Thesis no: MSCS-2016-07

# Filtering estimated series of residential burglaries using spatio-temporal route calculations

**Jaswanth Bala**

Faculty of Computing
Blekinge Institute of Technology
SE–371 79 Karlskrona, Sweden

This thesis is submitted to the Faculty of Computing at Blekinge Institute of Technology in partial fulfillment of the requirements for the degree of Master of Science in Computer Science. The thesis is equivalent to 20 weeks of full time studies.


**Contact Information:**
Author(s):
Jaswanth Bala
E-mail: jaba14@student.bth.se

University advisor:
Dr. Martin Boldt
Department of Computer Science

| | | | |
|---|---|---|---|
| Faculty of Computing | Internet | : | www.bth.se |
| Blekinge Institute of Technology | Phone | : | +46 455 38 50 00 |
| SE–371 79 Karlskrona, Sweden | Fax | : | +46 455 38 50 57 |

# Abstract

**Context**. According to Swedish National Council for Crime Prevention, there is an increase of 19% in residential burglary crimes in Sweden over the last decade and only 5% of the total crimes reported were actually solved by the law enforcement agencies. In order to solve these cases quickly and efficiently, the law enforcement agencies has to look into the possible linked serial crimes. Many studies have suggested to link crimes based on Modus Operendi and other characteristic. Sometimes crimes which are not possible to travel spatially with in the reported times but have similar Modus Operendi are also grouped as linked crimes. Investigating such crimes could possibly waste the resources of the law enforcement agencies.
**Objectives**. In this study, we investigate the possibility of the usage of travel distance and travel duration between different crime locations while linking the residential burglary crimes. A filtering method has been designed and implemented for filtering the unlinked crimes from the estimated linked crimes by utilizing the distance and duration values.
**Methods**. The objectives in this study are satisfied by conducting an experiment. The travel distance and travel duration values are obtained from various online direction services. The filtering method was first validated on ground truth represented by known linked crime series and then it was used to filter out crimes from the estimated linked crimes.
**Results**. The filtering method had removed a total of 4% unlinked crimes from the estimated linked crime series when the travel mode is considered as driving. Whereas it had removed a total of 23% unlinked crimes from the estimated linked crime series when the travel mode is considered as walking. Also it was found that a burglar can take an average of 900 seconds (15 minutes) for committing a burglary.
**Conclusions**. From this study it is evident that the usage of spatial and temporal values in linking residential burglaries gives effective crime links in a series. Also, the usage of Google Maps for getting distance and duration values can increase the overall performance of the filtering method in linking crimes.

**Keywords:** Residential Burglaries, Serial Crimes, Spatial Analysis, Online Direction Services.

# Acknowledgments

Firstly, I would like to extend my sincere gratitude to my supervisor **Dr. Martin Boldt** for this incredible opportunity and also for his full support, expert guidance, understanding and encouragement throughout my master thesis. If not for his immense patience and timely wisdom this work would not have been possible.

Secondly, I would like to acknowledge my dad **Bala Venkateswara Rao** and my mother **Bala Sridevi** for giving me the opportunity to study abroad and for their continuous support throughout my studies.

Finally, I would like to thank all my friends and well-wishers for their knowledgeable discussions and valuable suggestions.

# List of Figures

# List of Tables

# List of Abbreviations

| | |
|---|---|
| **API** | Application Programming Interface |
| **CriMM** | Criminal Movement Model |
| **DSS** | Decision Support System |
| **DS1** | Data Set 1 |
| **DS2** | Data Set 2 |
| **HTTP** | Hyper Text Transfer Protocol |
| **JSON** | JavaScript Object Notation |
| **MO** | Modus Operandi |
| **ODS** | Online Direction Service |
| **REST** | Representational State Transfer |
| **ROC** | Receiver Operating Characteristic |
| **URI** | Uniform Receiver Identifier |
| **USD** | United States Dollar |

# Contents

# Chapter 1

# Introduction

Residential burglary is considered as one of the most common type of crimes and is defined as an illegal entry into a domestic home with an intention of committing an offense [1–4]. The seriousness of the burglary various based on many factors like the time of the day at which the burglary was committed, whether or not the victims were present at the dwelling, whether the offender was armed [3]. Residential burglary has a deep impact on the victims lives like financial losses, psychological distress etc [3, 4]. In most of the cases, it brings out severe stress, enormous anger, irritation and fear in direct victims and in some cases the consequences may lead to physical or psychological injury. [5]. Therefore such crimes have to be restricted as soon as possible.

According to the Swedish National Council for Crime Prevention, a total of about 22400 burglaries were reported to the Swedish police in 2014 which is 6% increase when compared to 2013 and a 19% increase over last ten years [6]. Only five percent of these reported burglaries were solved by the law enforcement agencies. So clearly the crimes related to the residential burglaries are a serious concern for the Swedish law enforcement agencies.

This document presents an approach to determine whether a particular crime can be attached to a series of crimes based on its spatial and temporal patterns. Existing state-of-the-art algorithms are used in order to group a series of residential burglaries. The obtained series of burglaries are further filtered by comparing the actual duration of time for traveling between two crime scenes, which is obtained from various online mapping services (like Google maps, Bing maps etc.), with the time difference between the two crimes. The identified anomalies are removed from the estimated series, which assists the law-enforcement agencies by decreasing the number of cases to investigate. Hence, the resources can be used more efficiently and the crime investigation time can be improved.

## 1.1 Background

A crime is defined as an offense that is committed against an individual or a group of individuals or the society that is often prosecuted by the law enforcement agencies and punishable by the law [7]. Residential burglary is one of the most common types of the crimes that are present in the society and such crimes are a serious concern to Swedish law enforcement agencies. Literature shows that many burglaries were committed by a minor number of offenders and most of them are under age 30 [2, 3, 8–10]. As some offenders tend to commit multiple burglaries, it is helpful for the law enforcement agencies to identify the similar crimes which helps them catch the offender faster by gathering additional evidence.

A serial offender is an individual who commits a series of multiple crimes over a specific period of time, with similar modus operandi (MO) and patterns, that occur in different geographic locations [11]. The process of identifying these series of crimes is known as the crime series identification [12]. By investigating multiple crimes there is a scope for the investigators to gather some additional evidence, which potentially increases the quantity and quality of the evidence against an offender [13]. For example, given a series of burglaries, the investigators can estimate the possible connection between them by examining their respective crime scenes and reports. As a result, the usage of the law enforcement resources can be optimized by crime series identification [8].

In order to catch these serial offenders, usually the law enforcement agencies rely on physical forensic evidence such as DNA matching, fingerprint analysis and footwear impressions that are available at the crime scene [14]. However, in most cases the offenders are smart enough to clean up their forensic evidence at the crime scenes [14]. Even if the investigators found such forensic evidence, many law enforcement agencies have very limited resources available to them and also testing these forensic evidence is a time-consuming process [15]. Hence, the investigators cannot always afford to analyse a large amount of forensic data on a regular basis [14]. In such cases, the investigators have to go for alternatives techniques for linking similar crimes.

Many researchers had said that the geographical location, time at which the crime was committed, the inter crime distance could be very useful in predicting the series of similar crimes [16]. Usually most of the serial burglaries tend to have a low spatial and temporal proximity [8–11,17]. If the location of a particular crime is too far away (i.e. if it is impossible to travel within the amount of time available) from the rest of the crimes in a series of residential burglary crimes then that crime should be removed from the series. As shown in figure 1.1, different offenders tend to take different routes to travel between the crime locations based on the means of transport available to them [18]. By using online direction services (e.g. Google maps, Bing maps) the different routes between crimes as well as the respective travel times can be identified for different transportation modes. By using such a spatial route analysis, it is possible to remove crimes that could not be included in the same series, which in turn could save investigation resources.

