion

The aim of this paper was to prove that a combination of Scene Analysis with NN technique improves performance of target indoor localization compared with other fingerprinting techniques. To confirm this, the simulation model and the physical experiment stand were designed, implemented and suitable tests were carried out in the indoor environment. The obtained results show that for a physical experiment, the mean of positioning uncertainty was 5.0 cm with standard deviation of 20 cm. Whereas, the accuracy achieved from virtual experiments was 3.3 cm with standard deviation of 21 cm.

The experimental results summarized in Table 1 also show that the standard deviation $\sigma=2.7$ of AWGN used in the LDPLM, matches the noise standard deviation level used for indoor applications. Moreover, the validation experiment proves that the LDPLM is a suitable representation of radio wave propagation phenomena useful for modeling RSS based distance measurement. The estimated system’s offset vector can be introduced to the system to correct the result and increase the positioning accuracy.

The performance of the proposed virtual and physical systems was collated with data from others reported positioning systems applying SA approach. The result analysis confirms the advantage of the proposed method over the others SA based solutions.

Further research on the Scene Analysis technique may concern ToA-based distance measurement. However, this approach would need a consideration of trade off between a cost and accuracy.

Complementary research may concern improvement of RSS map by optimizing a sampling procedure. The optimized sampling step should increase an accuracy of target tag positioning.
References


Analiza Systemu Lokalizacji 3D w Pomieszczeniu Opartego na Technologii RFID i Łączącego Metodę Analizy Sceny ze Sztucznymi Sieciami Neuronowymi

Głównym celem tej pracy badawczej jest poprawa dokładności systemu lokalizacji 3D w przestrzeni zamkniętej, aktywnego identyfikatora RFID. Proponowany system lokalizacji stanowi hybrydę dwóch metod: Analizy Sceny oraz Sztucznych Sieci Neuronowych. W pracy tej przedstawiono model proponowanego rozwiązania, a w celu walidacji systemu wykonano badania symulacyjne modelu komputerowego wykorzystującego m.in. Logarytmiczny Model Propagacji Fali Radiowych. Przeprowadzono również badania na modelu rzeczywistym w pomieszczeniu zamkniętym o rozmiarach geometrycznych 5,13 m×4,50 m×2 m, które potwierdziły poprawność wybranego parametru propagacji sygnału radiowego. Uzyskane wyniki potwierdzają a, że proponowany system lokalizacji 3D, charakteryzuje się wysoką dokładnością pozycjonowania aktywnego identyfikatora RFID. Uzyskana dokładność pozycjonowania, jest lepsza niż 0,5 m. Badania potwierdzają założoną hipotezę, że proponowany system lokalizacji 3D w przestrzeni zamkniętej charakteryzuje się lepszą dokładnością niż znane rozwiązania oparte na technice Analizy Sceny.

**Słowa kluczowe:** Analiza Sceny; Identyfikacja Radiowa; System Pozycjonowania Wewnątrz Pomieszczeń; Sztuczne Sieci Neuronowe.
Hybrid Scene Analysis-Neural Network System for 3D Indoor Positioning
Optimal System Arrangement Approach

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RFID - Hybrid Scene Analysis-Neural Network System for 3D Indoor Positioning Optimal System Arrangement Approach

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Abstract

The purpose of this research is to find an optimal number and configuration of readers in RFID based 3D Indoor Positioning System. The system applies a Hybrid Scene Analysis - Neural Network algorithm to estimate target’s position with a desired accuracy. The system’s accuracy and cost depend on a number of utilized readers and their arrangement. Readers’ deployment is crucial for the localization accuracy too. The system optimization enhances the system cost-efficiency. The arrangement analysis was based on simulations and validated by physical experiment. The results of this research define a trade-off between a number of readers and their deployment and the system performance in terms of localization accuracy.

Keywords: Optimization; Radio Frequency Identification; Reader Configuration; RFID Network Planning.
1. Introduction

An effective localization and tracking of an object or person in a 3D indoor space can be carried out using a short range wireless technology called Radio Frequency IDentification, RFID. Systems based on this technology are widely used in healthcare facilities [1], [2], hospitals [3] and kindergartens [4]. Such systems can be used for emergency monitoring of tumble detections of solitary people [5]. RFID systems are also used for tracking and recognition of products and goods in warehouses [6], [7] or markets [8]. Localization accuracy is a crucial issue in all these applications.

Many algorithms and techniques are applied in RFID positioning systems. One of them is Scene Analysis, SA, technique, which is a type of RFID fingerprinting technique [9], [10]. It is based on comparison of actual measurements of the tag’s Received Signal Strength, RSS, or Time of Arrival, ToA, with a pattern called a radio map. This map is created from a set of measurements performed beforehand, with tags placed at points of given coordinates. To improve 3D indoor target localization, SA technique can be combined with Neural Network, NN [11]. The analysis of this solution considered a case of eight readers located in specified coordinates of an indoor space. The estimated system accuracy of about 26 cm proved advantages and usefulness of the solution for many applications.

This research is solving a Readers Planning Optimization, RPO, problem by searching for an optimal configuration of the RFID Scene Analysis - Neural Network, SA-NN, 3D indoor positioning system. To be cost-efficient, the system should assure a desired 3D localization quality for a minimal number of readers. The results of simulation and physical experiment analysis show how the localization accuracy depends not only on the number of readers, but also on their deployment.

2. Survey of Related Works

Sensor deployment optimization methods can refer to different localization and tracking systems using a variety of sensor types. Chen et al. propose a method for planning the position of multiple stereo sensors in an indoor space [12]. The solution, based on a combination of a greedy algorithm and a linear programming
model, minimizes the number of vision sensors needed to cover the target object in an indoor environment.

In the cases of acoustic systems, the optimal placement of sensors can be found by means of the probabilistic analysis [13]. The proposed algorithm optimally displaces the sensor to maximize detection probability.

There have been researchers who aimed to determine how localization quality depends on the RFID readers’ configuration. In [14] authors propose an optimal reader configuration for system localization performance by dividing an indoor space into several independent zones characterized by a sensing rate parameter.

Artificial intelligence methods and different algorithms are commonly used for the optimal reader deployment in a 3D indoor space. In [1], [15], [16] the main research objective was to develop a maximal covering optimization method for placement of a limited number of RFID readers. The approach based on Genetic Algorithms, determines the optimal placement of readers on the whole healthcare facility floor [1]. The Particle Swarm Optimization, PSO, methods are also suitable for RPO problems due to their high efficiency, fast convergence and strong robustness. In [15] Gong et al. used the PSO methods with a tentative reader elimination operator, to solve a RPO problem. In [16] multi-swarm PSO, which is an extended version of a typical PSO solver, was presented for a 2D RFID networking planning problem.

3. Problem statement and the proposed solution method

The results of the previous work [11] show that the RFID 3D indoor localization system, based on multiple readers and a hybrid SA-NN algorithm is able to estimate a target’s position with a desired accuracy. However, the system cost-efficiency depends on its configuration, i.e. a number of readers, antennas, wiring etc. Therefore, it has become crucial to define how the system performance depends on its configuration. Moreover, since the readers’ arrangement affects the system performance, further analysis is required to find a trade-off between the performance quality and costs.

The cost of the system can be minimized by reducing the number of required readers. The analysis of all possible arrangements for a different number of readers can clearly determine their optimal deployment. It provides a minimal number of readers for a desired localization accuracy.
In the case of RFID based 3D Indoor Positioning System, the SA-NN algorithm compares actual RSS or ToA measurements with RSS/ToA patterns, also called RSS/ToA map. The applied NN structure consists of three layers. The first one, an input layer, includes a number of inputs corresponding to active readers. The size of the second hidden layer is set to 23 neurons. The third output layer of network includes three neurons corresponding to the estimated tag’s 3D positioning coordinates. Activation functions used in the hidden layer are hyperbolic tangent sigmoid functions. Moreover, the linear function is used in the output layer. The Neural Network training process is based on the back propagation function, which updates weight and bias values according to the gradient descent momentum and adaptive learning rate. MSE is used as the best performance function [11]. The SA-NN model using RSS was validated by the comparison of the simulation results with the results obtained from the measurements. Eight RFID readers located in all corners of the cuboidal area of dimensions 5.13 m × 4.5 m × 2 m were used in the experiments. The virtual results matched the physical experiment results [11].

In this research the analysis performed using the same system in the same area 5.13 m × 4.5 m × 2 m as in [11]. The room model with possible readers’ deployment in the room corners is presented in Fig. 1. The six test cases correspond to three, four, five, six, seven and eight active readers respectively. Numbers of possible different deployment configurations for each test case are shown in Table I. Due to geometrical features of the room and radio wave propagation properties, the configurations can be grouped into a number of equivalent scenarios. For example, in the test case with four active readers, the configurations (A B A’ B’) and (C D C’ D’) are classified as a single scenario.

![Fig. 1 Room model with readers’ deployment.](image)
In this paper we apply a heuristic method based on an investigation of virtual and real systems to find out which cases and which scenarios are the most suitable for a desired localization accuracy and cost. To examine how system configuration affects the localization accuracy, simulations using Matlab are performed. Furthermore, a real system is examined. The results of simulations and measurement are compared to confirm the findings. The method covers three main approaches. The first approach deals with performance analysis of test cases. The following approach evaluates performances of possible scenarios. And the last approach searches for a cost-effective solution.

The average localization accuracy in each configuration is defined by coordinate mean values of estimation uncertainty calculated as:

\[
\bar{d}_x = \frac{1}{J \cdot I} \sum_{j=1}^{J} \sum_{i=1}^{I} (x_{j,i} - \tilde{x}_{j,i}),
\]

(1)

\[
\bar{d}_y = \frac{1}{J \cdot I} \sum_{j=1}^{J} \sum_{i=1}^{I} (y_{j,i} - \tilde{y}_{j,i}),
\]

(2)

\[
\bar{d}_z = \frac{1}{J \cdot I} \sum_{j=1}^{J} \sum_{i=1}^{I} (z_{j,i} - \tilde{z}_{j,i}),
\]

(3)

where \(J\) is the number of test sets, \(I\) is the number of tested tags coordinates, \(x_{ij}, y_{ij},\) and \(z_{ij}\) are coordinates of each \(ij\) tag position, refer to estimated tag’s coordinates, represent uncertainty mean values in \(x,y,z\) axes respectively.
Table 1. Numbers of configurations and scenarios of readers’ Deployment for each test case.

<table>
<thead>
<tr>
<th>Test case - Number of active readers</th>
<th>Number of configuration scenarios</th>
</tr>
</thead>
<tbody>
<tr>
<td>3</td>
<td>56</td>
</tr>
<tr>
<td>4</td>
<td>70</td>
</tr>
<tr>
<td>5</td>
<td>56</td>
</tr>
<tr>
<td>6</td>
<td>28</td>
</tr>
<tr>
<td>7</td>
<td>8</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
</tr>
</tbody>
</table>

To evaluate the performance for each scenario, mean value and respective standard deviation were calculated as follows:

\[
\bar{d} = \sqrt{\bar{d}_x^2 + \bar{d}_y^2 + \bar{d}_z^2}.
\]  

(4)

To evaluate localization quality by means of simulation, for each test case and for each reader configuration, 100 different sets containing 100 uniformly and uniquely distributed tags’ coordinates were simulated.

The experiment on a real system was carried out in a cuboidal room of the same dimensions as the virtual room equipped with basic office furniture. To evaluate localization quality, the experiment was performed for 20 randomly selected positions of the target tag. To reduce interferences during the real experiment only one person was present in the room.

4. Approach 1 – analysis based on number of active reader - test cases

In this approach we investigate performance of each test case under the conditions described in the previous section. The simulation and measurement results are used to find the cases with best localization quality.
A. Simulation Results

Simulation results presented in Fig. 2 show mean uncertainty and standard deviation of the estimated tags’ localization. The results indicate a significant correlation between a number of active readers and estimated localization accuracy. The results show that for the SA-NN system using seven active RFID readers, the average localization uncertainty is 0.5 cm with standard deviation of 50.0 cm, when the next best accuracy for eight readers is characterized by uncertainty mean value of 7.0 cm and standard deviation is equal to 50.0 cm.

![Mean detection uncertainty with standard deviations](image.png)

Fig. 2 Simulation results of mean localization uncertainty of test cases with different numbers of active readers.

Simulation results of test cases from three up to seven active readers follow the expectation that with a higher number of active readers, localization accuracy would be better. However, the results for the test case with eight active readers show slightly less accuracy than the results for the test case with seven active readers.
B. Experimental Results

In this approach average localization uncertainty and its standard deviation are measured for the three test cases: fourth, sixth and eighth. Table II shows the results of the best scenarios of test cases six and eight. To show differences in the fourth test case the table presents results of scenario 1, 11 and 12 with best, respectively medium and worst performances.

Table 2 Experimental results of localization uncertainty for five scenarios.

<table>
<thead>
<tr>
<th>Number of active readers</th>
<th>Scenario</th>
<th>Uncertainty</th>
<th>Configuration sample</th>
<th>Number of possible configurations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean [m]</td>
<td>STD [m]</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>1</td>
<td>0.22</td>
<td>0.54</td>
<td>A B A’ B’</td>
</tr>
<tr>
<td>4</td>
<td>11</td>
<td>0.25</td>
<td>0.59</td>
<td>A B C D’</td>
</tr>
<tr>
<td>4</td>
<td>12</td>
<td>0.30</td>
<td>0.64</td>
<td>A C B’ D’</td>
</tr>
<tr>
<td>6</td>
<td>1</td>
<td>0.27</td>
<td>0.55</td>
<td>A B C A’ B’ C’</td>
</tr>
<tr>
<td>8</td>
<td>1</td>
<td>0.24</td>
<td>0.49</td>
<td>A B C D A’ B’ C’ D’</td>
</tr>
</tbody>
</table>

The experimental results show a correlation between a number of active readers and estimated localization accuracy. The performance results of the SA-NN system using eight active readers achieved mean localization uncertainty of 24.2 cm with a standard deviation of 48.9 cm. The next best performance for the best scenario when four active readers is characterized by an uncertainty of 22.0 cm and a standard deviation of 54.3 cm. The data in Table II indicates that for the test case with eight active readers, localization accuracy is slightly better than the test case with four active readers. The presented results also show that in the case of the best scenario with six active readers, the mean localization uncertainty is 27.2 cm with standard deviation of 55.4 cm, which is worse than for the best scenario for four active readers.
C. Discussion

The results presented in the preceding sections confirm a correlation between a number of active readers and estimated localization accuracy. Fig. 3 presents a relationship between mean localization uncertainty and a number of used RFID readers for the best scenarios of the three chosen test cases: eight, six and four active readers. Experiment and simulation results for four and eight active readers differ slightly. However, in the case of eight readers, the experimental results show better localization uncertainty than for four readers, but the difference is less than 4.5%.

![Mean detection uncertainty with standard deviations](image)

Fig. 3 Simulation results of mean localization uncertainty of test cases with different numbers of active readers.

5. Approach 2 – analysis of different scenarios

In this approach we investigate the performance of different scenarios. The issue is to compare performances of different scenarios within one test case. But also comparison of the best performing scenarios of different test cases is an issue. The simulation and measurement results are used to find the scenario with the best localization quality.
A. Simulation Results

Table III presents mean localization uncertainty and its standard deviation, for each possible scenario when four RFID readers are active. These results show significant differences in localization accuracy between individual scenarios.

Table 3. Simulation results of localization uncertainty for all scenarios of the test case with four active readers.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Uncertainty</th>
<th>Configuration sample</th>
<th>Number of possible configurations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean [m]</td>
<td>STD [m]</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.11</td>
<td>0.49</td>
<td>A B A’ B’</td>
</tr>
<tr>
<td>2</td>
<td>0.15</td>
<td>0.63</td>
<td>B C C’ D’</td>
</tr>
<tr>
<td>3</td>
<td>0.16</td>
<td>0.62</td>
<td>C B’ C’ D’</td>
</tr>
<tr>
<td>4</td>
<td>0.16</td>
<td>0.64</td>
<td>C A’ C’ D’</td>
</tr>
<tr>
<td>5</td>
<td>0.17</td>
<td>0.58</td>
<td>A C C’ D’</td>
</tr>
<tr>
<td>6</td>
<td>0.18</td>
<td>0.71</td>
<td>B C B’ C’</td>
</tr>
<tr>
<td>7</td>
<td>0.16</td>
<td>0.61</td>
<td>B C A’ C’</td>
</tr>
<tr>
<td>8</td>
<td>0.17</td>
<td>0.62</td>
<td>A B C C’</td>
</tr>
<tr>
<td>9</td>
<td>0.12</td>
<td>0.54</td>
<td>A C A’ C’</td>
</tr>
<tr>
<td>10</td>
<td>0.20</td>
<td>0.60</td>
<td>B C A’ D’</td>
</tr>
<tr>
<td>11</td>
<td>0.16</td>
<td>0.59</td>
<td>A B C D’</td>
</tr>
<tr>
<td>12</td>
<td>0.26</td>
<td>0.62</td>
<td>A C B’ D’</td>
</tr>
<tr>
<td>13</td>
<td>0.19</td>
<td>0.88</td>
<td>A B C D</td>
</tr>
<tr>
<td>14</td>
<td>0.15</td>
<td>0.60</td>
<td>C D A’ B’</td>
</tr>
</tbody>
</table>

These differences are also observed between best scenarios of different test cases. Some best scenarios with fewer readers can show better localization accuracy then scenarios with more readers. For instance from Fig. 4 and Fig. 5 we can see that the best scenario in the case of four active readers is better than the best scenario when five RFID readers are present.
Fig. 4 Simulation results of mean uncertainty for all scenarios of test case with four active readers: in order from lowest to biggest mean uncertainty.