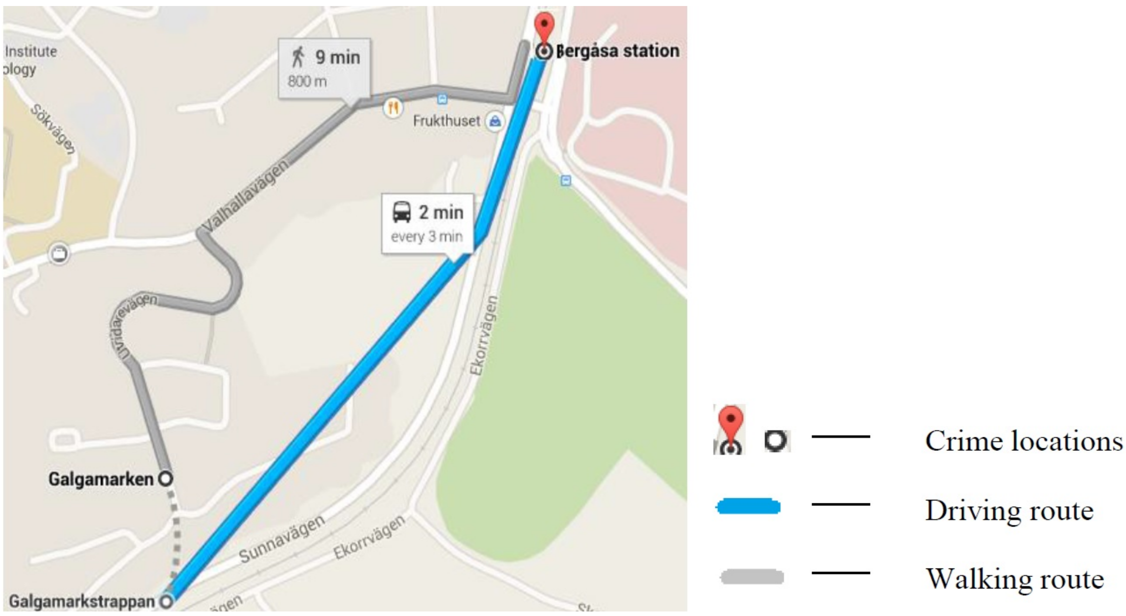


Figure 1.1: Different travel routes between two crime locations based on the transportation mode available to the offender

## 1.2 Online Direction Services

Over the last decade there is a huge advancement in the online direction services (ODS) like Google Maps, Bing Maps etc. People can utilize these services for finding directions to various destinations, satellite and topographical images, 3D images, and angled aerial photography [19]. Most of the map services have their own Application Programming Interfaces (API) that are made publicly available. These APIs can be used to integrate these online map services into different websites in order to show their respective business locations and can be used in location aware games etc [19]. The ODS that are used in this study are discussed below.

### 1.2.1 Google Maps

Google maps was launched in 2005 and since then it has become one of the major players in the area [20, 21]. Google maps is a web based mapping service that provides directions between different locations, of users choice, through various modes of transportation. These maps also shows additional data like traffic information, public transit, street and road names, famous landmarks and buildings [20]. The available map imagery is updated daily and the satellite imagery is no older than three years [21]. Users can utilize the services of Google maps through their publicly available API. Google maps API is free to use upto 2,500 map loads per 24 hours [21]. After the free limit is passed, it costs up to half a United States dollar (USD) per 1000 map loads [21].

### 1.2.2 Bing Maps

Bing maps was launched in 2005 and is a web mapping service which is mostly used to help the organizations with marketing performance, business opportunity and risk analysis etc [22]. Some of the services that are offered by Bing maps are geo-coding, reverse geo-coding, routing etc [22]. The available map imagery is updated monthly and the satellite imagery is no older than three years [22]. Users can utilize the services of the Bing maps through their publicly available API. Bing maps is free to use until 10,000 transactions per month and if the free limit is exceeded one can buy the subscription starting at 100,000 transactions per month for $4,500 [22].

### 1.2.3 Here Maps

Here maps was launched in 2011 and it offers various services to automotive industry, consumers and enterprises. Some of the services that are offered by Here maps are satellite tiles and images, geo-coding, reverse geo-coding, car and pedestrian routing etc [23]. The available satellite imagery is no older than three years [23]. Users can utilize the services offered by Here maps through their publicly available API. Here maps offers a 90-day trial period where the user can get access to all of its features and after that the subscription starts at $59 with access to limited features [23].

### 1.2.4 MapQuest

MapQuest was launched in 2004 and is an online web mapping service which provides services like geo-coding, street maps, satellite imagery etc [24]. The available satellite imagery is no older than four years [24]. Users can utilize the services of MapQuest through their publicly available API. MapQuest is free to use upto 15,000 transactions per month and after the free limit is exceeded one can buy the subscription starting at 30,000 transactions per month for $99 [24].

## 1.3 Related Work

Tonkin et al. performed binary logistic regression, on a sample containing both solved and unsolved crimes, for distinguishing the linked crimes from unlinked [14]. The distinguishing of crimes is done across crime categories, crime types and within crime types using geographical and temporal proximity. In order to examine the discrimination accuracy, receiver operating characteristic (ROC) analysis was performed on the sample. The results from the ROC analysis showed the notable levels of discrimination accuracy across crime categories, across crime types and within crime types. The work concludes stating behavioural case linkage as major aspect in linking crimes and assists in finding serial offenders based on behaviour of suspects among various crime scenes [14].

Fox and Farrington analysed the behavioural consistency in burglary styles among a sample of 405 solved burglaries that are committed on the east coast of Florida between 2008 and 2009 [25]. The Jaccard's coefficient, the forward specialization coefficient, the Diversity index are used to know the variations between the behaviour of various serial burglars who had committed burglaries in different offense styles. The results from these analyses show that the serial burglars are relatively consistent in their offense styles [25].

Iwanski et al. had develped a Criminal Movement Model (CriMM) for determining the relationship between the offenders activity space (where the offender performs his regular activities) and awareness space (where the offender has some awareness about the environment). This model simulates the travel routes, that an offender likely to take, between the offender's home location and the major attractors. These simulated routes are than compared with the actual crime locations that are committed by the offender. In order to perform this analysis, five major attractor locations within the Greater Vancouver Regional District in Canada were selected and also five years worth of real police data was collected and analysed for getting information about offenders. After the analysis it was found that most of the offenders are likely to commit crimes within their awareness space [26].

Daele and Bernasco explored the existing literature on directional consistency and proposed an enhanced measure of directional consistency and empirically used this measure to explore consistency in the offenders direction among a sample of 268 burglars (offenders) in the Greater Hague area between 2001 and 2006 [27]. The new measure investigated two main groups of offenders, the first having strong directional bias and the other shows no directional consistency. The authors suggested that directional consistency among offending patterns are constructed by daily routines and habitual behaviour. It thus resulted in deducing that routes towards the places visited by offender are more prone to burglaries. The study presents that offender behaviour is stable and displays spatial consistency in their journey to crime [27].

Bennell and Jones made an attempt for linking serial burglaries based on offender's MO by utilizing the readily available information about commercial and residential burglaries [28]. Logistic regression is performed to examine how different attributes or features contribute in differentiating the linked and unlinked burglaries. ROC is performed to present the validity of the work done. Results indicated that the distance between various crime sites is more effective than others in linking crimes rather than the physical evidence that is available at the crime scene [28].

Lisa et al. presented a method of risk distribution of crime incidents that follow a linear pattern named as Hot Routes [29]. This method addressed a number of the weaknesses like unclear range settings, poor geocoding and over smoothing associated with conventional hotspot mapping techniques such as thematic mapping. The method uses a linear distance to partition sections of roads into grids. Rather than providing the visualisation of data the authors method provided a localised low level view that makes it stand out for small-scale analysis. However the method also had some disadvantages of being usable only to small sections of roads rather being to a city wide level. This work is done by using the data of local bus routes in london. This method helping in viewing sections of road that are highly prone to bus crimes. By using this method the analysts can compare levels of crime and exclude the section of route that are attached with the physical and socio-demographic characteristics of the surrounding area [29].

Markson et al. compared the behavioural similarity, geographical proximity and temporal proximity of linked crime pairs with those of unlinked crime pairs from a sample of 160 residential burglaries (80 linked crimes and 80 unlinked crimes) committed between 2006 and 2008 which obtained from Northamptonshire police, UK [16]. The results are validated with logistic regression and ROC analyses. These analyses show that there is a high degree of predictive accuracy with geographical and temporal proximity when compared to other traditional modus operandi behaviours. This study stated that a combination of geographical and temporal proximity is more effective while separating linked from unlinked residential burglaries [16].

Borg et al. had developed a decision support system, using clustering algorithms, for grouping the similar residential burglaries [8]. They had developed a form with approximately 160 parameters for collecting and analysing the crime scene data. This form collects the data about the MO, residence properties, preventive measures taken by the resident and the other evidence found at the crime scene. Clusters were formed by analysing and grouping the similar residential burglaries from a sample of 180 residential burglaries collected by the Swedish police. Connectivity and Silhouette index were used in order to measure the quality of the cluster. The stability and the accuracy of the cluster was measured by using Jaccard index and Rand index respectively. This study states that the number of burglary cases that need to be manually analysed can be reduced by grouping the linked residential burglaries [8].

### 1.3.1 Identification of the Gap

Many clustering algorithms for identifying the linked burglaries are discussed in present literature. Such algorithms are based on the MO characteristics like target selection, method of entry at the crime scene, stolen goods etc. In a study conducted by Borg et al. a Decision

Support System (DSS) for estimating series of burglaries was developed [8]. This system compares and analyses the similarities between different burglaries in order to group them into sets of related crimes. By using such a DSS, a series of linked residential burglary crimes can be identified. Such algorithms are very helpful in identifying the serial burglaries but irrelevant crimes with similar MO will be grouped as the similar crimes. Investigating such irrelevant crimes would involve wastage of resources. Hence the serial crimes that are obtained by using the existing algorithms should be further filtered down in order to remove the irrelevant crimes from the investigation. In this study it is investigated to what extent this can be done based on spatio-temporal route analysis.