Table IV shows mean localization uncertainty and its standard deviation for the best scenario in each test case. The lowest mean uncertainty is obtained for the case when all eight readers are active. However, considering the standard deviation, the best results are obtained for the scenario with four active readers. The mean values of localization uncertainties for four and eight active readers are: 11.0 cm and 10.0 cm respectively with standard deviation of 49.0 cm and 51.0 cm respectively. Furthermore, the analysis shows that differences in mean uncertainty among the best scenarios of test cases with eight, seven, and four active readers do not exceed 3%.
B. Experimental Results

In this approach we investigate the average localization accuracy of three scenarios when four RFID readers are active. To discover variations of the three scenarios: 1, 11 and 12 are tested. Results presented in Table II show mean localization uncertainty and its standard deviation for the examined scenarios.

Table 4. Simulation results of localization uncertainty for the best scenario of each simulation test case.

<table>
<thead>
<tr>
<th>Number of active readers</th>
<th>Uncertainty</th>
<th>Configuration sample</th>
<th>Number of possible configurations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean [m]</td>
<td>STD [m]</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>0.15</td>
<td>0.66</td>
<td>C D B’</td>
</tr>
<tr>
<td>4</td>
<td>0.11</td>
<td>0.49</td>
<td>A B A’ B’</td>
</tr>
<tr>
<td>5</td>
<td>0.13</td>
<td>0.54</td>
<td>A B A’ B’ C’</td>
</tr>
<tr>
<td>6</td>
<td>0.12</td>
<td>0.54</td>
<td>A B C A’ B’ C’</td>
</tr>
<tr>
<td>7</td>
<td>0.12</td>
<td>0.49</td>
<td>A B D A’ B’ C’ D’</td>
</tr>
<tr>
<td>8</td>
<td>0.10</td>
<td>0.51</td>
<td>A B C D A’ B’ C’ D’</td>
</tr>
</tbody>
</table>
The best mean localization uncertainty is achieved for the scenario one when all four readers are mounted either on the ceiling (A B A’ B’) or near the floor (C D C’ D’). In this scenario the real mean localization uncertainty is 22.0 cm with standard deviation of 54.3 cm.

The second examined scenario 11 with a sample deployment (D A’ B’ C’), when three tags are placed in the corners of the shorter wall and fourth tag is on the opposite wall, is characterized by mean localization uncertainty of 24.6 cm and standard deviation of 58.7 cm.

The last tested scenario 12 with a sample deployment (B D A’ C’), when tags are placed diagonally of the examined room, mean localization uncertainty was 22.9 cm with 64.1 cm standard deviation. Those results are consistent with the simulation results.

C. Discussion

The results presented in preceding sections confirm that there is also a strong correlation between the arrangement of used RFID readers and localization accuracy. Results from Fig. 6 confirm that the experimental results follow the relationship among different scenarios’ performances from the simulations. There is a clear correlation between virtual and physical experiments’ results for four active RFID readers. The best, medium, and worst localization accuracies of examined scenarios in simulation and physical experiment correspond to each other.

![Mean uncertainty for 4 active readers](image.png)

Fig. 6 Simulation and experimental results of mean uncertainty for three scenario of test case with four active readers.
6. Approach 3 – cost-effectiveness analysis

The RPO problem refers not only to system complexity and localization accuracy, but also to the system cost. The aim of the cost-effective solution is to localize the target in a 3D indoor space with maximum accuracy using a minimal number of readers. Therefore, additional analysis is needed to define a trade-off between the cost of the system and its performance quality [1], [15].

The simulation results shown in Section V show that the test case when four RFID readers in their optimized scenario assures better accuracy compared to a more expensive eight active reader solution. Considering the three best scenarios for test cases with four, eight, and seven active readers, localization accuracy differs only by about 3%. However, the system cost for eight and four active readers varies significantly, and differences can reach 40% in favour of four readers. Then, substantial savings, without compromising the system localization accuracy, can be reached by applying four readers arranged in (A B A' B') or (C D C' D').

The experimental results presented in Section V show that using SA-NN algorithm, the best mean localization uncertainty, is achieved for the case when all four RFID readers are placed either near the ceiling or floor corners. However, considering the standard deviation, the best results are observed for the test case with eight active readers. The localization accuracy with four and eight active readers differs only by about 4%, but the cost concerning a system with four active readers can be 40% smaller than a system with eight readers. Then, we can conclude that the system with four readers placed either near the ceiling (A B A' B') or near the floor (C D C' D') is the most suitable solution.

The presented analysis leads to the conclusion that both simulation and experimental results prove that the system consisting of four active readers, mounted near the ceiling (A B A' B'), or near the floor (C D C' D'), provides the optimal solution to a given problem.
7. Conclusion

The aim of the paper was to discover the most suitable arrangement of the RFID based 3D Indoor Positioning System. For this purpose we applied a heuristic method using the SA-NN model tested under various conditions. The result of this research defines an optimal number of RFID readers and their arrangement for a cost-effective solution.

To achieve the research goal three approaches were investigated. In Approach 1 we investigated performance of all test cases corresponding to a different number of readers under the desired conditions. In Approach 2 we examined the performance of different scenarios within various test cases. The aim of Approach 3 was to find the cost-effective solution assuring best accuracy using a minimal number of readers.

All three approaches were based on the analysis of performances of virtual and real RFID based 3D Indoor Positioning Systems. The simulations and measurements were performed in the same area of size 5.13 m × 4.5 m × 2 m. The six test cases correspond to the various numbers of active readers implemented, from three to eight. Due to geometrical features of the room and radio wave propagation properties, readers’ placements in each test case were grouped into a number of equivalent scenarios.

The simulation results indicate a significant correlation between a number of active readers and localization performances in the cases with three to seven active readers. While the localization accuracy for the SA-NN positioning system using seven active RFID readers was better, even when compared to the configuration using eight readers. The average localization uncertainty for seven readers was 0.5 cm with a standard deviation of 50.0 cm, whereas, for the eight readers solution, the respective results were 7.0 cm and 50.0 cm. However, good localization accuracy was obtained while optimally placing four readers, resulting with an uncertainty of 11.0 cm mean value and 49.0 cm standard deviation. The experimental results verified a significant correlation between a number of active readers and localization performance. The best localization accuracy is for eight active readers; however, the localization accuracy for four active readers was only lower by 4.5%.

Our research on the performance of the SA-NN localization system shows crucial meaning of readers’ arrangement. For instance, the smallest localization uncertainty including mean value and standard deviation was obtained while using four readers arranged in the way that readers are placed in (A B A’B’) or
(C D C’ D’) position, with a mean value of 11.0 cm and 49.0 cm standard deviation. The experimental results verified this however with worse uncertainty of 22.0 cm with a standard deviation of 54.3 cm.

Research results show that the difference in localization accuracy among the best scenarios, when eight, seven or four readers are active, does not exceed 3% in case of simulation. For the experimental results the difference between the two best scenarios with four and eight active readers, do not exceed 4.5%. However, costs associated with the equipment can by 40% lower in case of four active readers than of eight readers. This leads to the conclusion that the solution with four active readers located in ceiling corners is the most cost-effective.

The additional advantage of the arrangement of readers on the ceiling (A B A’ B’) is its user-friendliness. Moreover, all readers located in this way are more robust and avoid obstacles that would most likely occur if positioned on the floor.

Further research may concern the development of SA-NN technique applying a Real Time Location System, enabling ToA measurements. Complementary research may concern the application of another artificial intelligence method with SA technique, i.e. swarm intelligence or fuzzy rules, and compare it with SA-NN results.

References


Performance Improvement of NN Based RTLS by
Customization of NN Structure – Heuristic
Approach

Authors:
Bartosz Jachimczyk, Damian Dziak and Wlodek Kulesza

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Auckland, December, 2015

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Dziak, Wlodek Kulesza „Performance Improvement of NN Based RTLS by
Customization of NN Structure – Heuristic Approach,”, The 9th International
Performance Improvement of NN Based RTLS by Customization of NN Structure – Heuristic Approach

Bartosz Jachimczyk, Damian Dziak and Wlodek J. Kulesza

Abstract

The purpose of this research is to improve performance of the Hybrid Scene Analysis – Neural Network indoor localization algorithm applied in Real-time Locating System, RTLS. A properly customized structure of Neural Network and training algorithms for specific operating environment will enhance the system’s performance in terms of localization accuracy and precision. Due to nonlinearity and model complexity, a heuristic analysis is suitable to evaluate NN performance for different environmental conditions. Efficiency of the proposed customization of a Neural Network is verified by simulations and validated by physical experiments. This research also concerns the influence of size of Neural Network training set. The results prove that, better localization accuracy is with a NN system which is properly customized with respect to a training method, number of neurons and type of transfer function in the hidden layer and also type of transfer function in the output layer.

Keywords: accuracy and precision; indoor localization; neural network architecture; optimization; real-time locating system; RFID; RSS; scene analysis.
1. Introduction

Effective and rapid localization and tracking of an object or person in a 3D indoor space can be carried out using, Real-time Locating Systems, RTLSs. These may operate on various technologies like Radio Frequency IDentification, RFID, Ultra-Wideband, UWB, ultrasound or optical techniques.

RTLSs based on radiofrequency technology are widely used in real-time applications in healthcare e.g. for patients monitoring, for tracking and recognition of products and goods in warehouses or markets and in many other facilities [1], [2], [3]. In all these the high quality of localization is required.

Many algorithms and techniques are applied in RFID based indoor positioning. One of them is the Scene Analysis, SA, which is a type of fingerprinting technique [4], [5]. It is based on comparison of actual measurements of the tag’s Received Signal Strength, RSS, Time of Arrival, ToA, or Angle of Arrival, AoA, with a pattern called a radio map. This map is created from a set of measurements performed beforehand, with tags placed at points of given coordinates. To improve 3D indoor localization, the SA technique can be combined with a Neural Network, NN [6]. The estimated system accuracy of about 22 cm with a standard deviation of 54.3 cm proves its usefulness for different applications [7].

Artificial Neural Networks are computational models commonly used in structurally and computationally complex applications [8]. Due to the models’ generalization properties and real-time operation ability they have gained popularity in many areas e.g. financial [9], electrical, control and biomedical engineering [10], [11], as well as in wireless indoor localization systems using radio wave propagation models, which are characterized by a high non-linearity [6].

Because of relatively big influence of environmental conditions such as room size and of the radio wave propagation model there is a need to customize each RTLS for its operating environment. This research concerns the customization of the NN algorithm architecture used in a RFID Scene Analysis - Neural Network system, SA-NN applied to 3D indoor positioning. Evaluating the system performance for different NN architecture in different environments is analytically inconvenient. This is why a heuristic analysis of influence of NN structures and training methods needs to be carried out.

The results of simulations and physical experiments showed how to customize both, NN structural features and training method. They proved that
2. Survey of related works

Artificial NNs techniques are widely applied in wireless localization systems. Because of generalization properties, the NN structure complements fingerprinting based real-time localization techniques. In [12] Xu and Sun propose a Neural Network-based Accuracy Enhancement localization method for Wireless Local Area Networks, WLANs. For real-time RSS data, the NN system calculates positioning errors by nonlinear data mapping. In [13] an underground radio localization system based on UWB technique is proposed. In a geolocation algorithm the NN technique is applied with the real-time fingerprinting method.

Various localization techniques based on probabilistic and stochastic NNs are combined with different sensor networks. In [14] the localization algorithm based on Discriminant-Adaptive Neural Network is used to identify and localize objects in WLAN environment.

It has been proven that traditional locating solutions are less accurate in case of RSS because of a nonlinear relationship between the RSS and a target’s position [12]. Thus, the appropriate NN structure ensures more adequate interpretation of measurements. Chen, Yin, Chen, and Hwang present an indoor localization system with a Modified Probabilistic Neural Network operating in ZigBee network [15]. The system is designed to estimate an object’s position with distorted RSS. The results show superiority of the proposed method over traditional triangulation technique.

To ensure an accurate real-time localization using combination of NN and fingerprinting technique, the type and structure of NN need to be chosen properly. The role and importance of NN architecture in UWB localization system are presented [13]. For different scenarios, approximation capabilities are tested for Generalized Regression Neural Network, GRNN, and Multilayer Perceptron, MLP. In [16] the different types of NNs are evaluated under various conditions. The authors determine the most reliable and accurate type of NN architecture among: Nonlinear Autoregressive Network with eXogenous, Feed Forward Time-Delay Neural Network and Layer-Reccurrent Network.

The structure analysis and performance evaluation of NN is carried out in [17], where the authors applied Radial Basis Function Neural Network using RFID signal strengths to estimate locations of objects. The architecture of a NN is
selected to minimize the Localized Generalization Error. To improve the localization accuracy virtual reference tags are adopted.

3. Problem statement and objectives

The results of previous work [7] show that the RFID 3D indoor localization system, based on multiple readers and a hybrid SA-NN algorithm is able to estimate a target’s position with an accuracy of about 11 cm and a precision of 49 cm, where the accuracy and precision correspond to mean value uncertainty and its variance respectively and which will be defined in more details in the following section. It is also proven that the system performance in terms of accuracy and precision, and cost-efficiency among others depends on sensors’ deployment and configuration, i.e. on the number and placement of readers. The heuristic analysis proves that a solution with four active readers located in the ceiling corners is the most cost-effective arrangement [7]. However, further performance improvement of the SA-NN localization algorithm can be achieved by customizing the NN structure features and its training method. Furthermore, due to model nonlinearity and complexity it can be assumed that a heuristic analysis is a suitable method to customize NN for different environmental conditions.

The before mentioned problem and assumptions lead to the objective of the paper, which is to find out how the NN based indoor localization system can be adjusted to improve its localization performance. We assume that system performance can be improved by customization of NN structural features such as the number of neurons and type of transfer function in hidden layer and a type of transfer function in output layer of SA-NN localization algorithm can be achieved by customizing the NN structure features and its training method. This can be done using heuristic analysis based on simulation and experimental results.

The main contribution of the paper can be summarized as:

I. Performing different Matlab-based simulation scenarios to examine how training methods and NN structural features, such as the number of neurons and type of transfer function in hidden layer and a type of transfer function in output layer of SA-NN affect the localization accuracy.

II. Performing physical experiments to validate simulation results.

III. Heuristically analysing the simulation and experimental results to customize NN structural features and training methods to optimize locating system performance.
4. Indoor positioning system structure and performance

A. Indoor Positioning System

The proposed 3D indoor positioning system is based on the RFID technology and fingerprinting method. The system consists of four RFID readers located in ceiling corners of a cuboid and an active tag indicating target position. All receivers send requests and receive the tag’s response. Response data are processed by the positioning algorithm based on a fingerprinting technique called Scene Analysis, which applies generalization properties of NN to estimate the tag’s position [6].

B. Scene Analysis - Neural Network Algorithm

The hybrid SA-NN algorithm performs in two stages. During the first, an offline stage, the radio map is established from RSSs measurements at given points of 3D coordinates. During the second, an estimation online stage, the identified target coordinates are found by referring the actual RSS measurements to the previously created map.

In the estimation stage of the algorithm, the NN is used for approximation purposes. We apply the NN structure consisting of three layers, since for most of the fitting applications, a structure with just one hidden layer is sufficient. The first layer, the input layer, includes a number of inputs corresponding to the number of active readers. The second layer, the hidden layer consists of a varying number of neurons. The third one is an output layer of the network consisting of three neurons corresponding to the tag’s 3D positioning coordinates. During the training process of NN, the Mean Squared Error, MSE, is applied as the training criterion.

C. Adjustable Structural Features and Training Methods of Neural Network

Some NN structural features can be customized to improve the system performance in a given working environment. In this paper we consider the size and type of transfer function of hidden layer, and the transfer function of output layer as adjustable structural features of NN. The considerable size of a hidden layer varies from 5 to 50 neurons. Each of evaluated NN structure with one hidden layer, contains a combination of two transfer functions from the following set of possible transfer functions of hidden and output layers:
In order to find the most suitable training method for the feedforward SA-NN based system, we analyse three back-propagation methods. The first training method is called Gradient Descent Backpropagation, GDB, which calculates the gradient of a loss function for all weights in the NN layers. The second training technique considered is the Lavenberg-Marquardt Backpropagation method, LMB, which is an optimization algorithm that provides a solution to the least squares curve-fitting problem. The third method is the Variable Learning Rate Backpropagation algorithm, VLR, which makes the training process stable.

**D. Localization System Performance**

The performance quality of the proposed SA-NN localization system can be evaluated using two measures, system accuracy and precision [18]. Mean localization uncertainty is the measure of the system’s accuracy and when it is high the mean localization uncertainty is low and vice versa. The accuracy property expresses the system’s capability to obtain the true value of measurand [18]. The mean uncertainty component $\Delta x$ of the x coordinate estimated for N randomly selected points $P_i(x_i, y_i, z_i)$ from the test area, can be expressed as:

$$\bar{\Delta x} = \frac{1}{N} \sum_{i=1}^{N} (\hat{x}_i - x_i) = \frac{1}{N} \sum_{i=1}^{N} \Delta x_i,$$  \hspace{1cm} (1)

where $P_i(x_i, y_i, z_i)$ refers to true localization coordinates at i-th position of the tag, $\hat{P}_i(\hat{x}_i, \hat{y}_i, \hat{z}_i)$ refers to the mean of M-th times measured localization coordinates at i-th position of the tag, and $\Delta x_i$ is the localization uncertainty of x coordinate at i-th position.

If the remaining two mean uncertainty components $\bar{\Delta y}$, and $\bar{\Delta z}$, of y and z coordinates respectively can be specified analogically to (1), then based on the set of selected positions, the system localization uncertainty $\bar{\Delta}$ can be calculated as follows:
The second measure, localization system’s precision is used for system performance evaluation. It describes the measurements repeatability and is based on an estimate of mean standard error $\overline{\sigma}$ of mean localization uncertainty. A low value of standard error means high precision and vice versa. For the set of $N$ randomly selected positions of the tag which are estimated from $M$ measurements each, a mean standard error $\overline{\sigma}_x$ of component $x$, can be expressed in relation to variance as:

$$\overline{\sigma}_x = \frac{1}{N} \sum_{i=1}^{N} \overline{\sigma}_{x_i} = \frac{1}{N} \sum_{i=1}^{N} \sqrt{\frac{\sigma_{x_i}^2}{M'}},$$

(3)

where $\overline{\sigma}_{x_i}$ and $\sigma_{x_i}^2$ are the standard error and variance respectively of $x$ component at $i$-th tag’s position. Mean standard error components $\overline{\sigma}_y$, $\overline{\sigma}_z$ of $y$ and $z$ coordinates respectively can be described analogically. The corresponding mean system standard error $\overline{\sigma}$ of localization estimate can be calculated as follows:

$$\overline{\sigma} = \sqrt{\overline{\sigma}_x^2 + \overline{\sigma}_y^2 + \overline{\sigma}_z^2}.$$

(4)

The simplified 2D interpretation of the accuracy and precision measured for $i$-th position is presented in Fig. 1.
5. Effects of NN architecture, training methods and size of training set

Since NN is the core of the SA-NN algorithm, then to improve a system’s performance its structure and training method have to be adjusted to the operating environment. Because of a lack of analytical methods for customizing NN structures, a heuristic approach is a solution. In this paper, the heuristic analysis is carried out based on a series of simulations where various NN architectures are tested in different environmental conditions. The simulation results and corresponding customized structures of SA-NN are validated experimentally.

A. Effect of NN Structural Features and Training Method

1) Performance Evaluation

To analyse effect of NN customization on a localization performance, different NN structures and a various training methods are implemented and simulated in Matlab. Simulations are carried out in such a way that for each training method (GDB, LMB and VLR) and each combination of NN structural features (a number of neurons and type of transfer function of hidden layer, and a type of transfer function of output layer) the localization coordinates are estimated from contaminated RSS. To reduce radio interferences each input data representing specified position was established as mean value of 100 RSS samples. Performance
of the SA-NN is evaluated for two pairs of sets of training and test data. Each pair of data corresponds to one scenario of the system operating environments.

Two test scenarios representing different indoor operating environments have been defined and examined. Table I shows the sizes of the applied indoor space and corresponding radio wave propagation characteristics. The test environment A is related to a medium size room without obstacles. The test environment B considers a large living space with many obstacles. Both test environments represent Line of Sight scenarios according to [19], [20].

Table I. Test environment size and radio propagation characteristics.

<table>
<thead>
<tr>
<th>Environmental scenario</th>
<th>Environment parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Size [m×m×m]</td>
</tr>
<tr>
<td>Test environment A</td>
<td>5.13 × 4.5 × 2.5</td>
</tr>
<tr>
<td>Test environment B</td>
<td>15 × 6 × 2.5</td>
</tr>
<tr>
<td></td>
<td>Path Loss Exponent</td>
</tr>
<tr>
<td></td>
<td>2.7</td>
</tr>
<tr>
<td></td>
<td>6</td>
</tr>
</tbody>
</table>

Since the heuristic modelling is based on real measurements, all readers’ propagation characteristics are included in the model. Used radio waves propagation characteristics depict environmental interferences and noise, which affect the quality of transmission. Each simulation applies a Log-Distance Path Loss model as the radio wave propagation model. Mean signal loss over an indoor distance \( d \) between readers and tags in the specified environment is described as:

\[
PL(d) = A(d_0) + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_δ, \tag{5}
\]

where \( PL(d) \) is a path loss at transmitter-receiver distance \( d \), \( A(d_0) \) refers to the path loss for reference distance \( d_0 \), \( n \) represents a propagation factor. The inferences are represented by \( X_δ \), which depicts a log-normal Additive White Gaussian Noise, AWGN, a random variable with zero mean and standard deviation \( σ \) [6].

A size of NN training sets in the form of RSS map depends on the size of the test room since the virtual area is sampled with a constant step in all directions. Furthermore, in order to evaluate NN performance, 100 random tag positions, out of the training set, are simulated 100 times each, which after averaging are fed to a trained NN for every considered NN structure.

The simulation results presented in Fig. 2, Fig. 3 and Fig. 4 show accuracies and precisions as average values of mean localization uncertainties and their standard errors respectively of the 100 estimated tags’ localizations, for GDB, LMB and VLR training methods respectively and for a varying number of neurons
in the hidden layers from 5 up to 50. The figures show simulation results for the test environment A. The NN structure with more than 50 neurons is not considered because of ascertained deterioration of localization accuracy. With just a few exceptions, the results confirms that system accuracy is better than 10.0 cm and at confidence level of 68.3%, for the most of cases the localization is estimated with uncertainty better than 15.0 cm. However, one can see that a number of neurons plays a crucial rule in system customization and a difference between the best and worst case can be triple.

Table II compares simulation results for the two test operating environments. The best accuracy and precision for customized NN structural features i.e. an output layer transfer function, and a hidden layer transfer function and number of neurons are shown. For both test environments and all training methods, the TAN function is proved to be the optimal transfer function of a hidden layer, which assures the best system performance. For GDB and LMB training methods optimal output layer transfer functions are LIN and SAT, respectively. The optimal output layer transfer function for the VLR training method differs in both test environments and for case A it is SAT while for case B it is LIN. The number of neurons in a hidden layer differs between the training methods and varies from 11 for the VLR training method and 40 for the GDB training method. Among all the VLR training method assures the best results of accuracy 1.2 cm and precision 3.2 cm. For the test operating environment A, the remaining training methods are characterized by slightly worse accuracy of 1.6 cm and 2.4 cm and precision 3.5 cm and 3.4 cm for LMB and GDB respectively.
However, because of more demanding conditions of test operating environment B, the performance results are worse compared to case A. The GDB training method shows the best accuracy of 5.5 cm but slightly worse precision of 7.6 cm compared to VLR training method, which contrariwise depicts worse accuracy. The optimal transfer functions in hidden and output layers are the same as for test operating environment A.
B. Experimental Validation

The simulated SA-NN model using RSS was validated by comparison of its results with measurement data. Four RFID readers located in all ceiling corners of the cuboid of dimensions $5.13 \times 4.50 \times 2.00$ m, the same as in test operating environment A, were used in the experiment. To reduce interferences during the real experiment only one person go to be present in the room. The experiment was performed for 20 randomly selected positions of the target tag, which at each position was sampled 100 times. The results from the best customized NN system for each training method, established by simulation for test environment A, are compared with data from the physical experiment.

<table>
<thead>
<tr>
<th>Test Environment</th>
<th>Training method</th>
<th>System performance</th>
<th></th>
<th></th>
<th>Optimal hidden layer</th>
<th>Optimal output layer</th>
<th>Optimal number of neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Accuracy [cm]</td>
<td>Precision [cm]</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>GDB</td>
<td>1.6</td>
<td>3.5</td>
<td>TAN</td>
<td>LIN</td>
<td>36</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LMB</td>
<td>2.4</td>
<td>3.3</td>
<td>TAN</td>
<td>SAT</td>
<td>11</td>
<td></td>
</tr>
<tr>
<td></td>
<td>VLR</td>
<td>1.2</td>
<td>3.2</td>
<td>TAN</td>
<td>SAT</td>
<td>19</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>GDB</td>
<td>5.1</td>
<td>8.0</td>
<td>TAN</td>
<td>LIN</td>
<td>40</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LMB</td>
<td>7.2</td>
<td>7.7</td>
<td>TAN</td>
<td>SAT</td>
<td>29</td>
<td></td>
</tr>
<tr>
<td></td>
<td>VLR</td>
<td>5.5</td>
<td>7.6</td>
<td>TAN</td>
<td>LIN</td>
<td>35</td>
<td></td>
</tr>
</tbody>
</table>

Experimental results presented in Table III for the same NN structural features as for the simulation in test environment A, indicate that for both cases GDB and VLR show the better localization accuracy and precision than LMB. However in the case of real experiment, the best accuracy of 19.5 cm but a worse precision of 13.3 cm was obtained with the GDB training method. For the VLR training method, the accuracy was slightly worse at 22.6 cm, but precision was better, about 11.0 cm.
Table III. Simulation and Experimental Results of System Performance for Different Training Methods and Test Environment A for the Same NN Structural Features.

<table>
<thead>
<tr>
<th>Training method</th>
<th>System performance</th>
<th>Hidden layer transfer</th>
<th>Output layer transfer function</th>
<th>Number of neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Accuracy [cm]</td>
<td>Precision [cm]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Simulation</td>
<td>GDB</td>
<td>1.6</td>
<td>3.5</td>
<td>TAN</td>
</tr>
<tr>
<td></td>
<td>LMB</td>
<td>2.4</td>
<td>3.4</td>
<td>TAN</td>
</tr>
<tr>
<td></td>
<td>VLR</td>
<td>1.2</td>
<td>3.2</td>
<td>TAN</td>
</tr>
<tr>
<td>Experiment</td>
<td>GDB</td>
<td>19.5</td>
<td>13.3</td>
<td>TAN</td>
</tr>
<tr>
<td></td>
<td>LMB</td>
<td>25.0</td>
<td>15.3</td>
<td>TAN</td>
</tr>
<tr>
<td></td>
<td>VLR</td>
<td>22.6</td>
<td>11.0</td>
<td>TAN</td>
</tr>
</tbody>
</table>

In general, the experimental system performed much worse compared to simulation one especially in case of accuracy. The reason of system performance degradation can be an additive error introduced when the real training set was established.

C. Effect of Size of Neural Network Training Set

Analysing the effect of NN training set size of the RSS Map is the final step of customization of the SA-NN algorithm. The investigation of the influence of the training set size has been done for two different sizes of training sets, where training set $T_{S_{big}}$ was five times bigger than $T_{S_{small}}$. The results are shown in Table IV.

The improvement of localization accuracy for the bigger training set is observed only for the LMB training method. For the remaining training methods one can observe accuracy degradation compared to the smaller training set. However, for all training methods, the bigger training set causes an improvement of localization precision.
Table IV. Simulation Results of System Performance for Optimal NN Structural Features and Different Training Methods and Sizes of Training Sets for Test Environment A

<table>
<thead>
<tr>
<th>Size of training sets (RSS Map)</th>
<th>Training method</th>
<th>System performance</th>
<th>Optimal hidden layer transfer function</th>
<th>Optimal output layer transfer function</th>
<th>Optimal number of neurons</th>
</tr>
</thead>
<tbody>
<tr>
<td>TS\textsubscript{small}</td>
<td>GDB</td>
<td>1.6</td>
<td>3.5</td>
<td>TAN</td>
<td>LIN</td>
</tr>
<tr>
<td></td>
<td>LMB</td>
<td>2.4</td>
<td>3.3</td>
<td>TAN</td>
<td>SAT</td>
</tr>
<tr>
<td></td>
<td>VLR</td>
<td>1.2</td>
<td>3.2</td>
<td>TAN</td>
<td>SAT</td>
</tr>
<tr>
<td>TS\textsubscript{big}</td>
<td>GDB</td>
<td>2.8</td>
<td>3.1</td>
<td>SAT</td>
<td>LIN</td>
</tr>
<tr>
<td></td>
<td>LMB</td>
<td>1.7</td>
<td>3.2</td>
<td>TAN</td>
<td>SAT</td>
</tr>
<tr>
<td></td>
<td>VLR</td>
<td>2.8</td>
<td>3.0</td>
<td>TAN</td>
<td>SAT</td>
</tr>
</tbody>
</table>

6. Conclusion

The aim of this research was to find how the customization of the SA-NN algorithm affects its performance in terms of localization accuracy and precision. An heuristic analysis was applied to define how the NN structural features in terms of a number of neurons and transfer function in hidden layer and transfer function in output layer, and training methods influence performance of the SA-NN 3D Indoor Positioning System for different operating environments.

The results of simulations and experiments prove that NN structural features and training methods strongly influence system’s accuracy and precision. The difference in accuracy between systems using different training methods is 100% and 41% for test environment A and B respectively, while the precisions remain at the same level. Also the number of neurons in the hidden layer can cause big difference in system’s accuracy and precision and therefore needs to be closely concerned with the customization.

The experimental results from the system, which was customized based on simulation optimization results show the performance depends on structural features and training function. However, the real localization show much worse performance compare to simulation results what can be caused among other by accuracy of training set, what can be improve using some calibration method.
This research has proven that increasing the size of the training set does not necessarily lead to performance improvement. This can be an issue of future work to find a suitable size of training set. A solution of this problem may save time needed to collect training data and then to train the system.

Further research may also concern the development of the SA-NN technique, enabling ToA measurements for a Real-time Location System. Complementary research can deal with the application of another artificial intelligence method together with the SA technique, i.e. swarm intelligence or fuzzy logic. More research on physical experiment concerning influence of NN training sets on SA-NN localization accuracy would be also required.

Objective customization of NN algorithm is another future work proposal. Different techniques can be applied and tested for the purpose.

References


Using the Fingerprinting Method to Customize RTLS Based on the AoA Ranging Technique

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Bartosz Jachimczyk, Damian Dziak and Wlodek Kulesza

Reformatted version of paper originally published in:
Using the Fingerprinting Method to Customize RTLS Based on the AoA Ranging Technique

Bartosz Jachimczyk, Damian Dziak and Wlodek Kulesza

Abstract

Real-time Locating Systems (RTLSs) have the ability to precisely locate the position of things and people in real time. They are needed for security and emergency applications, but also for healthcare and home care appliances. The research aims for developing an analytical method to customize RTLSs, in order to improve localization performance in terms of precision. The proposed method is based on Angle of Arrival (AoA), a ranging technique and fingerprinting method along with an analytically defined uncertainty of AoA, and a localization uncertainty map. The presented solution includes three main concerns: geometry of indoor space, RTLS arrangement, and a statistical approach to localization precision of a pair of location sensors using an AoA signal. An evaluation of the implementation of the customized RTLS validates the analytical model of the fingerprinting map. The results of simulations and physical experiments verify the proposed method. The research confirms that the analytically established fingerprint map is the valid representation of RTLS’ performance in terms of precision. Furthermore, the research demonstrates an impact of workspace geometry and workspace layout onto the RTLS’ performance. Moreover, the studies show how the size and shape of a workspace and the placement of the calibration point affect the fingerprint map. Withal, the performance investigation defines the most effective arrangement of location sensors and its influence on localization precision.

Keywords: accuracy and precision; angle of arrival; calibration point; fingerprinting method; indoor localization systems; uncertainty map; real-time locating systems.
1. Introduction

Emerging wireless technologies increase the potential and effectiveness of wireless Indoor Localization Systems (ILSs). Hence, recently, Real-time Locating Systems (RTLSs), an example of ILS, have gained increasing attention, mostly in the industrial sector, due to their capabilities and performance. RTLSs have the ability to locate the position of an item anywhere in a defined space at a point in time that is, or is close to, real time [1]. As fast-acting ILSs enhance safety, they become highly important in security and emergency systems. Moreover, they are widely used in healthcare facilities [2], [3], social, and home care applications [4] for precisely tracking the movement of people. Besides that, RTLSs are widely applied in assets by tracking management systems in warehouses [5], container terminals [6], and hospitals [3].

Due to the radio wave propagation phenomena caused by environment structures and movements in indoor spaces, many wireless technologies based on Received Signal Strength (RSS) have, in practice, unreliable measurement methods. RSS-based ILSs are also disqualified from security applications, where attackers can influence the signal strength by attenuating or amplifying the signal. The usefulness of time-measurement-based localization systems is also limited because of hardware requirements. The Time of Arrival (ToA) method requires a highly accurate system clock and a precise synchronization module, which increase the system’s cost significantly. Therefore, Angle of Arrival (AoA) based RTLSs seem to be a reliable and cost-friendly solution.

The fingerprinting technique is a pattern-based indoor localization technique useful for characterizing an indoor environment. It is established on matching measurement data with a previously defined pattern for instant and uncertainty pattern characterizing of a specific indoor environment. However, such patterns may take various forms, depending on the pattern nature. In the case of furnished indoor spaces, the pattern concerns structures and the arrangement of objects in the space. For people monitoring, it may include movement and an attendance probability map.

This paper proposes an analytical method for enhancing the performance of indoor RTLSs. The AoA ranging technique and fingerprinting technique, along with an analytical uncertainty analysis, are applied.

An implementation of the proposed customized RTLS method validates the analytical approach to fingerprinting mapping. The presented results of simulation and physical experiments verify the proposed method.
2. Survey of Related Works

RTLSs are usually in the form of radio frequency communication systems. They are able to localize a target in indoor spaces with relatively high accuracy, up to 15 cm for typical Ultra Wideband (UWB)-based ILS. An RTLS’s performance highly depends on the system architecture and configuration, as well as on the localization algorithm and method. Depending on the application and indoor environment character, ILSs may operate based on many different algorithms and the most common are proximity trilateration, angulation, fingerprinting, and dead reckoning. Localization methods producing ranging calculations are related to characteristics of measuring signals, such as RSS, ToA, and AoA [7].

The AoA ranging technique, a versatile method of the RTLS widely used in indoor environment applications, applies direction-sensitive antennae as a location sensors to estimate the direction (the angle) of the signal from a tag [8]. Kim et al. propose an improvement of the AoA-based RTLS on the application of a Dual Indirect Kalman Filter and weight filters, enhancing the estimation of the target’s position [9]. The hybrid algorithm is designed for Non-line-of-sight (NLoS) environments. In [10], the localization algorithm utilizes a biased estimation technique to increase the system performance. Moreover, the authors apply a statistical calibration method to improve the localization quality.

AoA-based localization techniques are also applicable in Wireless Sensor Networks (WSNs). In [11], the authors combine a hybrid AoA with the ToA method for localization purposes in a mobile WSN. The algorithm contains a particle-filtering module combined with an adaptive fuzzy controller. The multihop localization method is proposed by Park et al., who base the AoA ranging method on iterative calculations of mutual distances and relative angles between neighbour nodes [12]. To increase performance of AoA-based WSNs, Y. Wang and K.C. Ho propose an AoA source localization estimator, which handles the sensor position error in WSNs [13].