## 1.4 Aims and Objectives

The aim of this thesis is to develop a method for filtering the estimated series of residential burglaries, which are obtained from the existing state-of-the-art algorithms, based on geographical and temporal features. This would assist the law enforcement agencies in filtering the irrelevant crimes from their investigation. The aim of this study is fulfilled by accomplishing the following objectives.

- To investigate various online direction services for determining the travel times and distance between two locations.
- To estimate the travel route distance between two different crime locations and the time it takes to travel from the first crime location to the second crime location, given a predefined mode of transportation.
- To develop a method that can filter the crimes by geographical and temporal features.
- To evaluate the proposed method by filtering the known true series of burglaries and the automatically estimated series of burglaries.

## 1.5 Research Questions

The following research questions are formulated in order to satisfy the above mentioned objectives so that the aim of this thesis study can be achieved.

**RQ 1:** *What are the different online direction services that are freely available and by what factor do their respective travel times differ from each other?*

This research question is formulated in order to find various mapping services that are available and also to investigate the variation in their respective measurements, so that the best suitable mapping services can be selected for this study.

**RQ 2:** *To what extent is the series of known residential burglaries (ground truth) affected by filtering spatially irrelevant crimes based on viable travel times between crime locations?*

This research question is formulated in order to validate the proposed filtering method so that it does not produce false positives.

**RQ 3:** *To what extent is the estimated series of residential burglaries affected by filtering spatially irrelevant crimes based on viable travel times between crime locations?*

This research question is formulated in order to find out whether the use of online direction services in linking residential burglaries gives promising results or not.

**RQ 4:** *Does the usage of the proposed method performs better than the usage of the exiting state of the art methods, based on line-of-sight analysis, in linking serial residential burglaries?*

This research question is formulated in order to find out whether the proposed method gives better results than with the usage of straight line distances between the crime locations in linking serial residential burglaries.

**RQ 5:** *What is the initial indication of the time duration of burglary events found in the data?*

This research question is formulated in order to find out the total time that is available for the burglars to commit a particular residential burglary.

## 1.6 Contribution

The purpose of this thesis is to develop a method for filtering estimated series of crimes, provided by already existing state-of-the-art algorithms, by comparing the actual duration of time for traveling between two crimes with the time difference between the two crimes. The distance between the crime locations and the travel time are obtained from online direction services. Identified anomalies are removed from the estimated series, which assist law-enforcement agencies by decreasing the number of cases to investigate. Hence the resources can be used more efficiently and the crime investigation time can be improved.

# Chapter 2

# Method

## 2.1 Data

The following section describes about the data that was collected from the Swedish law enforcement agencies and how it was made ready for this study.

### 2.1.1 Data Collection

The law enforcement officers use a digital form which consists of approximately 160 parameters for recording a particular residential burglary crime scene [8]. These parameters describe the offender's behaviour in the crime scene along with the spatial and temporal details of the crime scene in a standard way [8]. The data sets used in this study are the actual residential burglary crimes that are committed in Sweden. Two data sets which consists a total of 3895 residential burglary reports (as shown in figures 2.1 and 2.2), collected by the Swedish law enforcement officers, are used in this study.

These residential burglary crimes were happened between 1 January, 2012 and 31 December, 2013 and the reports were gathered from the Stockholm area and the Southern part of the Sweden. The first data set (DS1) consists of 3000 reports which are known series or linked crimes (there is at least a single burglar associated to a particular residential burglary crime) and the second data set (DS2) consist of 895 reports which are estimated linked crimes (i.e. the suspects are yet to be found). The description about the parameters of first data set that are used in this study are shown in the following table 2.1.

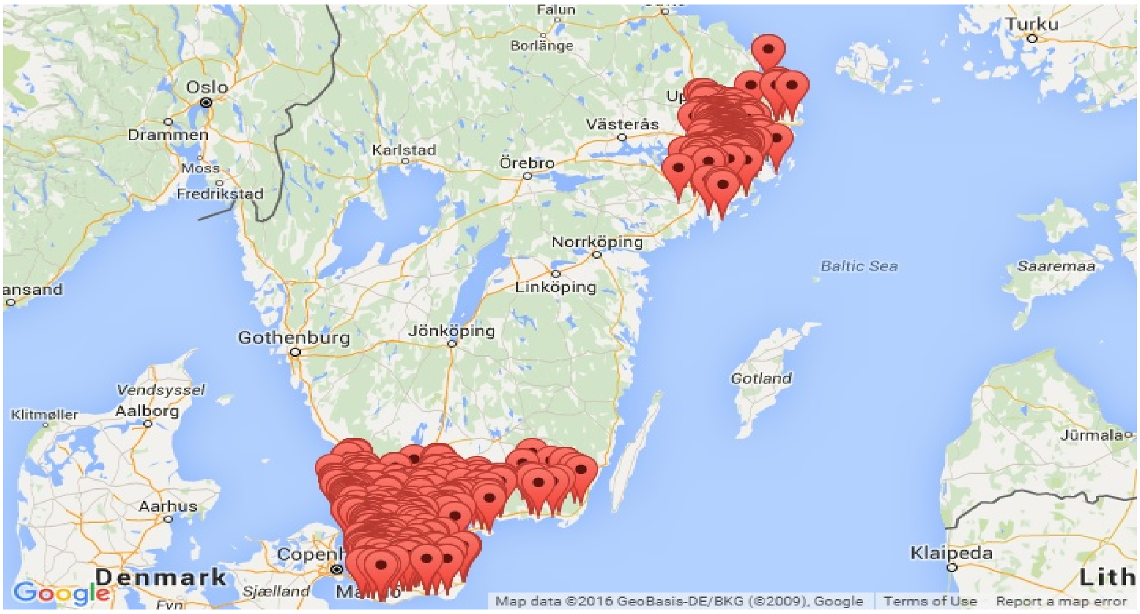


Figure 2.1: The locations of the crimes in Google Maps that are present in Data set 1

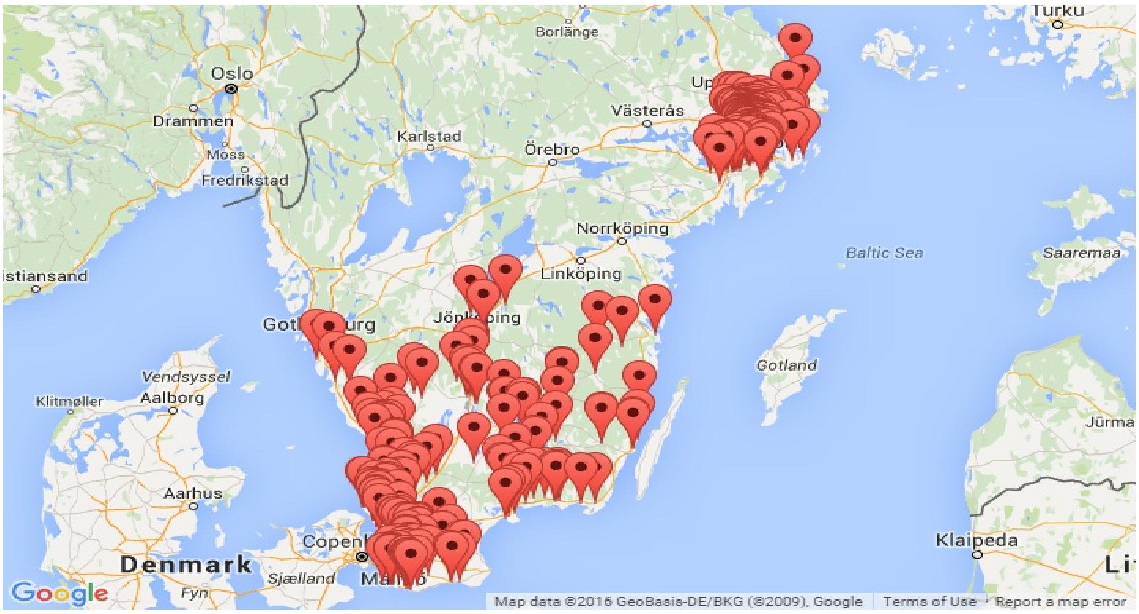


Figure 2.2: The locations of the crimes in Google Maps that are present in Data set 2

| Parameters | Description |
|---|---|
| idval | It is an unique but anonymized identifier given to identify a particular crime by the Swedish police. |
| pHash | It is an unique but anonymized identifier given to identify a particular suspect by the Swedish police. |
| Longitude | The longitude of the crime scene. |
| Latitude | The latitude of the crime scene. |
| date start | The expected date on which the crime had started. |
| time start | The expected time at which the crime had started. |
| date end | The expected date on which the crime had ended. |
| time end | The expected time at which the crime had ended. |
| timediff | The time difference between the start and end times of the crime. |

Table 2.1: Parameters in DS1.