Localization uncertainty is the crucial parameter of an RTLS’ performance and the key factor limiting the performance in indoor environments. Measurement accuracy of AoA antennas of RTLSs affects the quality of the localization estimation. Therefore, the Dilution of Precision (DoP), the concept originally used in satellite navigation systems, is derived for AoA-based positioning systems to characterize the positioning quality [14]. In [15], the authors show an impact of signal interferences on location accuracy in multipath environments. Cho et al. [6] apply an enhanced trajectory estimation method to estimate the track of mobile equipment with reduced uncertainty applied in container port terminals. The
algorithm consists of “interpolation mechanism used to overcome omitting location estimation” caused by packet loss and an enhanced Kalman filter to correct the estimation error caused by the multi-path effect. Since the RTLS’ performance depends on a type and characteristic of antenna, and also on a type of indoor environment, then the antenna, properly matched to the indoor environment, may significantly improve localization accuracy [16]. The localization accuracy is also increased by optimal placement of the calibration emitter, which was investigated in [17].

To characterize an indoor environment, one can apply a suitable environmental pattern. Spatial AoA patterns may depict interferences caused by environment and localization factors and indicate sensitive areas. In [18], the evolutionary algorithm with the AoA ranging technique is used for selecting sampling points in multi-obstacle environments, and for this purpose the indoor pattern is established. The evolutionary algorithm is used to choose optimal Line-of-sight (LoS) measurement positions. A spatial pattern in the form of a channel impulse response map, which characterizes an indoor environment, is proposed in [19]. The pattern using a single-access point is applied as a database in the real position estimation process.

Fingerprinting is another pattern-based indoor localization technique useful for characterizing an indoor environment. Fingerprinting is based on matching measurement data with a beforehand-established pattern; moreover, a classification algorithm needs to be implemented. In [20], the authors present the WiFi-based RTLS using the fingerprinting algorithm with the K-nearest neighbour method to estimate the unknown location. Also, Artificial Neural Networks are widely applied in fingerprinting ILSs due to their pattern-matching features [21]. To enhance the fingerprinting-based location system in terms of localization accuracy, Kalman filtering has also been proposed [22].

3. Objectives and Main Contribution

In radio wave-based ILSs, interferences in signal propagation influence localization quality, which affects the system performance. Indoor environment specifics are important causes of the interferences. The geometry and structure of an indoor space, furnishing, and other obstacles influence the localization process. Customization of the RTLS’ algorithm concerning the indoor environment may reduce the impact of these interferences and then reduce localization uncertainty. From the review of related works, one can see that customization of the RTLS’ structure can be performed by creating an indoor environment pattern consisting of uncertainty map and sensors deployment. However, an analytical approach to
establishing an uncertainty map that would correspond to the specified indoor environmental pattern is lacking.

The main objective of the paper is to develop an analytical method to customize RTLSs by improving the performance of indoor RTLSs based on the AoA ranging technique. The proposed method applies a fingerprinting technique with the defined uncertainty pattern in the form of an AoA localization uncertainty map. To establish such a map, an analytical method estimating the uncertainty of the AoA is needed. To address this task, a localization-uncertainty estimation method has to be established. The proposed estimation method uses a statistical approach to the AoA precision of a pair of specified location sensors, geometry of indoor space, and RTLS arrangement.

The main contribution of the paper is modelling of the fingerprinting technique. The model consists of ranging techniques and the uncertainty pattern of the AoA. To verify the RTLS model it is implemented in Matlab on indoor test environments. The performance of the models is evaluated and validated by results from physical experiments.

4. Customized RTLS Method Using AoA

The proposed customized RTLS method applies the fingerprinting technique based on the comparison of the measurements with the established pattern. The method is illustrated in block diagram in Figure 1.

First, the offline analytical phase of customization consists of environmental and fingerprint analyses. The environmental analysis applies parametric data, such as shape and size of workspace, deployment of sensors, and location of the calibration tag, etc. The analytical phase is used to define environmental characteristics needed in the further steps. The workspace model is employed for the fingerprint analysis, where an uncertainty map is derived from the ranging technique model and the localization uncertainty distribution model.

Then, the environmental model and uncertainty map are implemented into the online synthesis phase when measured AoA data are processed. The synthesis applies the AoA ranging technique, estimating the relative tag’s positions in relation to all pairs of location sensors. The following estimation algorithm is used to find out the final tag’s position from a set of considered locations and the AoA uncertainty map defined in the fingerprint analysis stage. The method is described in the following sections.
4.1. Ranging Technique Model

The AoA ranging technique, simplified to a 2D azimuth approach, is implemented in both phases of the proposed customization-based method, in an offline analysis to establish the uncertainty map, and in an online synthesis phase to process actual measured AoAs.

The AoA ranging technique is used to establish the tag’s position by estimating distances from the tag’s position to each LS (Localization System) placed in its fixed position. This technique is based on measurements carried out by LSs equipped with antenna array elements able to measure the AoA of radio waves emitted by the tag. Its geometrical interpretation is shown in Figure 2. In our approach, AoAs are angles (in Figure 2, angles $\alpha_A$ and $\alpha_B$) between the line connecting a tag with a given LS, and the calibration line passing through the LS and the calibration point. The calibration point, $O$, is the coordinate system origin established in a calibration procedure. At least two AoA measurements are required to establish the tag’s position in a 2D scenario.

On the basis of the installation data, during the calibration procedure, the workspace geometric shape is defined and the related positions’ coordinates $A(x_A, y_A)$ and $B(x_B, y_B)$, of the LSs are established. Moreover, the calibration
procedure defines the calibration point’s \( O \) coordinates \((x_O, y_O)\) as the origin of the coordinate system. Furthermore, calibration angles \( \varphi_A, \varphi_B \), between the abscissa or horizontal axis and the calibration lines are depicted as:

\[
\varphi_A = \tan^{-1} \frac{y_A - y_0}{x_A - x_0}, \tag{1}
\]

\[
\varphi_B = \tan^{-1} \frac{y_B - y_0}{x_B - x_0}. \tag{2}
\]

Since the coordinates of the LSs of each pair are known, each LS provides measures of AoAs \( \alpha_A, \alpha_B \), which are referred to as primary established calibration lines. The coordinates \((x_i, y_i)\) of the tag position \( \hat{T} \) can be estimated as an intersection of two lines determined by angles of arrival \( \alpha_A, \alpha_B \) to the respective LS [8]. Therefore, the tag position \( \hat{T}(x_i, y_i) \) can be calculated using the following formula [14]:

\[
\begin{bmatrix}
  x_i \\
  y_i
\end{bmatrix}
= \begin{bmatrix}
  \tan(\alpha_A + \varphi_A) & -1 \\
  \tan(\alpha_B + \varphi_B) & -1
\end{bmatrix}^{-1}
\begin{bmatrix}
  x_A \cdot \tan(\alpha_A + \varphi_A) - y_A \\
  x_B \cdot \tan(\alpha_B + \varphi_B) - y_B
\end{bmatrix}
\]

\( \tag{3} \)

Figure 2. Graphical interpretation of the AoA ranging technique.
4.2. Offline Analysis

The offline analytical stage covers two steps: an environmental analysis and a fingerprint analysis. To define the uncertainty map, the indoor environment characteristics, ranging technique, and uncertainty distribution models are applied.

4.2.1. Modelling of Indoor Environment

Performance of an indoor RTLS depends non-exclusively on the system arrangement and the space characteristics. The geometry of space and sensor arrangement affect the performance of the wireless indoor localization, due to interferences and reflections phenomena.

The modelled indoor environment as an RTLS workspace presented in Figure 3 is a 3D rectangular cuboidal indoor space with an aspect ratio of its longer side a to its shorter side b and height c. The coordinate system’s origin \(O(x_0, y_0, z_0)\) corresponds to the calibration point, where the calibration tag was located. The calibration tag needs to be located in the LoS of all LSs, however, the most desirable location is the central area of the workspace.

The optimal deployment of LSs in a 3D indoor positioning system is considered in [23]. The most efficient solution consists of four RTLS location sensors LSA, LSB, LSC, and LSD located in workspace corners \(A(x_A, y_A, z_A)\), \(B(x_B, y_B, z_B)\), \(C(x_C, y_C, z_C)\), and \(D(x_D, y_D, z_D)\), (Figure 3 and Table 1).

![Figure 3. Model of 3D indoor environment.](image-url)
Table 1. Location sensors arrangement.

<table>
<thead>
<tr>
<th>LS</th>
<th>General Coordinates</th>
<th>Specific Coordinates</th>
</tr>
</thead>
<tbody>
<tr>
<td>LSA</td>
<td>$A(x_A, y_A, z_A)$</td>
<td>$A(a/2; b/2; c/2)$</td>
</tr>
<tr>
<td>LSB</td>
<td>$B(x_B, y_B, z_B)$</td>
<td>$B(-a/2; b/2; c/2)$</td>
</tr>
<tr>
<td>LSC</td>
<td>$C(x_C, y_C, z_C)$</td>
<td>$C(-a/2; -b/2; c/2)$</td>
</tr>
<tr>
<td>LSD</td>
<td>$D(x_D, y_D, z_D)$</td>
<td>$D(a/2; b/2; c/2)$</td>
</tr>
</tbody>
</table>

The top view of the modelled indoor environment, presented in Figure 2, is used to illustrate the azimuth AoA, which is an angular measurement projected on the $XY$ plane. The top view considers a workspace for further analysis, where the height dimension $Z$ is neglected.

The workspace can consist of furnishing and other obstacles. Furthermore, the walls usually are heterogeneous and include windows, doors, etc. The materials that are used can also be multifarious. However, all these factors cannot be included in the model in an easy way. Therefore, a heuristic method can help to comprise all these factors into the model and customize it. The fingerprint approach is a possible solution to the problem.

4.2.2. Uncertainty Model

The fingerprint map formation, applied for localization using the ranging technique, is based on the model of the indoor environment and on an uncertainty model, both in the same coordinate system. The exemplary analysis concerns a pair of $LS_A$ and $LS_B$ placed in the fixed positions $A(x_A, y_A)$ and $B(x_B, y_B)$, and the specified tag $T$ at the position $T(x_i, y_i)$, shown in Figure 4. The proposed statistical uncertainty model, defines localization uncertainty in a specified position $T$ on the workspace.

We assume that in each tag’s position on the workspace, there are two corresponding sets of angles represented by matrices $AoA_A$ and $AoA_B$ of $N$ samples of angles of arrival $\alpha_{ai}$ and $\alpha_{bi}$ measured by LSs placed in positions $A$ and $B$, respectively. Based on the ranging technique, those sets define $N$ samples of tag position $T_i$, specified by intersections of lines corresponding to paths of arrival. Based on experimental data, we assume that the distribution functions of
measurement precision and possible interferences of measurement signals are normal. Then, the probability of the single standard deviation of the mean is 68.3%, the angles $\alpha_{Al}$ and $\alpha_{Bl}$ are within the ranges

$$\alpha_{Al} \in (\bar{\alpha}_A - \sigma_A, \bar{\alpha}_A + \sigma_A)$$

and

$$\alpha_{Bl} \in (\bar{\alpha}_B - \sigma_B, \bar{\alpha}_B + \sigma_B),$$

which define the angles of precision (AoP). Mean values $\bar{\alpha}_A$ and $\bar{\alpha}_B$ represent AoA mean values, which are used to calculate the best estimate of the tag’s position $\hat{T}$. Standard deviations of the AoA for both LSA and LSB are represented by $\pm \sigma_A$ and $\pm \sigma_B$, respectively. Thus, the AoA normal distribution of $N$ samples for location sensor LSA is defined as $\mathcal{N}_A(\bar{\alpha}_A, \sigma_A)$.

The distribution function of the intersection of two AoPs (Figure 4) is the multivariate normal distribution as a linear combination of the two normal distributions. The probability that the true value is placed in the common area of these two distributions equals 46.6% as the product of two probabilities of 68.3% corresponding to single standard deviation probability.

The common area of AoPs forms the tetragon of vertices $M_{1-4}$. The area of the tetragon depends on the uncertainty of AoA measurements represented by variances $\sigma_A$ and $\sigma_B$, and on distances $r_A$ and $r_B$ from LSs to the estimated position $\hat{T}$. Then the uncertainty of AoA ranging technique can be estimated in terms of:

I. Surface area of the tetragon, which can be calculated using the Shoelace formula [24],

II. Lengths $d_x$ and $d_y$ (Figure 4) corresponding to maximum uncertainty of $x$ and $y$ components, respectively.

The surface area of the tetragon as an estimated uncertainty is the angular measure of precision analogically to Geometric Dilution of Precision (GDoP), which is a measure of positional measurement precision used in satellite navigation.

The uncertainty of the AoA ranging technique can be described by the angular precision non-exclusively assuming the same distribution in the whole workspace. Due to the physical properties of the LS, the best measurements of the AoA are for small angles, which means for the tag placed centrally or near to the calibration point. Then, it is reasonable to combine two components of uncertainty, one constant and one varying. The constant component corresponds to a basic standard deviation $\pm \sigma_A$ and $\pm \sigma_B$ for LSA and LSB, respectively, and can be derived empirically. The varying component increases linearly with coefficient $t$ depending on the angle of inclination $|\alpha|$ to the calibration axis. Absolute angular
uncertainty $\Delta_A$ of measure the AoA for the location sensor LSA is described by equation:

$$\Delta_A = \sigma_A + t \times |\overline{\alpha_A}|,$$

(4)

where $\sigma_A$ is a standard deviation of the AoA measurement, $\overline{\alpha_A}$ is a mean angle value of the AoA for the location sensor LSA and $t$ is a coefficient of the uncertainty varying component. Clearly, if the coefficient $t$ equals zero, then the case of constant uncertainty component over the whole workspace takes place.

Figure 4. Graphical interpretation of the AoA uncertainty.

In the further analysis, the localization uncertainty is considered as the surface area of the tetragon defined by vertices $M_1 – M_4$ (Figure 4).

**4.2.3. Uncertainty Map**

An uncertainty map may be represented by the fingerprint map within the workspace. For this purpose, for the entire workspace, uncertainties are calculated using the AoA statistical geometrical model presented in the previous section.

The workspace of size $a \times b$ was sampled with a constant step $s$ in both $X$ and $Y$ directions which resulted in $S$ samples. As a result, a grid of sampling points
of the size $I \times J$ is formed. Meanwhile, $M$ location sensors can create $K = \binom{M}{2}$ different pairs. For each of the $M$ pairs of LSs, at each of the $S$ sample positions, the localization uncertainty is calculated. Thus, if for $K$ pairs of LSs, the uncertainty maps take a form of multidimensional matrices $D$ of size $I \times J \times K$, where the third dimension corresponds to a number of possible pairs. Then the AoA fingerprint map $U$ is calculated using the following formula:

$$\bigwedge_{i,j} U(i,j) = p \in \{1, \ldots, K\} \text{ where } \bigwedge_{i,j,k} D(i,j,U(i,j)) = \min_{k \in \{1, \ldots, K\}} D(i,j,k),$$  \hspace{1cm} (5)$$

where $U(i,j)$ and $D(i,j,k)$ are elements of matrices $U$ and $D$, respectively.

For each grid coordinate $(i,j)$ from all $K$ pairs of LSs, the minimum value of the AoA uncertainty $\min D(i,j,k)$ is determined. The fingerprint map, represented by the matrix $U$ shows the distribution of these pairs of LSs for which the AoA uncertainty is minimal.

The fingerprint map $U$ represents a grid of points of given height and known $X, Y$ coordinates. If to each of the $K$ possible pairs of the LSs we assign a suitable $k$-marker, then the markers can establish the fingerprint map. Neighboring markers of the same type form homogenous groups of markers, which define zones with preferable pairs of LSs.

### 4.3. Online Synthesis

In the online synthesis, actual AoA measurements are compared with the fingerprint map established in the offline phase. The synthesis consists of two stages: the online ranging technique and an estimation algorithm, which determines the final tag’s position. The online synthesis is performed on the workspace, which corresponds to the defined environmental model.

The RTLS sampling frequency determines the measurement cycle in which each of the $M$ LSs sequentially measures the corresponding AoA from the tag. For each measurement cycle, the online ranging and estimation algorithms are performed. The block diagram of the online synthesis presented in Figure 5 corresponds to one cycle of online ranging and estimation algorithms.
The online ranging algorithm is based on actual AoA measurements and an environmental model defined during the offline phase. For tag $T$, the ranging algorithm calculates the tag’s position $\hat{x}_k, \hat{y}_k$ for each possible pair of LSs from $K$ available pairs.

Then, the estimation algorithm sets together the online ranging results and the fingerprint map prepared beforehand. The fingerprint map represented by the matrix $U$ defines the zones by indicating the preferable pairs of LSs. The set of intersection points $\hat{T}_k(x_k, y_k)$ determined for each of the $K$ available LS pairs is compared with the fingerprint map $U$. Thus, each $\hat{T}_k(x_k, y_k)$ point is assigned to the corresponding zone of the preferable pair $p$ of LSs. The zone, which includes most of the points is classified as the most precise zone and the zone’s corresponding pair $p$ of LSs is selected. The intersection point $\hat{x}_p, \hat{y}_p$, derived from the measurements of the $p$-th pair of LSs, becomes the result of the estimation algorithm.

![Online synthesis block diagram.](image)

**Figure 5.** Online synthesis block diagram.

### 5. Implementation and Evaluation

The implementation of the proposed 2D model is done in Matlab 2014b with Signal Processing and Optimization toolboxes.

The implemented solution is evaluated using three different test scenarios for three test environments given in Table 2. The space is sampled with a constant step 25 cm in the $X$ and $Y$ directions resulting in a grid of samples. Since the samples, which are localized beyond the workspace, are filtered out from the
analysis, then the sampling coordinates located on the border of the workspace are not in the sampling grid.

<table>
<thead>
<tr>
<th>Environmental Scenario</th>
<th>Size $a \times b$ [cm $\times$ cm]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test environment TE1</td>
<td>500 $\times$ 500</td>
</tr>
<tr>
<td>Test environment TE2</td>
<td>500 $\times$ 1000</td>
</tr>
<tr>
<td>Test environment TE3</td>
<td>500 $\times$ 1500</td>
</tr>
</tbody>
</table>

In each test scenario, the RTLS consists of four LSs located in the workspace corners and the calibration point located in the center of the workspace. The calibration point constitutes an origin of the coordinate system. For each sampling point, the uncertainty tetragon area is calculated according to the AoA’s estimated angle of precision. The AoA standard deviation value for the specified workspace was statistically determined from results of tests performed in several random locations of workspace for all LSs. The empirically estimated value of the average AoA standard deviation was 0.3°. The implemented model was also tested on four coefficients $t \in \{0.1, 0.5, 1.0, 2.0\}$ of the uncertainty varying component.

The proposed model is used to estimate the uncertainty for each pair of LSs. Because of test environment symmetry, the uncertainty distribution analysis can be reduced to three of six possible pairs: $AB, BD, AD$.

To evaluate the method, we compared uncertainty distributions and relevant AoA fingerprint maps for six LS pairs: $AB, AC, BC, AD, BD, CD$. The evaluation of uncertainty distributions and AoA fingerprint maps was performed for the constant uncertainty component. The influence of the angular uncertainty varying component was evaluated and is presented in the end of this section.

### 5.1. Uncertainty Distribution Evaluation

Modelled AoA uncertainty distributions for three pairs, $AB, BD, AD$, for different test environments are presented in Figures 6–8, respectively. From a comparison of uncertainty maps of the same pair for different test environments, it can be seen that the size of the indoor space significantly influences uncertainty distribution. For the $AB$ pair, for the test environment $TE1$ the maximum uncertainty is about 45 cm², for the test environment $TE2$ it is 280 cm², and finally, the test environment $TE3$ has the maximum uncertainty of 750 cm².
For non-square test environments, the level of uncertainty is also affected by pair selection. For the AB pair located on a longer room wall, the uncertainty near the LS location wall is very high. For the AD pair located on a shorter room wall, the uncertainty increases along with the distance from LSs and, therefore, on the opposite side of the workspace the uncertainty is the highest. Moreover, for all environments, if the active LSs are arranged on diagonal corners, i.e., BD, the uncertainty in the central part of the workspace and around the diagonal is very high.

The lowest uncertainty for pairs AB and AD is observable near the active pairs of LSs. Moreover, in the centre of the workspace the level of uncertainty is also relatively low. For the diagonal BD pair, the lowest uncertainty is visible near to the non-active A and C LSs.
Figure 7. Uncertainty distributions for location sensors BD in (a) test environment TE1; (b) test environment TE2; and (c) test environment TE3.

Figure 8. Uncertainty distributions for location sensors AD in (a) test environment TE1; (b) test environment TE2; and (c) test environment TE3.
5.2. Fingerprint Map Evaluation

The fingerprint map represents a grid of markers, corresponding to the preferable pairs of location sensors for which the AoA uncertainty is smallest at the grid point; the map is presented in Figure 9.

The size of workspace influences the uncertainty map layout. In the test environment $TE_1$, the pattern is a symmetric composition of 12 rhombic zones for four pairs arranged on the sides of the workspace, i.e., $AB, BC, AD, CD$. In the test environments $TE_2$ and $TE_3$, the patterns are generally divided into two zones: green (LSs $BC$) and red (LSs $AD$), i.e., the pairs of sensors located on the shorter dimension. Along with the increase in the aspect ratio of the rectangular room, pairs $AB$ and $CD$ become more important in the central zone of the pattern. The level of uncertainty for the pairs arranged in diametrical corners, i.e., $AC$ and $BD$, is relatively high, thus, they do not contribute to the uncertainty map.

![Figure 9. Uncertainty maps for (a) test environment TE1; (b) test environment TE2; and (c) test environment TE3.](image)
5.3. Evaluation of Varying Components of Angular Uncertainty

An effect of the angular uncertainty varying component is investigated in a scenario similar to the real experiment scenario described in section 6.1, and it means that the \(AB\) pair is examined on the test environment \(TE2\) with the reference point slightly moved from the workspace center. The varying component emphasizes a variation of uncertainty distribution caused by the sensor’s varying sensitivity on different AoAs. Thus, the uncertainty of the AoA measurement of a tag located near the calibration point is smaller than for a tag located on the workspace borders.

The investigated influence of the angular uncertainty-varying component on the uncertainty maps is presented in Figure 10. For a small value of coefficient \(t\) from Equation (4), the pattern mainly consists of markers corresponding to \(AD\) and \(BC\) pairs arranged on the shorter sides of the workspace. Along with an increasing value of the coefficient \(t\) of the varying component, \(AB\) and \(CD\) pairs, located on the longer sides, increase their contribution to the map, especially around the calibration point and along the shorter sides.

![Figure 10](image)

Figure 10. Uncertainty map for test environment TE2 with different uncertainty varying component coefficients: (a) 0.1; (b) 0.5; (c) 1.0; and (d) 2.0. The reference point was not located symmetrically.
Simulation results show that the calibration point becomes a demarcation point around which the pattern zones are specified. Along with an increasing value of coefficient \( t \) of the varying component, the pattern zones evolve, but the calibration point still defines the demarcation point.

6. Verification

The proposed method was verified by physical experiments, evaluating uncertainty distributions for different pairs. Moreover, the experimental fingerprint maps illustrating the workspace zones with preferable pairs were analysed.

To be able to verify the proposed customized technique, definition of the coherent uncertainty measures, both for the simulation and for the physical experiment, is needed. In simulations, the proposed model of uncertainty is defined as the tetragon area presented in Figure 4, which depends on the AoA and distances from the location sensors. In the experimental approach, it was assumed that \( X \) and \( Y \) components of the standard error define the uncertainty of the tag’s position estimate. For this application, the 2D standard error takes the form of an ellipse area, the axes of which represent \( X \) and \( Y \) components of standard deviations.

The physical experiment was carried out on a Ubisense Real Time Localization System Series 7000, consisting of four LSs connected to a PC, and tags, which communicate with LSs on the telemetry channel 2.4 GHz and transmit localization pulses on UWB channel 6–8 GHz. The used tags were Ubisense Compact Tags with the maximum tag update rate 33.75 Hz. LSs were connected with Ubisense Location Platform 2.1 software on a PC by Ethernet. The RTLS operates in AoA, Time Difference of Arrival (TDoA), and RSS physical measurements, however, just AoA raw measurements without filtration are analysed.

6.1. Physical Experiment Arrangement

The physical experiment was performed in the workspace of the size 10.2 m × 5.2 m × 2.7 m, as presented in Figure 11. In the workspace, there were two large windows located on the shorter wall, one entrance door, and a wardrobe placed at the middle of the longer wall. The calibration point was located at a position 4.4 m × 3 m × 1 m from the corner on the floor near the entrance door. The LS, presented in Figure 12a, was installed in the corner on the ceiling. The tag was mounted on a 1 m high tripod (Figure 12b).
The whole room was sampled with a 0.5 m step in all directions, which resulted in the sampling grid of 168 samples. The workspace with marked sampling positions is presented in Figure 12c. The area where the wardrobe was mounted was excluded from the workspace. In each position, 100 samples of the AoA from all LSs were collected.

The simulation test environment TE2 corresponds to the workspace size of the physical experiment.

Figure 11. Workspace model where the physical experiment was carried out.

Figure 12. Photos of (a) RTLS sensor; (b) tripod with mounted tag; and (c) indoor environment.
6.2. Standard Error Distribution

For each pair, in each sampled position, the standard error was calculated, which resulted in a map of standard error distributions, see Figure 13 for three LS pairs. Because of the obstacles and the environmental interferences, some gross errors and samples out of the workspace were filtered out. The impact of the windows and wardrobe is noticeable in the results. For instance, the zone in the upper left-hand corner is visibly overshadowed by the wardrobe.

Figure 13. Standard error distributions for pairs: (a) AB; (b) BD; and (c) AD. Sampled positions with white frame markers show the sampling points with gross error.

For most of the sampled positions, the localization standard error was less than 10 cm², which denotes high precision. Considering experimental results, the best arrangement of the LSs is of the AD pair, showing not only the best precision, but also for this pair, the number of points, characterized by the gross error, was the lowest. In the case of the LSs arranged on diametrical corners, the results are consistent with simulated results. For the BD pair, the localization standard error is biggest on the diagonal, which is also in line with an expectation from simulation.
6.3. Fingerprint Map

The fingerprint map shown in Figure 14, represents a grid of markers of preferable pairs of LSs for which the experimental localization standard error is lowest. On this map, there may be specified three main zones for three pairs: BC and AD arranged on shorter sides and the AB pair on the longer side of the indoor space. The experimental results are in line with simulated results; this indicates the calibration point as a demarcation point around which the pattern zones are specified. In Figure 10, to the right of the calibration point, minimum localization standard error is noticed mostly for the AD pair. To the left of the calibration point, the BC pair shows the most precise AoA localization. A relatively small zone located centrally is visible, where the minimal standard deviation for the AB pair is arranged on the longer wall of the room, as it is in the simulated map. However, due to obstacles, the contribution of the CD pair is not as noticeable as it is in simulation.

![Figure 14. Uncertainty map from: (a) simulation; (b) physical experiment.](image)

The likeness of uncertainty maps derived from simulation and physical experiment proves that the analytical method based on the AoA statistical geometrical model is a good representation of AoA uncertainty distribution in an indoor space.
7. Validation

To validate the proposed solution, the AoA statistical geometrical model of uncertainty of the constant component was compared with real measurements. To quantitatively measure the correlation between the proposed analytical uncertainty model and the experimental results of the localization standard error, at each sample position in the workspace, a matching ratio was determined as a percentage of experimental locations inside the theoretical tetragon estimated from the proposed model.

Histograms with the matching ratio vs. the occurrence rate for three analysed LS pairs are presented in Figure 15. It shows that for all considered pairs, and the vast majority of sample positions, the matching ratio is very high. For the $AD$ pair located on the short wall, about 80% of the sampled positions meet the matching ratio, close to 100%. Even for the worst $BD$ pair, the 100% matching ratio level is achieved at about 45% of the sampled positions on the workspace.

![Histograms](a) Location sensors AB; (b) Location sensors BD; and (c) Location sensors AD.

Figure 15. Histograms with matching ratio results for (a) location sensors AB; (b) location sensors BD; and (c) location sensors AD.
The matching ratio maps for three considered pairs, presented in Figure 16, show the matching ratio distribution on the workspace. This map depicts zones with the best matching ratio for different pairs, but can be also used to detect the zones with the lowest matching ratio caused by higher interferences.

Figure 16. Validation of proposed model with physical experiment results for pairs: (a) AB; (b) BD; and (c) AD. Sampled positions with white frame markers show the sampling points with gross error.

The matching ratio maps reveal the environmental interferences caused by obstacles or constructions, such as doors, furniture, and windows. In Figure 16, the wardrobe shades the upper right and left zones, of the workspace. Furthermore, the interferences from the window and doors can be also noticed. However, even in cases of strong environmental interferences visible in Figure 16, the matching ratios are statistically valid. Figure 15b proves that the physical results are consistent with the theoretical model.
8. Results Discussion

The simulation results show how the uncertainty depends on the arrangement of LSs and on the size and shape of the workspace (Figures 6–8). The uncertainty distribution maps are specific for each LS pair, and it is proved that the level of uncertainty increases along with an increasing aspect ratio of the rectangular workspace. The diagonal pairs are the most adverse arrangement of LSs, showing the peak of the uncertainty around the workspace diagonals. Based on the simulation results, it can be seen that the uncertainty increases along with the distance from active LSs.

The fingerprint maps presented in Figure 10 illustrate the effect of the workspace size in terms of the aspect ratio of a rectangular workspace. One can observe how a number and size of pattern zones evolve. For the workspace with a small aspect ratio, the most suitable BC and AD pairs are located on the shorter walls of the room. Along with increasing the workspace’s aspect ratio, the AB and CD pairs, arranged on the longer dimension, contribute more, especially in the central zone of the pattern.

The validity of the proposed method is proven by a comparison of the simulated and experimental results presented in Figure 13. The results of both approaches confirm that the best localization precision is achieved for the AD pair. Likewise, the experimental results justify the respective simulation results for the diagonal pairs, where the uncertainty is the worst.

The impact of the indoor obstacles, such as windows, doors, wardrobe etc. is noticeable from experimental results. The zone along the walls with the wardrobe and windows required pre-processing, due to the strong interferences from the obstacles.

The fingerprint map of real measurements, shown in Figure 14, consists of three main zones for three pairs: BC, AD, AB. It is noticeable that the calibration point is a kind of demarcation around which the pattern zones are distributed. Generally, the pairs BC and AD, along the shorter walls, contribute to the zones with the high AoA precision on their sides of the calibration point. In the central zone of pattern, the best results are acquired for the AB pair.

On the entire workspace, the fingerprint maps from the physical experiment are correlated with simulated ones, and Figure 16 proves that at most of the grid points, the matching between both approaches is at an expected level and statistically valid. Even for the worst BD pair, the maximal 100% matching ratio is achieved at about 45% of the sample positions on the workspace.
9. Conclusion

The performance enhancement of the indoor AoA-based RTLS, by applying an analytical model of the AoA uncertainty, was accomplished by customizing the RTLS using the fingerprinting technique along with the AoA ranging technique. To execute the research objectives, the model of the fingerprinting technique applied to indoor environment scenarios was implemented in Matlab. The proposed analytical uncertainty model was evaluated and verified by a set of simulations and physical experiments.

The results derived from the simulations and physical experiments validate the analytical fingerprint maps as an adequate performance of RTLS in terms of precision. The proposed analytical uncertainty model is a suitable way to customize RTLS.

The results of simulations in line with the experiments show how the localization precision of the AoA-based RTLS depends on the LSs’ arrangement along with the workspace size and shape. For the analysed test scenarios, the simulation and physical experiment indicate that the pairs located on the shorter sides of the workspace are the most reliable and suitable for precise AoA localization. However, around the calibration point, even the pairs located along the long sides contribute to the fingerprint map, especially for the space with the high aspect ratio of rectangular spaces. The uncertainty level for the diagonal pairs is relatively high, particularly along the diagonals.

The experimental results evidence the significant interferences from the indoor obstacles, such as furniture, doors, and windows. However, the proposed model complies with the references with statistically valid robustness.

Moreover, the presented studies show how the size and shape of the workspace affect both a number and shapes of pattern zones of the fingerprint map.

The study depicts an important role of the calibration point as a demarcation point around which pattern zones are placed. It justifies why the calibration point should be located as centrally as possible.

To complement this research, which focuses mostly on localization precision, further research may also concern the accuracy of AoA-based RTLSs. The accuracy, interpreted as a systematic error, can be compensated based on the previously prepared accuracy map. Such research, combined with the results of this paper, may provide a holistic approach to the AoA-based RTLS.
Improving the classification method determining optimal pairs of LSs, should enhance the estimation algorithm reliability. Such algorithm may be implemented and tested on various indoor environments to prove its versatility.

It seems that modelling of the localization uncertainty map is also possible for the signal of ToA or TDoA, which can be used along with the ranging technique. Therefore, the proposed analytical fingerprint method may be implemented in the TDoA-based RTLS. A similar localization uncertainty map, but based on a heuristic approach, can even be established for RSSI signals and, accordingly, a heuristic fingerprint solution can be used in RSSI-based RTLS.

References


Customization of UWB 3D-RTLS Based on the New Uncertainty Model of the AoA Ranging Technique

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Bartosz Jachimczyk, Damian Dziak and Włodek Kulesza

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Customization of UWB 3D-RTLS Based on the New Uncertainty Model of the AoA Ranging Technique

Bartosz Jachimczyk, Damian Dziak and Wlodek Kulesza

Abstract

The increased potential and effectiveness of Real-time Locating Systems (RTLSs) substantially influence their application spectrum. They are widely used, inter alia, in the industrial sector, healthcare, home care, and in logistic and security applications. The research aims to develop an analytical method to customize UWB-based RTLS, in order to improve their localization performance in terms of accuracy and precision. The analytical uncertainty model of Angle of Arrival (AoA) localization in a 3D indoor space, which is the foundation of the customization concept, is established in a working environment. Additionally, a suitable angular-based 3D localization algorithm is introduced. The paper investigates the following issues: the influence of the proposed correction vector on the localization accuracy; the impact of the system’s configuration and LS’s relative deployment on the localization precision distribution map. The advantages of the method are verified by comparing them with a reference commercial RTLS localization engine. The results of simulations and physical experiments prove the value of the proposed customization method. The research confirms that the analytical uncertainty model is the valid representation of RTLS’ localization uncertainty in terms of accuracy and precision and can be useful for its performance improvement. The research shows, that the Angle of Arrival localization in a 3D indoor space applying the simple angular-based localization algorithm and correction vector improves of localization accuracy and precision in a way that the system challenges the reference hardware advanced localization engine. Moreover, the research guides the deployment of location sensors to enhance the localization precision.

Keywords: accuracy and precision; angle of arrival; correction vector; indoor localization systems; real-time locating systems
1. Introduction

The continuing development of wireless technologies has led to an enhancement of the capabilities and efficiency of Real-time Locating Systems (RTLSs), which are a particular example of Indoor Locating Systems (ILSs). RTLSs have the ability to define the position of an item anywhere in a defined space at a point in time that is, or is close to a real time [1]. Ultra-wideband (UWB) is a short-range and energy efficient radio technology useful in a high-bandwidth wireless communication. Due to their functionalities and performances, the use of UWB-based RTLSs as tracking management systems has gained increasing attention in industrial and logistic applications, for instance container terminals [2], and warehouses [3]. Besides that, RTLSs have been widely applied in security applications in construction sites as a safety system [4,5], in healthcare for precisely monitoring and tracking people and goods [6–8] and in agriculture for animal behaviour monitoring [9].