The date start, time start, date end and time end values are provided by the victims of the respective residential burglaries. In most of the cases this time period was believed to be that the victims were away from their respective residences.

The second data set is the estimated series, which are obtained by associating a set of crimes to a particular crime based on different parameters that are recorded from their respective crime scenes. Hence in this data set there is a parameter named r_idval, which is the reference crime to which a series of crimes are associated to. In these crime series, the suspects are not associated to the crimes yet. So, there is no pHash value in this data set. The rest of the parameters are same as the DS1.

### 2.1.2 Data Preparation

Sometimes there might be some inconsistencies (like duplicate data, missing values, garbage values etc) present in the data. If this data is used in the analysis, then they may produce ambiguous results. So the following precautions were taken for removing this irrelevant data.

- Identify and remove the duplicate records present in the data sets.
- Identify and remove the irrelevant parameters that are not useful for this analysis.
- Identify and remove the records which have missing values or garbage values.

After going through the above mentioned steps, a total of 173 records were removed from both the data sets. Later, the first data set was carefully analyzed and it was found the many suspects are associated with only one crime, i.e. no crime series and also it was found that one of the suspects was associated with 33 residential burglary crimes. The complete list was depicted in the following table 2.2. In this data set each series is identified with *pHash* value.

The similar analysis of the second data set were illustrated in the following table 2.3. In this data set each series is identified with *r_ idval* value. Sometimes a single crime is committed by a group of offenders but in this study only individual crimes are considered as there is limited information available in these data sets about the group of offenders.

## 2.2 Representational State Transfer (REST) Services

REST is a lightweight web service which is based on client-server model and it is used for retrieving and updating the data over the internet [30]. This data transactions over the internet is done through the communication protocols like Hypertext Transfer Protocol (HTTP). REST uses HTTP methods, like GET, POST, PUT and DELETE, for data transactions [30]. These REST services are used in this study for retrieving the distance and travel times between different crime locations from different ODS. The request to different ODS are made through their respective Uniform Resource Identifiers (URIs). The response from the ODS is the JavaScript Object Notation (JSON)

| Number of Crimes per series | Number of Series |
|---|---|
| 33 | 1 |
| 23 | 1 |
| 21 | 1 |
| 20 | 3 |
| 19 | 1 |
| 18 | 1 |
| 13 | 1 |
| 11 | 1 |
| 10 | 3 |
| 9 | 1 |
| 8 | 1 |
| 7 | 4 |
| 6 | 12 |
| 5 | 33 |
| 4 | 45 |
| 3 | 107 |
| 2 | 241 |
| 1 | 1334 |
| Total: | 2827 crimes |

Table 2.2: Summary of crime series in data set 1.

| Number of Crimes per series | Number of Series |
|---|---|
| >300 | 11 |
| >200 & <=300 | 222 |
| >100 & <=200 | 453 |
| >1 & <=100 | 209 |
| Total: | 136679 crimes |

Table 2.3: Summary of crime series in data set 2.

data (see Appendix B for sample requests and responses of different ODS).

## 2.3 Experiment Design

An experiment is a process of influencing one or more dependent variables by manipulating the independent variables [31]. The independent variables in this study are geographical and temporal features and the dependent variable is linking residential burglaries. The quasi experimental design is best suited for this study as there are no control variables and also there is no randomization while selecting the sample. Convenience sampling technique is used as the data is conveniently accessible for experimentation.

### 2.3.1 System Specifications

The hardware environment in this experiment consists of a HP ENVY PC and the underlying processor is an Intel core i7 4700M. The following table 2.4 provides the summary of the environment on which the experiment was conducted.

| **System Specification** | **Environment Variable** |
|---|---|
| Operating System | Microsoft Windows 7 |
| System type | X64 |
| Processor | Intel Core i7 |
| RAM | 8 GB |
| Free hard disk space | 100 GB |
| Video Display | 136 x 768 |
| Programming Language | Java 8 |
| Database | MySQL |
| IDE | NetBeans |
| Server | WAMP |

Table 2.4: Summary of the System Requirements.

### 2.3.2 Design of the Filtering Method

After analyzing the residential burglary crime series that was collected from the Swedish police, a filtering method was designed such that it utilizes the distances and travel times between the crime locations that are obtained from various ODS. This filtering is done in two phases. First phase is based on the distances and second phase is based on the travel times.

### Phase One

At first a particular crime series is taken from the data set and the crimes are arranged based on the dates on which the crime had happened. Later it was found that some inconsistencies might present in the order of the series if the data looks something as shown in table 2.5.

| Crimes | Date Start | Time Start | Date End | Time End |
|---|---|---|---|---|
| Crime 1 | 2012-01-01 | 09:00:00 | 2012-01-01 | 10:00:00 |
| Crime 2 | 2012-01-02 | 12:30:00 | 2012-01-03 | 12:30:00 |
| Crime 3 | 2012-01-02 | 12:30:00 | 2012-01-03 | 18:30:00 |

Table 2.5: A sample data of series of crimes.

From table 2.5, it is difficult to tell whether the suspect had committed crime 2 or crime 3 after committing crime 1. As mentioned in section 1.1, the serial crimes tend to have low spatial proximity. So, if the distance between the crime 1 and crime 2 is less than distance between crime 1 and crime 3 then the order crime 1, crime 2, crime 3 is considered. Otherwise the order crime 1, crime 3, crime 2 is considered.

### Phase Two

After placing the crimes in a series in an order that they were expected to be happened, this crime series is further filtered for removing the unlinked crimes with travel time as the parameter. From the above table 2.5, if the order crime 1, crime 2 and crime 3 is considered then first crime 1 is assumed as origin and crime 2 as destination. The latitude and longitude values of these two crimes are sent to the ODS and from the response the travel duration is noted. If this travel duration is less than the time difference between these both crimes from the above table 2.5, than crime 1 and crime 2 can be part of a series. An additional parameter, estimated crime duration (i.e. the time taken by the burglar to commit the felony), is also considered in this filtering method.

### 2.3.3 Validation of the method

After the designing of the method, it is validated by using the DS1. As DS1 consists of the known linked crimes, the filtering method has to accept all the crime links that are present in this data set. The offender might travel between the crime locations by using various transport modes (like driving, walking etc.). So if the offender is able to travel between any two given crime locations by using one or more transport modes within the given time duration, then it is likely that these two crimes are committed by the same offender. Any crime link is filtered out only if the offender is unable to travel between the locations by any means of transport within the given time duration. After validating the method, it is supplied with the DS2 for removing the unlinked crime links from the estimated linked crime series. The results are discussed in the later sections. Also, in this study the public transportation is not taken into consideration due to the influence of external factors such as delay in the respective services, the schedule of these services might have changed.

## 2.4 Threats to Validity

The following section discusses about the internal validity and external validity. This study was designed in such a way that the validity threats are reduced to maximum extent.

### 2.4.1 Internal Validity

Internal validity refers to the changes in dependent variable that are caused by the independent variable [32]. In this study, the independent variables are geographical and temporal features and the dependent variable is linking residential burglaries. A threat to internal validity is the possible inconsistencies in the data. If there are inconsistencies in the data, then it is difficult to generate efficient crime links. This threat can be eliminated by removing the missing values and garbage values from the data.

One potential threat lies in the possible bias in the crimes that are solved by the police, which affects the ground truth. This threat can be mitigated by verifying the data sets with the police.

### 2.4.2 External Validity

External validity refers to the extent to which the outcomes of this study can be generalizable [32]. The data sets that are used in this study are the real world residential burglaries. The distance and time values that are used for linking the residential burglaries are also real travel distances and travel duration's between the crime locations. This helps to generalize the results of this study to a wider population.

# Chapter 3

# Results

**RQ1**. *What are the different online direction services that are freely available and by what factor do their respective travel times differ from each other?*

**Usage Limits**

After going through different state-of-art online direction services, it was found that there is no API that is entirely freely available for the users. There are certain usage limits with the number of requests that can be made to their respective online direction services. The following table 3.1 shows the free usage limits and also the premium usage limits of different services that are used in this study. These four ODS are used in this study because they are available at low cost and also there is an easy access to their respective APIs.

| ODS | Free usage limit | Paid usage limit |
|---|---|---|
| Google Maps | 2500 requests/day | 1000 requests - $0.50 USD (up to 100000 requests/day) |
| Bing Maps | 10000 requests/month | 100000 requests/month - $450 USD |
| Here Maps | 10000 requests/month | 700000 requests/month - $399 USD |
| Mapquest | 15000 requests/month | 500000 requests/month - $799 USD |

Table 3.1: Usage Limits for different ODS.