The UWB-based indoor RTLSs are able to estimate a target’s location with high accuracy and precision, which depend, inter alia, on the working environment, system architecture, and localization algorithm. The estimation process uses ranging techniques, which vary for different signals such as Received Signal Strength (RSS), Time of Arrival (ToA), Time Difference of Arrival (TDoA) and Angle of Arrival (AoA) [10]. Some commercial UWB-based RTLSs use hybrid localization methods, however the performance improvement is mitigated by the system price and complexity.

The AoA-based ranging technique is commonly used in UWB-based RTLSs. This technique uses direction-sensitive antennas as location sensors to estimate the direction of the RF signal from a tag [11]. The disadvantage of the AoA approach, compared with e.g. the TDoA solution, is its accuracy. It is counterpoised by the system’s simplicity, which leads to a lower price and simplicity of real time implementation. The customizations of the AoA-based RTLS for different working environments help to overcome the accuracy disadvantage by improving the efficiency and localization performance. The performance assessment and analytical uncertainty model of AoA localization for the given environmental characteristics and RTLS’s architecture are needed for the customizations.

This paper focuses on an improvement of the system’s performance by applying the analytical customization method for different working environments. The proposed approach is based on the RTLS’s performance assessment using the new analytical uncertainty model of AoA localization in a 3D indoor space. The
uncertainty model comprises two localization performance measures: accuracy and precision. Furthermore, the paper introduces the angular-based 3D localization algorithm combining the ranging technique and extrapolation method.

An implementation of the proposed customization method of UWB-based RTLS has been verified and shows an accuracy improvement of 55%. The used analytical model of uncertainty in terms of precision has been validated and proved the entire matching with the experimental results. The analytical and experimental evaluation of the performance of the proposed AoA-based localization algorithm has been applied for different LSs configurations in the given test environment. The comparison of the AoA-based localization results with the commercial RTLS’s algorithm results confirms the expediency of the proposed approaches.

2. Survey of Related Works

Due to their localization capabilities and reliability, UWB-based RTLSs, as a kind of wireless RF-based ILSs, are widely used in the industrial sector, but also in other logistic and security applications. These systems are able to localize a target with accuracy up to several centimetres in an indoor space. The performance of these systems highly depends on their architecture, LSs arrangement, and the location engine [12].

Depending on the application character and system structure, localization platforms apply a variety of ranging techniques such as RSS, ToA, TDoA, AoA [13], along with different position estimation algorithms such as trilateration, triangulation, fingerprinting, dead path reckoning, and some others [11]. The most basic ranging technique is based on the power measure of RF, called RSS. However, the RSS methods are highly affected by obstacles and multipath fading, along with environmental interferences [14,15]. Therefore, currently RTLSs use the RSS rather as a complementary measure, for instance in data filtration [16], and the other measures like ToA/TDoA and AoA are more commonly used in position determination [13].

Due to their popularity, ToA and TDoA-based estimation algorithms are widely researched. In [17], the authors discuss the main sources of errors in the ToA-based ranging in the multipath environments. These include the multipath fading and direct path excess delay, but also blockage, narrowband and multi-user interferences and clocks drift. The authors of [18] present a quality-enhancing and novel ToA-based ranging scheme with an improved detection of distorted UWB pulses in dense environments, such as a residential office or factory. Selimis et al. propose and evaluate in a real scenario the ToA-based estimation algorithm
consisting of an improved acquisition unit, which detects and synchronizes UWB pulses. The acquisition unit applies a single peak identification procedure, which detects the strongest multipath component of the signal using the channel impulse ratio estimation [19]. Shen et al. focus on ToA technology for range-based localization in UWB sensor networks [20]. The authors apply the Constant False Alarm Rate adaptive algorithm, which is based on the detection theory applied to radar systems. They also propose the Maximum Probability Detection method estimating the ToA by finding the maximum probability of the multipath signal components.

Range-based AoA approaches, also commonly used in RFID and UWB-based RTLSs, apply direction-sensitive antennas as location sensors to estimate the direction (the angle of arrival) of the signal from a tag [11]. The performance of AoA-based estimation algorithms are studied among others in [21–23]. Kim et al. propose an improvement of the AoA-based RTLS designed for Non-line-of-sight (NLoS) environments. The proposed algorithm, enhancing the estimation of the target’s position, applies a Dual Indirect Kalman Filter and weight filters [24]. In [25], the authors suggest a localization algorithm, which utilizes a biased estimation technique to increase the system performance. Moreover, the authors apply a statistical calibration method to improve the localization quality. Zampella et al. propose the sensor fusion of UWB RTLS with Inertial Measurement Unit (IMU) mounted in a mobile phone [26]. They combine the commercial UWB RTLS algorithm with the dead path reckoning estimation algorithm to carry out the localization both indoor and outdoor around a building. The performance analysis of AoA-based localization systems is studied in [27,28]. Using kinds of Fisher Information Matrices, the authors determine the optimal configuration of sensors to enhance the angle-related information in 3D space. An optimal configuration of sensors depends inter alia on the intensity of the measured noise, configuration constraints and the probabilistic distribution that defines the prior uncertainty in the target position.

The performance assessment of RTLSs can apply different physical measures depending on the type of RTLS and application. In [4], the authors investigate the performance in terms of accuracy, precision and reliability of an UWB-based RTLS tracking of multiple tags simultaneously. Furthermore, they analyse the impact of a number of receivers on localization performance under common conditions of construction sites i.e., occurrences of metal surfaces. Silva et al. evaluate the UWB-based Symmetrical Double Sided Two-way Ranging RTLS, which does not require synchronization [29]. They assess the indoor localization performance in terms of precision, accuracy, refresh rate and reliability in Line of Sight (LoS) and NLoS scenarios.
The measurement uncertainty of AoA may be evaluated using the measure of accuracy and precision, and the quality of the localization estimates of AoA measurements is an issue of several papers. It is proved that a type and characteristic of antenna [30], their deployment [31] and also a type of indoor environment significantly affect the measurement precision [12]. To reduce impacts of these factors, Crespo et al. perform the experimental study of different types of RTLS antennas in different indoor environments and find out the matching conditions [32].

The precision of AoA measurement uncertainty is related with the concept of Dilution of Precision (DoP), originally used in satellite navigation systems. Among others, Dempster et al. apply the DoP measure to characterize the quality of AoA-based positioning systems [33]. Arafa et al. investigate an effect of DoP on the localization performance of the optical wireless ILS [34]. In [12], the authors propose an analytical DoP-based uncertainty model of precision and apply it with the fingerprinting method to customize the RTLS aimed in an improvement of its performance in terms of localization precision.

The localization uncertainty in terms of accuracy can be characterized as a systematic error whose influence may be mitigated by an appropriate identification and compensation. Junhuai et al. in [35] propose a localization algorithm based on region divisions and error compensation to enhance the localization accuracy. Their algorithm divides the localization area into many sub-regions and a specific propagation model is defined for each sub-region. In [36], the authors show the influence of the calibration tag’s placement on AoA measurement uncertainty. They propose a suboptimal criterion how to allocate the calibration emitter in relation to sensors’ positions in an indoor space. Ghazaany et al. in [37] investigate how a mutual coupling compensation matrix influences the performance of the AoA-based small size uniform circular array. The authors propose a complex compensation matrix corresponding to the coupling effect between antennas’ elements. Myong et al. show an impact of signal interferences on the location accuracy of RFID-based RTLS in multipath environments [38]. The authors consider direct and indirect path components with time and phase delay differences.

3. Problem Statement and Main Contribution

From the review of related works, one can notice that localization methods for RTLSs perform differently. The accuracy, precision, processing time, cost and simplicity are the main measures of the system performance. Then, the challenge is to find out trade-offs of various aspects of the system’s performance for different
methods. Furthermore, there are many factors influencing the performance of an indoor 3D localization, inter alia the system architecture, working environment, possible interferences etc. Most of the localization algorithms estimating the tag’s position in the indoor environment use ranging techniques, which are based on different measurement signals such as RSS, TDoA, AoA. Among these solutions, the angle-based (AoA ranging technique) localization algorithms show a big potential of performance improvement, especially in 3D applications. Therefore, one of the possible enhancement approaches is to develop a measurement analytical model, which can facilitate the customization of the AoA ranging technique in different 3D environments.

The main objective of this paper is to develop and then to implement in a simulation environment the geometrical (analytical) uncertainty model of AoA localization in a 3D indoor space, while considering the localization uncertainty in terms of accuracy and precision, which extends and enhances the uncertainty model proposed in [12]. The goal of modelling is to determine the efficient system configuration. Furthermore, the proposed model facilitates the system customization by defining and implementing the correction vectors for different working environments in order to improve the system’s performance in terms of its accuracy. Additionally, the angular-based 3D localization algorithm, which estimates the tag’s position in 3D from interfered measurement signals of azimuth and elevation angles, is introduced.

The main contribution of this paper is an improvement method of system’s performance by applying the analytical customization for different working environments. The method is based on a new holistic approach to localization uncertainty in terms of precision and accuracy, and defining a geometrical model of the AoA localization method in 3D. The model facilitates an uncertainty analysis of the AoA ranging technique. The analytical model is implemented in Matlab and used to show how different the system’s features influence its performance. The measurement precision model is verified by analysing the matching ratio of the simulated and experimental results. To show the accuracy enhancement, by applying the correction vector, the proposed customization of the system for a given working environment is validated by physical experiment. The reference RTLS localization algorithm is applied to verify that the customization of AoA ranging techniques can challenge the advances in hardware of the UWB-based RTLS technology.
4. RTLS’s Performance Assessment

The assessment of RTLS’s performance is necessary to find trade-offs among different technologies and methods. In general, the assessment needs to be considered separately for static and dynamic localization modes [4,39]. In the static mode, it can be evaluated using different measures inter alia localization uncertainty, sensitivity [9] and response time. In the dynamic mode, these measures are affected by the speed of a tag, a number of tags, and the complexity of their paths.

The simplified interpretation of 3D localization uncertainty in terms of accuracy and precision measures at the true tag’s position $P_i$ in coordinates $(x_i, y_i, z_i)$ is illustrated in Figure 1.

![Figure 1. Illustration of 3D localization accuracy and precision for i-th tag’s position.](image)

The accuracy measure $\Delta_i$ represents the distance between the true position $P_i$ and the location estimate $\hat{P}_i$ obtained from the RTLS, whereas, the precision is illustrated by the sphere with an estimate’s standard error $\sigma_i$ as a radius. The sphere is centered in the estimated position $\hat{P}_i$ and includes respectively 68% of N measured localization samples. Both localization uncertainty measures: accuracy
and precision characterized dispersion of measured results from the tag’s true position. In the following sections, the localization performance is modelled in a static mode using the two measures: accuracy and precision [40].

4.1. Accuracy

The accuracy property expresses the capability to obtain the true value of a measurand [40]. The mean uncertainty component, the localization accuracy, $\Delta x_i$ of the x coordinate estimated for the point $P_i$ located in the test environment, can be expressed as:

$$\Delta x_i = \bar{x}_i - x_i,$$

where variables of $P_i(x_i, y_i, z_i)$ respectively refer to the true localization coordinates at i-th position of the tag, whereas variables of $\bar{P}_i(\bar{x}_i, \bar{y}_i, \bar{z}_i)$ refer to the mean of N-th times measured localization coordinates at i-th tag’s position. If the remaining two mean uncertainty components $\Delta y_i$, and $\Delta z_i$, of y and z coordinates respectively are specified analogically to Equation (1), then the localization uncertainty $\Delta_i$ at i-th tag’s position can be shown as follows:

$$\Delta_i = \sqrt{\Delta x_i^2 + \Delta y_i^2 + \Delta z_i^2}.$$  

(2)

4.2. Precision

The second uncertainty measure, the localization precision, describes the measurement’s repeatability and is based on an estimate of the mean standard error $\bar{\sigma}$ of the mean localization uncertainty. A low value of the standard error means high precision and vice versa. For the i-th tag’s position, which is estimated from N measurements, a standard error of the mean (SEM) $\overline{\sigma}_x$ of the component $x$, can be expressed in relation to its variance as:
\[
\bar{\sigma}_{x_i} = \frac{\sigma_{x_i}^2}{\sqrt{N}},
\]

(3)

where \(\bar{\sigma}_{x_i}\) and \(\sigma_{x_i}^2\) are SEM and variance respectively of the x component at i-th tag’s position. The remaining two SEMs \(\bar{\sigma}_{y_i}\) and \(\bar{\sigma}_{z_i}\) of y and z coordinates respectively can be described analogically. Then the corresponding SEM \(\bar{\sigma}_i\) of the localization estimate of i-th tag’s position can be calculated as follows:

\[
\bar{\sigma}_i = \sqrt{\bar{\sigma}_{x_i}^2 + \bar{\sigma}_{y_i}^2 + \bar{\sigma}_{z_i}^2}.
\]

(3)

5. The AoA-Based Localization Algorithm

The angular-based localization algorithms of RTLSs use angles of arrival of the radio wave, measured by a pair of LSs. For each measurement cycle, to determine the tag’s location, AoA ranging and extrapolation procedures are processed one by one. In [12], the simplified 2D AoA localization algorithm using azimuth angles is presented. In the following subsection, a specific model of ranging technique using azimuth and elevation angles for the 3D localization is proposed. Moreover, the tag’s location is estimated based on an extrapolation technique described in the second subsection of this chapter.

5.1. AoA Ranging Technique

The ranging technique, described in this section, is illustrated by the AB pair of LSs. The initial installation stage of the ranging technique procedure is performed only once, at the beginning of measurement process when the workspace and LSs’ coordinates are defined and the system is calibrated. Then, from the installation data the workspace geometry and the coordinates, \(A(x_A, y_A, z_A)\) and \(B(x_B, y_B, z_B)\) of the active LSs’ positions, are established. Moreover, the calibration procedures for azimuth and elevation angles are performed. The calibration procedure of UWB-based RTLS for azimuth angles is
described in [12] and the calibration procedure for elevation angles looks similarly. Therefore, after the initial phase, the workspace geometry, LSs’ coordinates, and even the calibration angles and lines are defined.

The basic stage of the AoA ranging technique is performed in each measurement cycle when the directions of the arrival paths from the tag to the two LSs are measured. Each LS consisting of antenna array element measures the direction of the receiving tag’s radio wave as azimuth and elevation angles of arrival. Radio waves take the form of UWB pulses with very short durations, which are emitted by the tag. A geometrical interpretation of 3D AoA ranging techniques for a pair of LSs AB is illustrated in Figure 2. The line $l_A$ represents the arrival path, which passes through the tag’s position $\hat{T}$ and LS A’s coordinates $A(x_A, y_A, z_A)$. The line is projected perpendicularly onto the XY plane, called reference plane. The azimuth angle $\theta_A$ is the angle between the line projected on the reference plane and the axis X. The elevation angle $\phi_A$ is the angle between the line $l_A$ and the axis Z. Azimuth and elevation angles measured by the LS B are defined analogically.

Figure 2. Graphical interpretation of the 3D AoA ranging technique.

The lines $l_A$ and $l_B$ can be represented by direction vectors $u$ and $v$ with initial points in A and B respectively. Both $u$ and $v$ direction vectors are computed from measured azimuth angles $\theta_A$ and $\theta_B$ and elevation angles $\phi_A$ and $\phi_B$ respectively. Then the vectors between the LSs placed in A and B and the tag are depicted as:
\[ \lambda_A \mathbf{u} = \lambda_A \begin{bmatrix} u_x \\ u_y \\ u_z \end{bmatrix} = \lambda_A \begin{bmatrix} \sin \varphi_A \cos \theta_A \\ \sin \varphi_A \sin \theta_A \\ \cos \theta_A \end{bmatrix}, \]  

\[ \lambda_B \mathbf{v} = \lambda_B \begin{bmatrix} v_x \\ v_y \\ v_z \end{bmatrix} = \lambda_B \begin{bmatrix} \sin \varphi_B \cos \theta_B \\ \sin \varphi_B \sin \theta_B \\ \cos \theta_B \end{bmatrix}, \]  

where \( \lambda_A \) and \( \lambda_B \) are length parameters of the distance vectors, and \( u_x, u_y, u_z \) and \( v_x, v_y, v_z \) are direction vectors’ \( \mathbf{u} \) and \( \mathbf{v} \) components respectively. Both direction vectors \( \mathbf{u} \) and \( \mathbf{v} \) along with the length parameters \( \lambda_A \) and \( \lambda_B \) and the coordinates of the initial points \( A \) and \( B \) determine the end-points \( T_A \) and \( T_B \) of distance vectors \( \lambda_A \mathbf{u} \) and \( \lambda_B \mathbf{v} \) respectively. Therefore, resultant points \( T_A \) and \( T_B \), which estimate the tag’s location are depicted as:

\[ T_A = A + \lambda_A \mathbf{u}^{-1}, \]  

\[ T_B = B + \lambda_B \mathbf{v}^{-1} \]  

In an ideal case, the tag’s position \( \hat{T} \) is defined by \( T_A = T_B \), since both points should have the same coordinates. Using Equations (7) and (8), a set of three separate linear functions is formed and the coordinates of the tag’s position \( \hat{T}(x_T, y_T, z_T) \) along with the two parameters \( \lambda_A \) and \( \lambda_B \) can be calculated.