**Variations in distances and travel time values**

After the data is prepared for the study, the longitude and latitude values present in DS1 are supplied to online direction services through

REST services by selecting two crime locations from a series (as origin and destination) at a time. The response from the ODS is the JSON data. After receiving the JSON data, the distance and travel time between the crime locations are noted (see Appendix B for sample request and response to different ODS). The averages of differences between distances and travel times between different ODS are taken for all the crime locations in the DS1. These values are depicted in the following table 3.2.

| ODS | Transport Mode | | | |
|---|---|---|---|---|
| | Driving | | Walking | |
| | Distance (meters) | Duration (seconds) | Distance (meters) | Duration (seconds) |
| Google & Bing Maps | 1125 | 254 | 1440 | 296 |
| Google & Here Maps | 427 | 126 | 399 | 719 |
| Google Maps & Mapquest | 308 | 97 | 387 | 154 |
| Here & Bing Maps | 2381 | 80 | 1590 | 310 |
| Here Maps & Mapquest | 558 | 78 | 539 | 153 |
| Mapquest & Bing Maps | 1347 | 236 | 592 | 51 |

Table 3.2: The difference of averages of distance and duration values between various Online Direction Services.

**RQ2**. *To what extent is the series of known residential burglaries (ground truth) affected by filtering spatially irrelevant crimes based on viable travel times between crime locations?*

At first a filtering method was designed (see section 2.3) for removing the spatially irrelevant crimes from a series of residential burglaries. Later this method is validated by using using DS1. As DS1 consists of the known linked residential burglaries, i.e., the crimes that are present in DS1 are already solved by the police. Therefore when DS1 is supplied to the filtering method, it should not remove any crime links from any series of crimes that are present in this data set as it does not contain any unrelated crimes in this data set.

As expected when DS1 is supplied to the filtering method, it did not remove any crime links from any series that are present in this data set. The proposed filtering method is also validated on various ODS that are mentioned in table 3.1. Whatever the ODS that was chosen to validate the method, the result was same (i.e., no crime links were removed). Therefore, the answer to this RQ is that there is no effect of the proposed filtering method on the series of known residential burglaries (ground truth).

**RQ3**. *To what extent is the estimated series of linked residential burglaries affected by filtering spatially irrelevant crimes based on viable travel times between crime locations?*

In order to answer this question, the filtering method (see section 2.3) is applied on DS2. This proposed filtering method was able to remove up to 6063 (4%) unrelated crime links from different crime series that are present in DS2 when the travel mode of the offender is considered to be driving (in this study driving by car is considered as the driving). It was able to remove up to 31753 (23%) unrelated crime links from different crime series that are present in DS2 when the travel mode of the offender is considered to be walking.

Figures 3.1 and 3.3 shows the total number of crimes in a series that are present in DS2 before and after filtering the crime links with the proposed filtering method. Figures 3.2 and 3.4 show the same analysis for crime series that have more than 300 crime links in it. So from these figures it is evident that the proposed method is able to filter out some unrelated crime links from different crime series that are present in DS2, thus increasing the efficiency in linking the residential burglaries. While removing these crime links, the choice of various ODS has a very little effect on the efficiency. The tables 3.3 and 3.4 shows the SD, median, mean, Min and Max values of crime series, that are present in DS2, before and after filtering of crimes for various transportation modes.

| Title | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Crime series before filtering | 2 | 155 | 153 | 68 | 358 |
| Crime series after filtering | 2 | 146 | 145 | 66 | 352 |

Table 3.3: The summary of crime series before and after filtering of crimes when the suspects transportation mode is considered as driving.

| Title | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Crime series before filtering | 2 | 155 | 153 | 68 | 358 |
| Crime series after filtering | 2 | 111 | 116 | 57 | 294 |

Table 3.4: The summary of crime series before and after filtering of crimes when the suspects transportation mode is considered as walking.

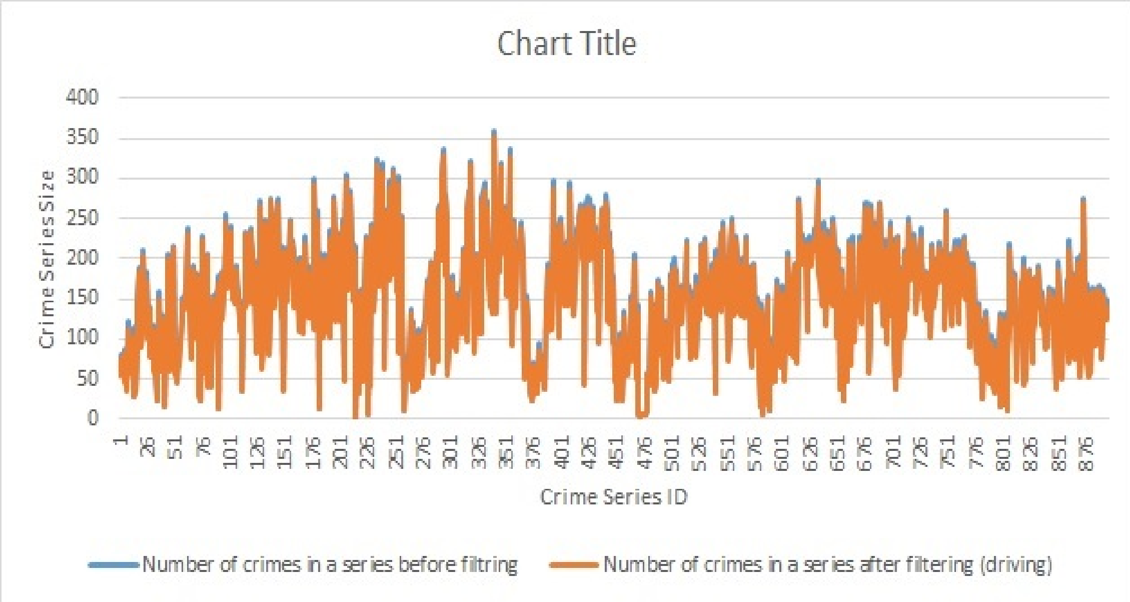


Figure 3.1: Number of crimes in a series before and after filtering if suspects transport mode is considered as driving.

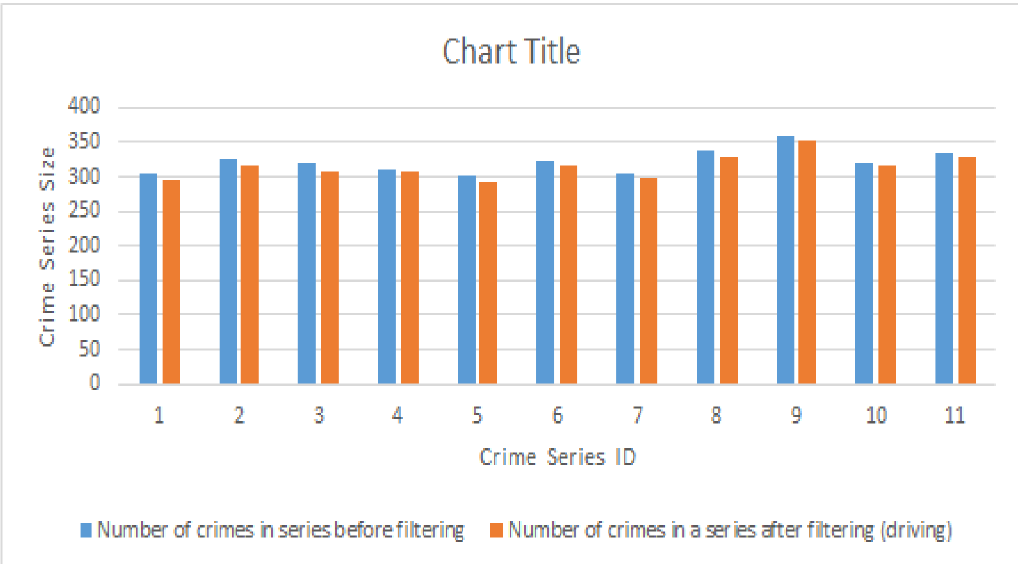


Figure 3.2: Number of crimes in a series before and after filtering if suspects transport is considered as driving (crime series size > 300).

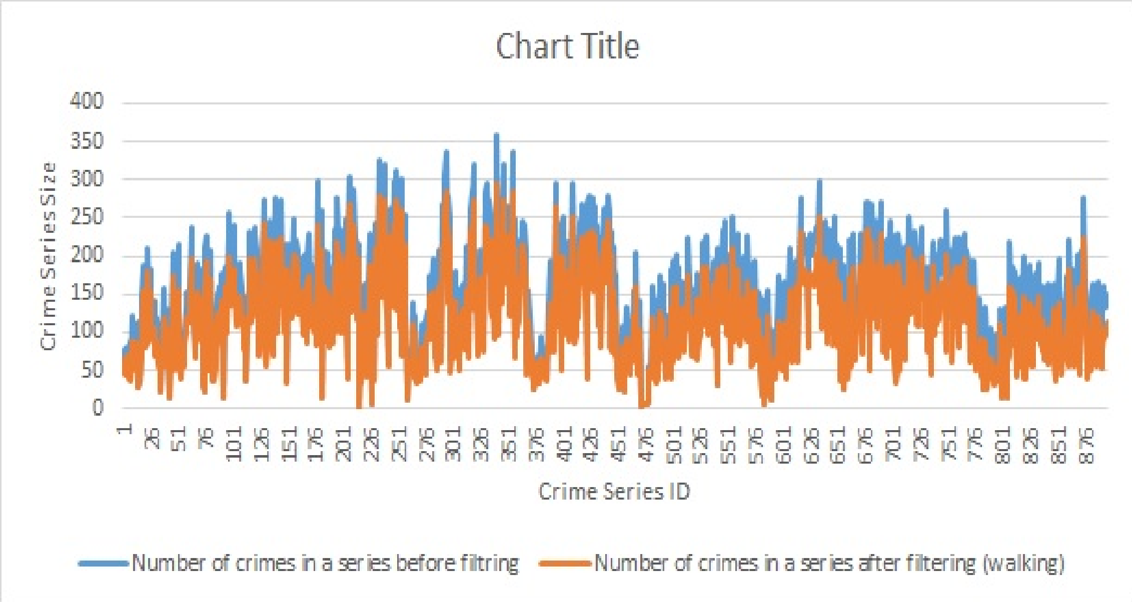


Figure 3.3: Number of crimes in a series before and after filtering if suspects transport mode is considered as walking.

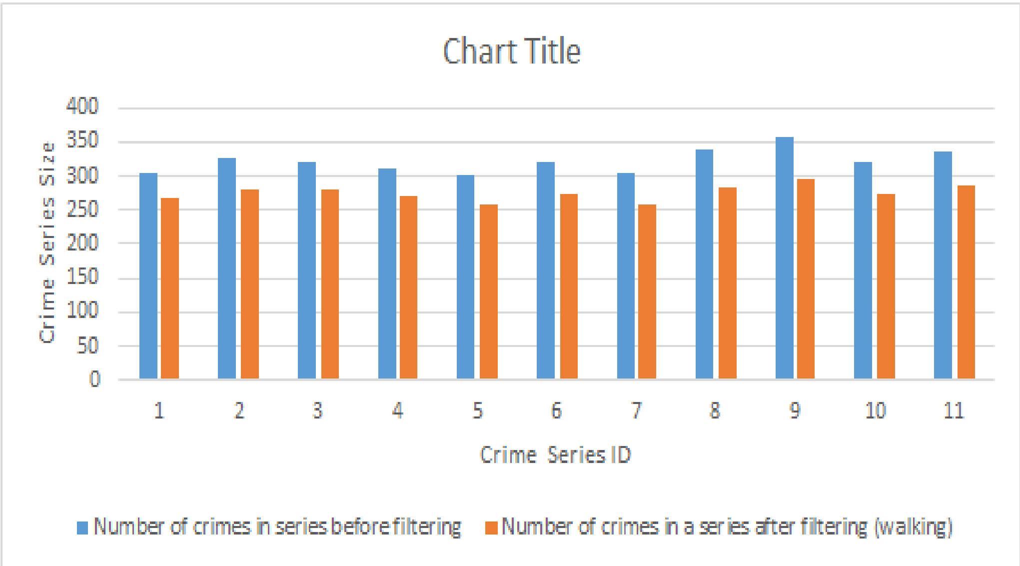


Figure 3.4: Number of crimes in a series before and after filtering if suspects transport is considered as walking (crime series size > 300).

Cohen's d is usually used in statistical testing for estimating the sample sizes. If the Cohen's d value is large than it indicates the necessity of smaller sample sizes, and vice versa [33]. The value of Conhen's d can be obtained by dividing the difference between the means with the pooled SD.

$$Cohen's\ d = \frac{mean\ difference}{pooled\ SD} \tag{3.1}$$

The Cohen's d value between the crime series before filtering and the crime series after filtering (when the suspects transport mode is considered as driving) is 0.12. A Cohen's d value of 0.12 indicates that the mean of the treated (or experimental) group is at the 54th percentile of the untreated (or control) group and also it indicates a nonoverlap of 7.7% in the two distributions [33]. Whereas the Cohen's d value between the crime series before filtering and the crime series after filtering (when the suspects transport mode is considered as walking) is 0.59. A Cohen's d value of 0.59 indicates that the mean of the treated group is at the 73rd percentile of the untreated group and also it indicates a nonoverlap of 38.2% in the two distributions [33].

**RQ4**. *Does the usage of the proposed method performs better than the usage of the exiting state of the art methods, based on line-of-sight analysis, in linking serial residential burglaries?*

In order to answer this question, similar analysis as above is performed with the straight line distances (i.e., Euclidean distances) between the crimes in DS2. With the usage of straight line distances a total of 3394 (2%) unrelated crime links were removed from different crime series that are present in DS2 when the travel mode of the offender is considered to be driving, whereas the proposed method filtered 6063 crimes. Also, a total of 20062 (14%) unrelated crime links were removed from different crime series that are present in DS2 when the travel mode of the offender is considered to be walking, whereas the proposed method filtered 31753 crimes. The tables 3.5 and 3.6 shows the SD, median, mean, Min and Max values of crime series, that are present in DS2, before and after filtering of crimes by using straight line distances for various transportation modes.

From the above results it is clearly evident that the proposed method filters 79% more irrelevant crimes than with the usage of straight line distances when the offenders travel mode is considered as driving. Whereas the proposed method filters 58% more irrelevant crimes than

| Title | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Crime series before filtering | 2 | 155 | 153 | 68 | 358 |
| Crime series after filtering | 2 | 150 | 148 | 67 | 349 |

Table 3.5: The summary of crime series before and after filtering of crimes when the suspects transport mode is considered as driving.

| Title | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Crime series before filtering | 2 | 155 | 153 | 68 | 358 |
| Crime series after filtering | 2 | 120 | 127 | 64 | 309 |

Table 3.6: The summary of crime series before and after filtering when the suspects transportation mode is considered as walking.

with the usage of straight line distances when the offenders travel mode is considered as walking Therefore, the answer to this RQ is that the proposed method performs better than the usage of the existing state of the art methods.

**RQ5**. *What is the initial indication of the time duration of burglary events found in the data?*

In order to find the time that an offender takes to commit a burglary, DS1 was supplied to the proposed filtering method. A new parameter *estimated_crime_duration* is introduced in the proposed filtering method. When a burglar commits a particular residential burglary, then it is implied that the burglar spends some time at that respective residence. Usually this time varies from crime to crime due to various factors like type of goods stolen, different burglary preventive measures taken at the residence, experience of the burglar etc. Also, all the series that contain at-least three crimes are considered for answering this RQ. Therefore a total of 216 crime series (i.e., 1011 crimes) are used for finding the time duration of burglary.

Let us consider three crime locations as show in figure 3.5. Let us say t1 and t2 are the travel durations between the crime locations A,B and B,C respectively and T is the time that a burglar spends at crime scene B. The values of t1 and t2 can be obtained from various ODS that are mentioned in table 3.1. The value of T is incremented from zero until it is no longer possible for the burglar to stay at that particular location. After running a series of tests on the DS1, it was found that a burglar can take on an average of 900 seconds (15

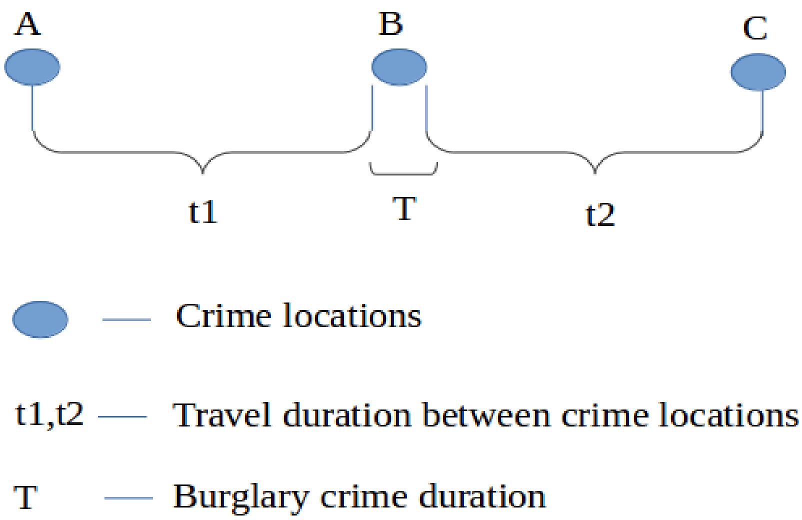


Figure 3.5: A burglar spending a time T at a particular crime scene.

minutes) for committing a particular burglary. Also it is not possible to estimate this time for the crimes A and C, i.e., the first and last crimes in a particular series. Moreover, in these calculations for crime location A (i.e., the first crime in a series) the end time is used and for crime location C (i.e., the last crime in a series) the start time is used. The following table 3.7 shows the standard deviation (SD), median, mean, minimum (Min) and maximum (Max) values of the burglary durations on various ODS.

| ODS | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Google Maps | 300 | 1065 | 899 | 342 | 1200 |
| Bing Maps | 333 | 1078 | 911 | 343 | 1260 |
| Here Maps | 360 | 1082 | 915 | 339 | 1260 |
| Mapquest | 300 | 1072 | 901 | 343 | 1200 |

Table 3.7: The summary of burglary durations (in seconds) on various ODS.