5.2. AoA Extrapolation Method

In general, due to the uncertainty of AoA measures, the arrival paths represented by the lines \( l_A \) and \( l_B \) for \( \text{LS}_A \) and \( \text{LS}_B \) respectively are askew and there is no intersection point, as shown in Figure 3.
Then, the lines \( l_A \) and \( l_B \) need to be extrapolated to lines \( m_A \) and \( m_B \) respectively, which intersect in the extrapolated tag’s position \( \hat{T} \) [41]. The extrapolated solution can be defined as the middle of the shortest distance between the lines \( l_A \) and \( l_B \), which can be calculated using formula:

\[
d(l_A, l_B) = \min_{T_A \in l_A, T_B \in l_B} d(T_A^T, T_B^T).
\] (9)

The shortest distance between the lines \( l_A \) and \( l_B \) can be represented as a vector \( d \) with the initial point’s coordinates \( T_A^T(x_AT, y_AT, z_AT) \) and the end point’s coordinates \( T_B^T(x_BT, y_BT, z_BT) \). Vector \( d \) is perpendicular to both direction vectors \( u \) and \( v \) defined in the previous section. The extrapolated tag’s position \( \hat{T} \) with coordinates \((x_T, y_T, z_T)\) is calculated as a midpoint of the vector \( d \) using the following formula:

\[
\hat{T}(x_T, y_T, z_T) = \left( \frac{x_A + x_B}{2}, \frac{y_A + y_B}{2}, \frac{z_A + z_B}{2} \right).
\] (10)
The extrapolated tag’s position \( \hat{T} \) and two extrapolated arrival paths represented by lines \( m_A \) and \( m_B \) intersecting at the tag’s position \( \hat{T} \) are used for the localization uncertainty modelling presented in the next section.

6. Modelling of Uncertainty of AoA-Based Localization

An uncertainty model of AoA localization in 3D is needed to customize the RTLS in different working environments to improve its performance. In [12] the localization uncertainty was represented by precision, sufficient for the applied enhancement method. However, the AoA localization uncertainty model might be upgrades with accuracy. For a specified RTLS architecture and working indoor environment, the model of localization measurement accuracy, defined here as an offset error, is presented in the first part of this chapter. The localization precision defined using a geometrical approach is introduced in the second subsection of this chapter.

6.1. Modelling of Offset Error and Correction Vector

For a specified UWB-based RTLS architecture used in a given working indoor environment, the uncertainty model of an offset error can be established heuristically. The offset error for a single measured position is systematic. However, for the given working environment consisting of a set of measured positions, the offset error consists of two components: random and systematic. Among others, the systematic component, which is constant for the whole environment, can be caused by the uncertainty of an initial calibration procedure when the calibration axes are defined in relation to the LSs’ positions. Whereas, the random component, varying at different localizations can be an effect of environmental characteristics specific at a given position. Another cause of the offset error can be heterogeneity of tags’ characteristics.

An effect of the localization offset error can be reduced by a correction vector, which depends on the system’s architecture and test environment, and is to be estimated heuristically. It may include the following sources:

I. AoA LSs deployment measurement [30],

II. AoA sensors array [42],

III. tags’ characteristics,

IV. calibration process.
In a given environment, the correction vector for a certain pair of LSs, may be estimated based on measurements from k tags each sampled N times at M locations. For these numbers of tags, locations and samples, the x component of the correction vector, \( k\nu_x \), may be calculated from:

\[
k\nu_x = \frac{1}{K \cdot M \cdot N} \sum_{m=1}^{M} \sum_{n=1}^{N} \sum_{k=1}^{K} \Delta x_{k,n,m},
\]

where \( \Delta x_{k,n,m} \) is the difference between the true localization and the n-th measurement at m-th localization of k-th tag. The remaining two correction vector components \( k\nu_y \) and \( k\nu_z \), of y and z coordinates respectively can be calculated analogically to Equation (11). Then the correction vector \( kv \) specified for the localization system in the test environment can be expressed as:

\[
kv = \begin{bmatrix}
k\nu_x \\
k\nu_y \\
k\nu_z
\end{bmatrix}.
\]

### 6.2. Modelling of the Precision of 3D Localization Based on AoA Technique

The precision model applied to the AoA ranging technique in 2D is described in [12]. The presented geometrical model is based on the azimuth component of AoAs. Since it was shown, that the pairs located on the shorter sides of the workspace ensure the most precise AoA-based localization [12], therefore, the following description concerns the pair LS\(_A\) and LS\(_B\) placed in the fixed positions \( A(x_A, y_A, z_A) \) and \( B(x_B, y_B, z_B) \) on the shorter side of the workspace. The specified tag T is located at the position \( T_i(x_i, y_i, z_i) \). However, the selected configuration does not limit the model’s versatility.

For the LSs pair AB, each tag’s position on the workspace is defined by a set of two azimuth angles and a set of two elevation angles. The first set consists of vectors \( \text{AoA}_A^\theta \) and \( \text{AoA}_B^\theta \) of azimuth angles of arrival \( \theta_{Ai} \) and \( \theta_{Bi} \) measured by
LSs A and B respectively. Analogically, elevation angles of arrival $\varphi_{Ai}$ and $\varphi_{Bi}$, measured by LSs A and B respectively, are represented by vectors $\mathbf{AoA}_A^\varphi$ and $\mathbf{AoA}_B^\varphi$, which constitute the second set.

Each measurement is repeated $N$ times and using the ranging and extrapolation techniques, then $N$ samples of i-th tag position $T_i$ are estimated as intersections (10) of lines $m_A$ and $m_B$ corresponding to the extrapolated paths of arrival. Based on experimental data, we assume that the distribution functions of azimuth and elevation measurements are normal. Then, at confidence level of 68.3%, the azimuth angles $\theta_{Ai}$ and $\theta_{Bi}$ are within the ranges $\theta_{Ai} \in (\overline{\theta_A} - \sigma_\theta^A, \overline{\theta_A} + \sigma_\theta^A)$ and $\theta_{Bi} \in (\overline{\theta_B} - \sigma_\theta^B, \overline{\theta_B} + \sigma_\theta^B)$ respectively, where the mean values $\overline{\theta_A}$ and $\overline{\theta_B}$ represent the best estimate of azimuth angles and $\pm \sigma_\theta^A$ and $\pm \sigma_\theta^B$ depict the SEMs of the azimuth AoA for LS$_A$ and LS$_B$ respectively. These ranges define the precision of the azimuth angle measurement called azimuth Angle of Precision, (AoP). Per analogy, the elevation angles $\varphi_{Ai}$ and $\varphi_{Bi}$ are within the ranges $\varphi_{Ai} \in (\overline{\varphi_A} - \sigma_\varphi^A, \overline{\varphi_A} + \sigma_\varphi^A)$ and $\varphi_{Bi} \in (\overline{\varphi_B} - \sigma_\varphi^B, \overline{\varphi_B} + \sigma_\varphi^B)$ respectively, which define the precision of the elevation angles measurement. The mean values $\overline{\varphi_A}$ and $\overline{\varphi_B}$ represent the best estimate of elevation angles, which are used to calculate the best estimate of the tag’s position $\hat{T}$. SEMs of the elevation AoA for both LSA and LSB are represented by $\pm \sigma_\varphi^A$ and $\pm \sigma_\varphi^B$, respectively. Thus, the normal distributions of the azimuth and elevation AoA of N samples for location sensor LS$_A$ can be defined as $\mathcal{N}_A^\theta(\overline{\theta_A}, \sigma_\theta^A)$ and $\mathcal{N}_A^\varphi(\overline{\varphi_A}, \sigma_\varphi^A)$ respectively [27]. The probability distributions of the azimuth and elevation AoA of the set of N samples for location sensor LS$_B$ can be described analogically as $\mathcal{N}_B^\theta(\overline{\theta_B}, \sigma_\theta^B)$ and $\mathcal{N}_B^\varphi(\overline{\varphi_B}, \sigma_\varphi^B)$ respectively.

The LS$_A$ is characterized by the elevation and azimuth AoPs, which can be used to form an elliptic cone representing the measurement precision in 3D, as shown in Figure 4. The cone’s vertex is placed at the LS’s position, $A(x_A, y_A, z_A)$ and its axis refers to the mean path of arrival $\overline{l}_A$, and its base at the estimated tag’s position is an ellipse with the axes defined by $r_A^\theta$ and $r_A^\varphi$ as follows:

\[
r_A^\theta = 2 \cdot \sqrt{(x_i - x_A)^2 + (y_i - y_A)^2 + (z_i - z_A)^2} \cdot \tan^{-1} \sigma_\theta^A,
\]

\[
r_A^\varphi = 2 \cdot \sqrt{(x_i - x_A)^2 + (y_i - y_A)^2 + (z_i - z_A)^2} \cdot \tan^{-1} \sigma_\varphi^A.
\]
From the equations, one can see that the size of the elliptic base depends on SEM of azimuth $\overline{\sigma}_A^\theta$ and elevation $\overline{\sigma}_A^\phi$ angles measurements and the distance from the active LS’s position to tag’s position $T_i$. Therefore, since the distribution functions of the measurement precision of azimuth and elevation AoAs are normal distribution functions, representing the dispersion of the path of arrival of N samples, then the surface area of the elliptic cone’s base at a given distance from the LS represents the bivariate SEM. The true localization occurs there with the confidence level of 68.2%.

Per analogy, the uncertainty of LS$_B$ is characterized by an elliptic cone with the vertex in LS’s position $B(x_B,y_B,z_B)$ and the axis refers to the mean path of arrival $\overline{l}_B$. The cone’s base at the estimated tag’s position is an ellipse, with the axes defined by $r_B^\theta$ and $r_B^\phi$, respectively.

The two elliptical cones with vertices at the active LSs’ positions $A(x_A,y_A,z_A)$ and $B(x_B,y_B,z_B)$ represent the precision of tag’s AoA measurements. The cones cross each other and their common part forms the solid where the tag is truly located with the 46.5% probability corresponding to the product of two SDs probabilities, see Figure 5. The volume of the solid depends on the:

I. precision of azimuth AoA measurements represented by SEM of $\overline{\sigma}_A^\theta$ and $\overline{\sigma}_B^\theta$ for LS$_A$ and LS$_B$ respectively,

II. precision of elevation AoA measurements represented by SEM $\overline{\sigma}_A^\phi$ and $\overline{\sigma}_B^\phi$ for LS$_A$ and LS$_B$ respectively,

III. distances from LSs positions $A(x_A,y_A,z_A)$ and $B(x_B,y_B,z_B)$ to the estimated tag’s position $\hat{T}$. 


The volume of the solid is a measure of the uncertainty-precision of 3D AoA ranging technique. Its shape depends on the tag’s location in the test environment. The result of the cones’ penetration is presented in Figure 5. This is a particular symmetrical case when both cones have the same shape since azimuth and
elevation AoP values are equal, i.e., elevation angles $\varphi_A$, $\varphi_B$ and azimuth angles $\theta_A$ and $\theta_B$ are equal.

The volume of the solid is calculated numerically using the 3D Delaunay triangulation computing method called Delaunay tetrahedralization [43]. The algorithm calculates the volume of the solid based on the sum of each individual tetrahedral volume. The boundaries of the 3D Delaunay triangulation represent the convex hull of the points set as shown on Figure 6. The shape of the convex hull matches the theoretical solid shape presented in Figure 5.

Figure 6. Convex hull of the points representing the solid.

7. Precision Model Evaluation

The implementation of the proposed 3D model is done in Matlab 2014b with the Signal Processing, Optimization and Computational Geometry toolboxes. Then the implemented solution is evaluated using a simulated cuboidal test environment of 11.00 m $\times$ 7.50 m $\times$ 4.00 m size. The space is sampled with a constant step of 50.00 cm in three directions resulting in a test grid of samples. The sampling coordinates located on the border of the workspace, which physically would be placed on the walls, are excluded from the sampling grid.

The RTLS consists of four LSs, two located in the workspace corners on height 4 m and two located on height 3 m, see Table 1. The origin of the coordinate system is arbitrarily located on the floor at the workspace corner under LSA. The calibration point is located approximately in the centre of the workspace, explicitly at 5.60 m $\times$ 4.00 m $\times$ 1.00 m.
The model is applied to estimate the map of location uncertainty in terms of precision for two pairs of LSs, AB and AD, located on the longer and shorter walls of the test room respectively. For each sampling point, the location precision expressed as a volume is calculated from the azimuth and elevation AoPs. The SEM of azimuth and elevation AoAs for the tested workspace were heuristically determined from results of tests performed on 36 arbitrary selected location points of workspace for all LSs. The heuristically estimated mean SEM values of both azimuth and elevation AoAs’ standard deviations were 0.45°. Therefore, the measurement uncertainty in terms of precision of each LS is represented by a cone with vertices in LSs’ positions, the axes are defined as the arrival path (Section 5.2) and the circular base with the radius calculated using Equation (13) or (14). The modelled localization precision was determined by using the common volume of two cones, whose axes intersect at the sample location. The localization precision was calculated using the 3D Delaunay triangulation computing method (Section 6.2).

The distribution map of the modelled AoA localization precision for an AD pair is presented in Figure 7. The LS_A and LS_D are located at slightly different heights of the shorter wall of the workspace, as shown in Table 1. The slices represent orthogonal planes through the volume of the workspace, and the colours correspond to precision levels.

The distinct cross-sections of the AoA measurement precision distribution maps for the AD pair are presented in Figures 8–10. Red dots represent the positions of active LSs and black dots show locations of inactive LSs. From the maps, it can be seen that the precision significantly depends on the distance from LSs. For the AD pair, located on the shorter room wall, the uncertainty increases along with the distance from LSs. At the bottom corners of the workspace, on the opposite side to the active sensors, the uncertainty is the highest, see Figures 8 and 9. The best precision is identified near the active LSs, which is depicted in Table 2. The precision range is from 150 cm³ to 6900 cm³. The effect of the LSs’ deployment on different heights is noticeable in Figure 8c, which illustrates the precision distribution at a distance 1 m from the wall where the active sensors are located. Figure 8c shows that the uncertainty level near the floor (z = 0.5 m) is lower around the LS_D of approximately 170 cm³, compared to the area around the LS_A where the uncertainty reaches 270 cm³.
Figure 7. Volumetric slice plot of uncertainty-precision distribution for location sensors AD.

Figure 8. Cross-section (YZ plane) plots of uncertainty-precision distribution for location sensors A and D at (a) x = 1.00 m; (b) x = 5.50 m; (c) x = 10.00 m. All plots are in different colour scales.
Figure 9. Cross-section (XZ plane) plots of uncertainty-precision distribution for location sensors A and D at (a) y = 1.00 m; (b) y = 3.50 m; (c) y = 6.00 m. All plots are in different colour scales.

Figure 10. Cross-section (XY plane) plots of uncertainty-precision distribution for location sensors A and D at (a) z = 1.00 m; (b) z = 2.00 m; (c) z = 3.00 m. All plots are in different colour scales.
Table 1. Sensors’ arrangement in simulation and physical experiment.

<table>
<thead>
<tr>
<th>LS</th>
<th>Simulation (x, y, z) (m)</th>
<th>Physical Experiment (x, y, z) (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS_A</td>
<td>(11.00, 7.50, 4.00)</td>
<td>(11.03, 7.42, 3.88)</td>
</tr>
<tr>
<td>LS_B</td>
<td>(0.00, 7.50, 4.00)</td>
<td>(0.17, 7.38, 3.89)</td>
</tr>
<tr>
<td>LS_C</td>
<td>(0.00, 0.00, 3.00)</td>
<td>(0.17, 0.17, 3.01)</td>
</tr>
<tr>
<td>LS_D</td>
<td>(11.00, 0.00, 3.00)</td>
<td>(11.00, 0.17, 2.92)</td>
</tr>
</tbody>
</table>

Table 2. Simulated extreme uncertainty values for AB and AD pairs.

<table>
<thead>
<tr>
<th>Pair of LSs</th>
<th>Best Precision</th>
<th>Worst Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Value (cm³)</td>
<td>Location</td>
</tr>
<tr>
<td>AB</td>
<td>20</td>
<td>corner of the LS_A</td>
</tr>
<tr>
<td></td>
<td></td>
<td>corner of the LS_B</td>
</tr>
<tr>
<td>AD</td>
<td>150</td>
<td>corner of the LS_A</td>
</tr>
</tbody>
</table>

For the AB pair, located at the same height of the longer room wall, see Table 2, evaluated AoA precision distribution map, is presented in Figure 11.

Figure 11. Volumetric slice plot of uncertainty-precision distribution for location sensors A and B.
The specific cross-sections of the localization precision distribution map for the AB pair are presented in Figures 12–14. As for the LS’s pair AD, also for the AB pair, the localization precision increases along with the distance from LSs, see Figures 12 and 14. The worst precision of 2650 cm$^3$ is depicted at the bottom corners most distant from the active LS’s AB pair. The best precision equals 20 cm$^3$, which is noticed at (10.5, 7, 3.5) and (0.5, 7, 3.5) coordinates near the active LSs, see Figure 14a and Table 2. At the top along the wall between LS$_A$ and LS$_B$, the level of precision is relatively higher, because the cones’ axes referring to the arrival path could be even parallel, which is shown in Figure 12b.

Figure 12. Cross-section (YZ plane) plots of uncertainty-precision distribution for location sensors A and B at (a) x = 1.00 m; (b) x = 5.50 m; (c) x = 10.00 m.
Figure 13. Cross-section (XZ plane) plots of uncertainty-precision distribution for location sensors A and B at (a) $y = 1.00$ m; (b) $y = 3.50$ m; (c) $y = 6.00$ m.

Figure 14. Cross-section (XY plane) plots of uncertainty-precision distribution for location sensors A and B at (a) $z = 1.00$ m; (b) $z = 2.00$ m; (c) $z = 3.00$ m.
8. The Test Systems

The real system was implemented on the Ubisense Real Time Location System Series 7000. The used UWB-based RTLS consists of four LSs in a master-slave configuration, see Figure 15a. One of the LSs is assigned as a master, which has two-way communication with a tag in the 2.4 GHz telemetry channel. All LSs, both master and slaves, are able to receive localization pulses on UWB channel 6 GHz–8 GHz from the tag as shown in Figure 15b. Also all the LSs communicate by timing and Ethernet connections. Timing connections are used to synchronize the slaves with the master for TDoA measurement. Via Ethernet, the collected raw data is transmitted between the LSs and the switch. It is also used to provide power supply for the LSs according to PoE standards. The switch is connected with the PC consisting of the location estimation platform Ubisense Location Platform 2.1.