# Chapter 4

# Analysis and Discussion

In this study, the travel distance and travel duration values between different crime locations are used for linking the residential burglaries. The distance and duration values are obtained from different ODS. There are many ODS that are available with different features and capabilities. These different ODS have slight variations between their respective distances and travel times. These variations can be seen in the following figures 4.1 and 4.2. The tables 4.1 and 4.2 show the SD, median, mean, Min and Max values of distances and times on various ODS.

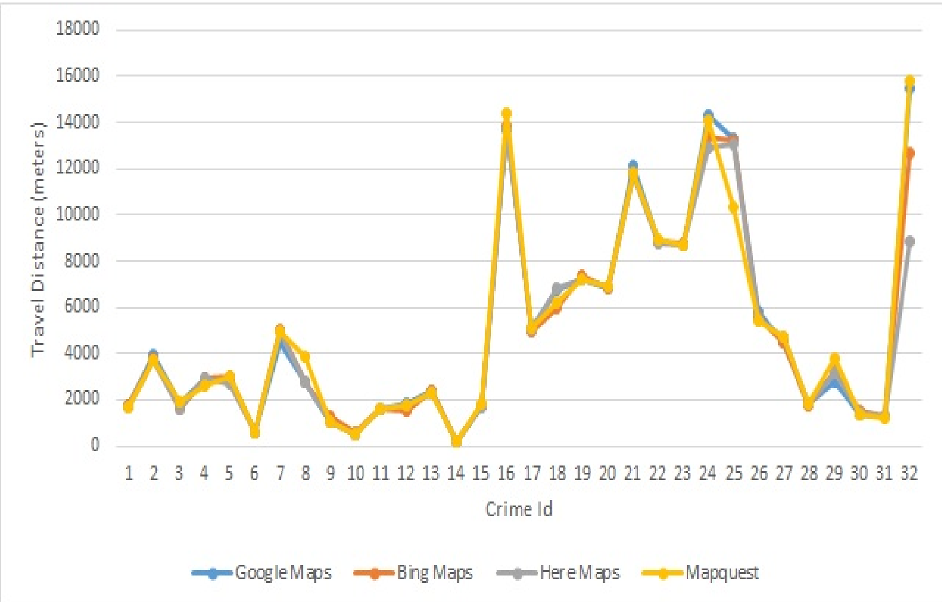


Figure 4.1: The distance between the crimes in a series which has 33 crime links in DS1 using different ODS (Transport - Driving).

| ODS | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Google Maps | 183 | 2929 | 5021 | 4500 | 15470 |
| Bing Maps | 193 | 3112 | 4881 | 4228 | 13850 |
| Here Maps | 191 | 3058 | 4741 | 4010 | 13690 |
| Mapquest | 197 | 3767 | 4993 | 4370 | 15820 |

Table 4.1: The summary of the travel distances (in meters) on various ODS.

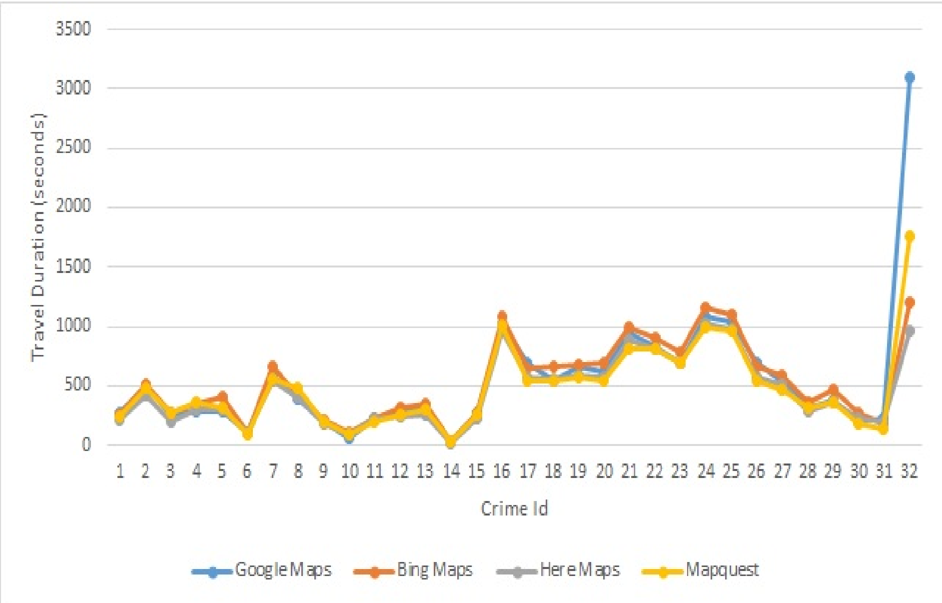


Figure 4.2: The travel duration between the crimes in a series which has 33 crime links in DS1 using different ODS (Transport - Driving).

| ODS | Min | Median | Mean | SD | Max |
|---|---|---|---|---|---|
| Google Maps | 39 | 390 | 553 | 547 | 3093 |
| Bing Maps | 27 | 443 | 529 | 328 | 1200 |
| Here Maps | 21 | 389 | 454 | 289 | 1023 |
| Mapquest | 29 | 419 | 481 | 355 | 1761 |

Table 4.2: The summary of the travel durations (in seconds) on various ODS.

These distance and time values along with the crime details in the datasets are supplied to the filtering method for further filtrations. As mentioned in section 2.3, this method works in two phases. In the first phase there is distance based ordering and in the second phase there is time based filtering. After designing the method, it was validated by using the DS1. As the crime reports present in DS1 are the known linked crimes, the method should not remove any links from the series.

As expected when DS1 is supplied to the filtering method, it has not removed any links from any series that are present in DS1. This is because the DS1 consists of the known linked residential burglaries, which are already solved by the police. Later the DS2 (estimated linked crimes) are supplied to the filtering method for removing the spatially irrelevant crimes from the estimated series. In DS2 there are a total of 136679 crimes. When the travel mode of the offender is considered as driving, the filtering method has removed a total of 6063 (4%) unrelated crimes from all the series that are present in DS2. Whereas when the travel mode of the offender is considered as walking, then the filtering method has removed a total of 31753 (23%) unrelated crimes from all the series that are present in DS2. These removed crimes can be linked with the other crimes that the police have in their database or they can be solved individually by the police.

Instead of the proposed method if the straight line distances were used for linking the serial residential burglaries then a total of 3394 (2%) unrelated crimes were removed from DS2 if the transportation mode considered as driving. Whereas when the travel mode of the offender is considered as walking then a total of 20062 (14%) unrelated crimes were removed from DS2. With the usage of straight line distances, only a little amount of unrelated crimes were removed. Therefore, it is clearly evident that the proposed method gives 2% better results than the usage of straight line distance between the crimes when the offenders transport mode is considered as driving. Also, the proposed method gives 9% better results than the usage of straight line distance between the crimes when the offenders transport mode is considered as walking.

An additional parameter, estimated crime duration, is also considered in this method for efficient results. Estimated crime duration means the total time taken by the burglar for committing the felony. This crime duration value was continuously incremented, starting from zero, for finding the efficient links between the crimes in a particular series. After running a series of tests on DS1, it was found that a burglar can take an average of 900 seconds (15 minutes) for committing a residential burglary.

The choice of different ODS for getting distance and travel time values has a very little effect on filtering the unrelated crimes from a series

| ODS | Transport Mode | |
|---|---|---|
| | Driving (seconds) | Walking (seconds) |
| Google Maps | 121 | 165 |
| Bing Maps | 283 | 382 |
| Here Maps | 197 | 248 |
| Mapquest | 522 | 734 |

Table 4.3: The total time taken for the execution of filtering method on DS1 using various ODS.

of linked crimes. Therefore these parameters have no effect on the performance of the proposed method. As DS1 is the known linked crimes, the total time taken for the execution of the proposed method on this data set by using various ODS has a significant effect on performance. Table 4.3 shows the total execution times that are taken for the execution of the filtering method on DS1 using different ODS. From table 4.3, it is evident that by using Google maps for getting the spatial and temporal values the performance of the proposed method is high when compared to the other ODS that are used in this study.

Results show that by using the proposed method, unrelated crimes can be removed from the series of estimated linked crimes. This helps the police by reducing the number of crimes to investigate and thus saves a lot of time for the police. Also the police have to go through large sets of crime scene data, so while analyzing the data it is beneficial to use the cheaper and efficient ODS. Therefore by using Google maps it not only gives efficient results but also it is available at lower cost when compared to other ODS. Thus the usage of police resources can be optimized and also the crimes can be solved quickly.