![Figure 15](image_url)

Figure 15. Photos of (a) RTLS sensor; (b) RTLS tags.

The used tags are Ubisense Compact Tags with a maximum tag update rate of 33.75 Hz. The tags attached to the targets communicate with the master on the telemetry channel 2.4 GHz, and send UWB chirps to all LSs. An exemplary structure of UWB-based RTLS is presented in [4]. Each tag sends UWB pulses to all LSs with a defined update rate, which depends on the number of tags in the system. Localization pulses received by each LS are analysed in terms of:

I. time difference of arrival to the LSs i.e., TDoA;

II. angles at which the signals are received by the LSs in terms of azimuth and elevation AoAs.
The power of signal, RSS, is used by the system for data filtration. The location estimation platform provides various static and dynamic filters, which improve estimation quality. However, in the following physical experiment, the proposed AoA-based localization algorithm operates on AoA raw measurements without filtration. The Ubisense algorithm is a part of the location estimation platform and it was used in validation. The Ubisense hybrid algorithm estimates the tag location based on AoA and TDoA measurements with static filtering.

The physical experiment was performed in a lecture hall with a size of 11.0 m × 10.0 m × 7.0 m located in the over 100 year old building of Faculty of Electrical and Control Engineering in Gdansk University of Technology, illustrated in Figure 16. However, due to the hall’s shape, the RTLS’s workspace does not cover the whole hall’s space. To cover the whole workspace, two additional LSs would be needed. Therefore, the effective size of the workspace is only 11.0 m × 7.0 m × 4.0 m. In the workspace, two environments can be specified, the stage with the lecture hall rostrum, and the tiered seating with 6 rows of desks along with 12 seats.

In the workspace, nine reference points on three desks were established using an electronic tachymeter. Two reference points were defined at the edges and one in the middle of each desk row. The calibration point located approximately in the centre of the workspace at coordinate (5.59, 3.96, 1.06), in the middle of the second desk row, was also one of the reference points.

Figure 16. Photo of the indoor environment with mounted LSs and the coordinate system origin.
The LSs CD, presented in Figure 16, were installed in the corners of the lecture hall on height 3 m. The two other LSs, A and B, were placed in the middle of sidewall, on height 3.9 m, see Table 1. All LSs were directed to the calibration point. The LSs positions were established using an electronic tachymeter South NTS-372 RC.

Four different tags, as shown in Figure 15b, were successively mounted on a tripod at four adjustable heights of 0 cm, 30 cm, 60 cm, and 90 cm. The measurements were performed on surfaces of the first, third and fifth desk rows, where each desk row has a different height relative to the floor. The tripod was placed successively at all reference points, at nine XY coordinates at four heights. In total, there were 36 spatial location samples with 200 samples at each location of the azimuth and elevation AoAs.

9. Experimental Verification

The suitability of the proposed systematic approach to the uncertainty, in terms of accuracy and precision of the AoA-based 3D localization, was verified by physical experiments for AD and AB LS pairs. The presented localization precision model was verified by evaluating how the model matches the real measurements for these LS pairs. Likewise, the suggested localization offset error model and effects of the correction vector were verified heuristically. Finally, the performance of the AoA-based 3D localization method, including its enhancement, was compared with the reference RTLS’s commercial algorithm results, where the reference localization technique combines the AoA and TDoA localization methods using all LSs.

9.1. Precision Model Verification

To verify the localization precision model, the simulation results of the proposed geometrical model of AoA localization in a 3D indoor space were compared with the results of physical experiments. The matching ratio, as a percentage of the experimental location estimates occurring inside the theoretical solid from the model, is used as a quantitative measure of how the precision model fits the reality. The matching ratio was determined at each of the 36 spatial location samples in the workspace, and an example is shown in Figure 17.

Cumulative distribution functions of matching ratios at 36 spatial location samples for LSs AB and AD are presented in Figure 18. The matching ratio for the pair AB, varies from 55% to 94% and the average value of matching ratio for these 36 spatial location samples is 74.6%. The cumulative distribution function for the
pair AD located on the shorter side of the workspace shows that the matching ratio varies from 41% to 91%, and the average value of matching ratio for the 36 spatial location samples is 68.4%. The AB pair of LSs placed on the longer side of the workspace shows better performance and even better fitting of the model to the real measurements. Moreover, for the 50% test points, the matching ratio was bigger than 68% for the AD pair and bigger than 75% for the AB pair of LSs. The cumulative distribution functions shown in Figure 18 verify that the results of the theoretical model and experiments are consistent.

Figure 17. The example of theoretical solid with a number of experimental location estimates outside the solid (red dots).

Figure 18. The cumulative distribution functions of the matching ratios for AB and AD pairs.
9.2. Validation of Localization Offset Error Approach

The validation of the proposed localization offset error approach is based on an analysis of the tags’ locations estimated using the AoA-based localization algorithm at the 36 spatial location samples in the test environment for the AB and AD LSs pairs. At each spatial location sample with known coordinates, each tag’s location was estimated from 200 samples. Then, the average offset error of \( x \), \( y \) and \( z \) components and the resultant average offset error of the location system in the tested environment were computed using Equations (1) and (2) and are shown in Tables 3 and 4 for AB and AD pairs, respectively. The estimated average offset error of the \( x \), \( y \) and \( z \) components defined a correction vector expressed by Equation (12) and calculated using Equation (11). The correction vector was applied to each of the 36 spatial location samples, by subtracting the vector’s coordinates from the estimated average \( x \), \( y \) and \( z \) localization coordinates. As result of applying the correction vector, the mean offset error components for these 36 spatial location samples were reset to zero, see Tables 3 and 4.

To judge the correction effect, the new estimated localizations were compared with the reference RTLS’s localization results as shown in Tables 3 and 4 for AB and AD LSs pairs respectively. The reference results were obtained using the commercial hybrid algorithm provided by Ubisense, which estimated the tag’s location based on TDoA measurements from four LSs [4].
Table 3. Characteristics of the experimental results of the offset error for the 36 spatial location samples for the AoA-based localization algorithm before and after correction and the reference algorithm for LSs AB pair.

<table>
<thead>
<tr>
<th>Component</th>
<th>Offset Error for the AoA-Based Localization Algorithm</th>
<th>Offset Error for the Reference Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Correction</td>
<td>After Correction</td>
</tr>
<tr>
<td></td>
<td>Mean (cm)</td>
<td>SD * (cm)</td>
</tr>
<tr>
<td>x</td>
<td>−15.9</td>
<td>23.4</td>
</tr>
<tr>
<td>y</td>
<td>−29.0</td>
<td>20.9</td>
</tr>
<tr>
<td>z</td>
<td>−32.7</td>
<td>13.4</td>
</tr>
<tr>
<td>Resultant</td>
<td>55.5</td>
<td>15.6</td>
</tr>
</tbody>
</table>

* SD of the mean offset error of 36 spatial location samples
Table 4. Characteristics of the experimental results of the offset error for the 36 spatial location samples for the AoA-based localization algorithm before and after correction and the reference algorithm for LSs AD pair.

<table>
<thead>
<tr>
<th>Component</th>
<th>Offset Error for the AoA-Based Localization Algorithm</th>
<th>Offset Error for the Reference Method</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Before Correction</td>
<td>After Correction</td>
</tr>
<tr>
<td></td>
<td>Mean (cm)</td>
<td>SD * (cm)</td>
</tr>
<tr>
<td>x</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>−31.8</td>
<td>13.4</td>
</tr>
<tr>
<td>y</td>
<td>−24.7</td>
<td>23.9</td>
</tr>
<tr>
<td>z</td>
<td>−38.1</td>
<td>18.6</td>
</tr>
<tr>
<td>Resultant</td>
<td>64</td>
<td>8.9</td>
</tr>
</tbody>
</table>

* SD of the mean offset error of 36 spatial location samples
9.2.1. AB Pair Case Study

The exemplary z offset error component, before and after applying the correction vector in each spatial location sample, is compared with the corresponding component from the reference system, see Figure 19. The resultant location offset errors, which are the modules of the relevant offset error vector are shown in Figure 20. After applying the correction vector, the mean resultant offset error for the AoA-based localization algorithm is reduced 43.8% from 55.5 cm with SD of 15.6 cm to 31.2 cm with SD of 13.9 cm see Table 3. For a comparison, the mean resultant offset error determined by the reference algorithm was 32.8 cm with SD of 12.2 cm. Moreover, the correction vector significantly reduces the minimum and maximum values of the resultant offset error by 19.3 cm and 26.1 cm respectively, which means 75.4% and 29.7% respectively. For a comparison, the range of resultant offset error determined by the reference algorithm was from 8.3 cm to 66.8 cm.

Figure 19. Comparative bar plots of the average offset errors of the z components for AB pair.
The presented data for the AB pair shows that for both localization algorithms, the z component of the offset error was biggest compared to x and y components, see Table 3. For the AoA-based localization algorithm without correction vector, z component’s mean value was −32.7 cm and standard deviation, SD, 13.4 cm, when for the reference algorithm z component’s mean value and SD were 20.7 cm and 14.5 cm respectively. For this LSs pair, the x component has the least impact on the resultant offset error. For both algorithms, the mean offset error x component was almost a half of z component.

The cumulative distribution functions of average offset errors from tests of AoA-based localization method before and after correction along with the reference method are presented in Figure 21. The presented plots show how the correction vector influences the average offset error. In a case the AoA-based localization algorithm without correction, the range of the error is from 25 cm to 87 cm and the median of the average offset error is 55 cm. The correction vector significantly shifts the distribution function to the left to the range from 6.3 cm to 61.8 cm with a median of 30 cm. For 80% of test locations, the average offset error, after applying the correction vector, is less than 40 cm.
Figure 21. Experimental cumulative distribution functions of the average resultant offset error for LSs AB pair for three algorithms.
9.2.2. AD Pair Case Study

The z offset error components before and after applying the correction vector at each spatial location sample are compared in Figure 22, and the resultant location offset errors are shown in Figure 23. It shows that the correction vector reduced the location offset errors at most of the examined positions, and the average offset error of these 36 locations is reduced 55.6% from 64.0 cm to 28.4 cm, see Table 3. However, the SD of mean offset error increased from 8.9 cm to 17.1 cm. For a comparison, the mean resultant offset error determined by the reference algorithm was 32.8 cm with the SD of 12.2 cm. Moreover, the correction vector significantly reduces the minimum and maximum values of the resultant offset error by 39.7 cm and 7.6 cm respectively to the range from 3.5 cm to 70.7 cm, what means improvement of 91.9% and 9.7% respectively. For a comparison, the range of resultant offset error determined by the reference algorithm was from 8.3 cm to 66.8 cm.

The presented data for AD LSs pair show that alike for the AB LSs pair, the z component of the offset error was the biggest, compared to x and y components. For AoA-based localization algorithm without the correction vector, z component’s mean value was −38.1 cm with a SD of 18.6 cm. When for the reference method, z component’s mean value was 20.7 cm with a SD of 14.5 cm. The y component with the mean value −24.7 cm with a SD of 23.9 cm is the smallest of the three components. However, the SD of this component is relatively high compared to the x and z components.
Figure 22. Comparative bar plots of the average offset errors of the z components for AD pair.

Figure 23. Comparative bar plots of the average resultant offset error for AD pair.
The cumulative distribution functions of the average offset errors of the AoA-based localization method before and after correction along with the reference method results for the 36 spatial location samples are presented in Figure 24. The presented distribution functions clearly illustrate how the correction vector influences the average offset error. For the results from the AoA-based localization algorithm without the correction vector, the median of the average offset error is 60 cm, whereas the range of the error is from 42 cm to 82 cm. The correction vector significantly shifts the distribution function to the left and the median of average offset error is reduced 63.3% to 22 cm. For 80% of the test locations, the average offset error is less than 40 cm.

Figure 24. Experimental cumulative distribution functions of the average resultant offset error for LSs AD pair.

10. Results Discussion

The simulation results for two LS pairs AD and AB shown in Figures 7–14 indicate that the localization uncertainty, in terms of precision, depends on the LS’s configuration in the workspace. The precision distribution maps demonstrate how the uncertainty increases along with the distance from LSs; the uncertainty is worst at the bottom corners of the side opposite to the side with the active LSs, which is summarized in Table 2.
The Table 2 points out that the best precision is identified near the active LSs. The simulation results indicate also how different deployment heights of active LSs influence the uncertainty maps. For instance, Figure 8c shows that the location uncertainty near the floor is significantly lower under the LSd, which is located lower than the LSa. The simulation results of the LSs AB pair placed at the same height show a relatively high uncertainty at the middle top along the wall between LSa and LSb, see Figure 12b. The reason for this phenomenon is that in this area, the volume of the common solid of the two crossing cones is relatively big since their axes referring to the paths of arrival could be almost coaxial. However, the cones are not coaxial due to the established 50 cm localization dead zone near the wall. To overcome a problem of bad uncertainty-precision near the wall, it can be suggested to arrange the active LSs at different heights.

The simulated uncertainty maps for the AB and AD LS pairs depict the advantage of the AB pair, which provide the localization precision in a range from 20 cm$^3$ to 2650 cm$^3$ compared to AD pair’s a range from 150 cm$^3$ to 6900 cm$^3$, see Table 1. The verification of this observation by the experimental results confirms that the best localization precision is achieved for the LSs AB pair and consequently for AD pair, the average value of matching ratio for the 36 spatial location samples is 74.6% compared to 68.4% for the LSs AD pair.

The customization verification proves a positive influence of the correction vector on localization accuracy. In the given test environment with 36 test points, for LSs AB pair, the correction vector reduces 55% the mean offset error from 55 cm to 31 cm and from 64 cm to 28 cm for AD pair, see Tables 3 and 4. Also for the AB pair the ranges of the offset error at these 36 test points have been diminished of 19.3 cm and 26.1 cm for lower and upper range limits respectively, from 25.6 cm and 87.9 cm to 6.3 cm and 61.8 cm respectively. The customization results challenges the mean offset error value of the reference algorithm of 32 cm, and even its range limits of 8.3 cm and 66.8 cm.

To comprehensively assess the correction vector’s effect, the estimated localizations’ accuracy without and with the applied correction vector are compared with the reference RTLS’s results for LSs AB and AD pairs, shown in the Figures 21 and 24, respectively. The figures clearly indicate improvement of the accuracy after applying the correction vector, which vitally moves the cumulative distribution curves towards the lower value of the offset error. Considering both LS configurations, after applying the correction vector, a half of the test locations, the offset error is less than 30 cm and 22 cm for LSs AB and AD pairs respectively, compared to 31 cm for the reference algorithm. One can see that the correction vector improves the accuracy of the AoA method in a way that it challenges the reference method. Similarities in shape of all cumulative distribution
11. Conclusions and Future Work

Due to its applicability and complexity, discovering a trade-off among different features of indoor localization systems working in a 3D environment is an important research subject. The proposed approach investigates the performance in terms of the localization uncertainty of AoA-based UWB-based RTLS’s. The improvement of localization accuracy and precision of the RTLS’s, without compromising its simplicity and price has been achieved by means of the system customization. The proposed analytical geometrical uncertainty model of the AoA localization method in a 3D indoor space is the concept’s foundation of the analytical customization method. The customization is based on the performance assessment in a given working environment.

A 50% improvement of system localization accuracy is gained by applying a correction vector, which is heuristically defined from an analysis of the system’s 3D accuracy distribution map of the given working space. The enhanced performance of the AoA-based UWB-based RTLS challenges the performance of the reference hybrid TDoA methods supported by AoA technology, whereas the proposed method excels the reference one in terms of simplicity and price. The experimental results prove that the correction vector is the suitable customization, which reduces the localization offset error caused by the variety of the system’s architecture and calibration process, and by the tags’ and working environments’ heterogeneity.

Another introduced customization approach considers the system’s performance in terms of precision in respect to the system’s configuration in the given working space. The system’s performance analysis for different LSs configuration was done for two different LSs pairs and for different LSs’ height placement in the space of the lecture hall. The results show a significant difference in precision, up to 7.5 times for its lower limit and 2.6 times for its upper limit, for the two considered configurations. Furthermore, the analysis indicates also a disadvantage of placing the active LSs at the same height. Moreover, the simulated precision distribution maps define the areas of the best and worst localization precision, in such a manner that the best performance is noticeably near to the active LSs and the worst are at the corners hindmost from these LSs.

The angular-based 3D localization algorithm estimating the tag’s location using azimuth and elevation angle measurements of a pair of LSs is proposed. The
extrapolation algorithm allows finding the localization estimate even in contaminated environments by using the principle of a distance between two skewed lines. Simulation and physical experiment results confirm that the proposed simple extrapolation angular-based 3D localization algorithm ensures a good localization performance and challenges the advanced UWB-based RTLS algorithms.

The proposed analytical geometrical model of the AoA localization method in a 3D indoor space was evaluated in the simulation environment of Matlab where the model was implemented. The proposed solution was verified by comparison of simulation and physical experiment results. The quantitative verification, in a form of matching ratios confirms that the analytical model matches the real measurement with a high probability level.

To further enhance the RTLS performance, the research may consider a region-based correction vector method, which adjusts the correction vector to the region of workspace. The distance from the active LSs can be used as an adaptive factor of the correction vector. The artificial intelligent approach, such as fuzzy logic or machine learning, may be implemented for estimation of regions’ boundaries and relevant suitable correction vectors. Additionally, the uncertainty analysis of the UWB LS’s array geometry used in the AoA-based RTLSs may provide guidance on how to enhance the estimation of the correction vectors.

Moreover, a similar localization uncertainty analysis can be applied to ToA and TDoA-based localization algorithms used in RTLSs. An analogical uncertainty model, including offset error sources of RTLS’s architecture, indoor environment and synchronization procedure, can be defined to enhance the system’s performance.

References