Chapter 5

# Conclusions and Future Work

In this study, a crime filtering method is designed for removing the unrelated crimes from a series of estimated linked residential burglaries. This method is based on the spatial and temporal values of different crime locations that are present in a series. This method can remove the crimes, which are spatially impossible to travel, from a linked series of crimes. This approach helps the law enforcement agencies by decreasing the total number of crimes to investigate. Hence the resources of the law enforcement agencies can be optimized and the crime investigation time can be improved.

The proposed filtering method was tested on two data sets. First, while filtering the known series (ground truth) no crimes were removed, i.e., filtering method was verified so that it does not produce any false positives. Secondly, when analyzed on the data set with estimated series, if the travel mode of the offender is considered as driving then the proposed filtering method removed 4% unrelated crimes from the estimated linked crime series. Also, if the travel mode of the offender is considered as walking then the proposed filtering method removed 23% unrelated crimes from the estimated linked crime series.

Results show that the usage of travel distance and travel duration values while linking the residential burglaries can potentially improve the links between the crimes in a particular series. Results also show that depending on the ODS selected to get the distance and time values, the performance of linking residential burglaries will vary. This study shows that by choosing Google maps for getting the spatial and temporal values, the performance of the filtering method in linking residential burglaries is increased. Hence from this study it is evident that by using spatial and temporal values in linking residential burglaries can give promising results.

## 5.1 Future Work

Usually the travel times in the online direction services are calculated based on the distance between the locations, speed limits, traffic, etc. But there is no guarantee that the offender will travel according to the specified speed limits. Hence in the future work, it could be interesting to add an additional parameter (varying speeds) to this filtering method so that the links between the crimes can be estimated more accurately.

In this study only individual crimes are considered. In future it would be more useful for the police if the similar analysis is performed on the crimes that are committed by group of offenders. Also, it would be interesting to perform the analysis by using the flight and rail routes.

# References


[1] J. Law and E. A. Martin, *A Dictionary of Law.* Oxford University Press, 2009.

[2] C. Tim and G. Max, “Police investigations into Residential Burglary,” in *Emerging Themes in Criminology*, 1998, vol. 1.

[3] Portland State University. Criminology and Criminal Justice Senior Capstone, "Prevention of Residential Burglary: A Review of the Literature" (2010). *Criminology and Criminal Justice Senior Capstone Project.* Paper 3.

[4] S. Winchester and H. Jackson, “Residential burglary The limits of prevention,” 1982.

[5] P. N. Grabosky, Burglary prevention. *Trends and Issues in Criminal Justice*, 49, 1-6, 1995.

[6] “Burglary.” [Online]. Available: https://www.bra.se/bra/bra-in-english/home/crime-and-statistics/burglary.html. [Accessed: 16-Nov-2015].

[7] D. Tayal, A. Jain, S. Arora, S. Agarwal, T. Gupta, and N. Tyagi, “Crime detection and criminal identification in India using data mining techniques,” *AI & SOCIETY*, vol. 30, no. 1, pp. 117 – 127, Feb. 2015.

[8] A. Borg, M. Boldt, N. Lavesson, U. Melander, and V. Boeva, “Detecting serial residential burglaries using clustering,” *Expert Syst. Appl.*, vol. 41, no. 11, pp. 5252–5266, Sep. 2014.

[9] M. B. Mitchell, D. E. Brown, and J. H. Conklin, “A Crime Forecasting Tool for the Web-Based Crime Analysis Toolkit,” in *IEEE Systems and Information Engineering Design Symposium*, 2007. SIEDS 2007, 2007, pp. 1–5.

[10] N. Iwanski, R. Frank, V. Dabbaghian, A. Reid, and P. Brantingham, “Analyzing an Offender’s Journey to Crime: A Criminal Movement Model (CriMM),” in *Intelligence and Security Informatics Conference (EISIC)*, 2011 European, 2011, pp. 70–77.

[11] J. Kent, M. Leitner, and A. Curtis, “Evaluating the usefulness of functional distance measures when calibrating journey-to-crime distance decay functions,” *Comput. Environ. Urban Syst.*, vol. 30, no. 2, pp. 181–200, Mar. 2006.

[12] B. J. Reich and M. D. Porter, “Partially supervised spatiotemporal clustering for burglary crime series identification,” *J. R. Stat. Soc. Ser. A Stat. Soc.*, vol. 178, no. 2, pp. 465–480, Feb. 2015.

[13] M. Tonkin, J. Woodhams, R. Bull, J. W. Bond, and E. J. Palmer, “Linking Different Types of Crime Using Geographical and Temporal Proximity,” *Crim. Justice Behav.*, vol. 38, no. 11, pp. 1069–1088, Nov. 2011.

[14] M. Tonkin, J. Woodhams, R. Bull, and J. W. Bond, “Behavioural case linkage with solved and unsolved crimes,” *Forensic Science International*, vol. 222, no. 1–3, pp. 146 – 153, Oct. 2012.

[15] “The DNA Field Experiment.” [Online]. Available: http://www.urban.org/research/publication/dna-field-experiment. [Accessed: 16-Nov-2015].

[16] L. Markson, J. Woodhams, and J. W. Bond, “Linking serial residential burglary: comparing the utility of modus operandi behaviours, geographical proximity, and temporal proximity,” *J. Investig. Psychol. Offender Profiling*, vol. 7, no. 2, pp. 91–107, Jun. 2010.

[17] M. Laukkanen, P. Santtila, P. Jern, and K. Sandnabba, “Predicting offender home location in urban burglary series,” *Forensic Sci. Int.*, vol. 176, no. 2–3, pp. 224–235, Apr. 2008.

[18] S. Haginoya, “Offender demographics and geographical characteristics by offender means of transportation in serial residential burglaries,” *Psychol. Crime Law*, vol. 20, no. 6, pp. 515–534, May 2013.

[19] T. KOITA, K. UEDA, and K. SATO, “Integrated Device Control System using Google Maps,” *International Journal of Computer Technology and Applications*, vol. 3, no. 1, pp. 283 – 287, Jan. 2012.

[20] C. Vandeviver, “Applying Google Maps and Google Street View in criminological research,” *Crime Science*, vol. 3, no. 1, Dec. 2014.

[21] “Google Maps Javascript API,” Google Developers. [Online]. Available: https://developers.google.com/maps/documentation/javascript/. [Accessed: 16-Nov-2015].

[22] "Microsoft Bing Maps," Bing Maps Developers, [Online]. Available: http://www.microsoft.com/maps/. [Accessed: 16-Nov-2015].

[23] "Here Maps Javascript API," Here Maps Developers. [Online]. Available: https://developer.here.com/javascript-apis. [Accessed: 17-Nov-2015].

[24] lbrinkk, “JavaScript Maps API,” MapQuest Developer Network, 12-May-2015. [Online]. Available: https://developer.mapquest.com/documentation/javascript-api. [Accessed: 17-Nov-2015].

[25] B. H. Fox and D. P. Farrington, “Behavioral Consistency Among Serial Burglars Evaluating Offense Style Specialization Using Three Analytical Approaches,” *Crime & Delinquency*, p. 0011128714540275, 2014.

[26] N. Iwanski, R. Frank, V. Dabbaghian, A. Reid, and P. Brantingham, “Analyzing an offender’s journey to crime: a criminal movement model (CriMM),” in Intelligence and Security Informatics Conference (EISIC), 2011 European, 2011, pp. 70–77.

[27] S. V. Daele and W. Bernasco, “Exploring directional consistency in offending: the case of residential burglary in The Hague,” *Journal of Investigative Psychology and Offender Profiling*, vol. 9, no. 2, pp. 135–148, 2012.

[28] C. Bennell and N. J. Jones, “Between a ROC and a hard place: A method for linking serial burglaries by modus operandi,” *Journal of Investigative Psychology and Offender Profiling*, vol. 2, no. 1, pp. 23–41, 2005.

[29] L. Tompson, H. Partridge, and N. Shepherd, “Hot routes: Developing a new technique for the spatial analysis of crime,” *Crime Mapping: A Journal of Research and Practice*, vol. 1, no. 1, pp. 77–96, 2009.

[30] J. C. Puras and C. A. Iglesias, “Disasters2. 0. Application of Web2. 0 technologies in emergency situations,” Proceeding of ISCRAM, vol. 9, 2009.

[31] J. W. Creswell, Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. SAGE Publications, 2013.

[32] R. L. Joyner, W. A. Rouse, A. A. Glatthorn, “Writing the Winning Thesis or Dissertation: A Step-by-Step Guide”, USA, Corwin Publication, 2013, Ch.9, p.p. 115-158.

[33] J. Cohen, "Statistical power analysis for the behavioral sciences (2nd ed.)", Hillsdale, NJ: Lawrence Earlbaum Associates, 1988.

# Appendix A

# Sample requests and responses of different ODS

### Google Maps (Transport Mode - Driving)

*Request*

https://maps.googleapis.com/maps/api/distancematrix/json?origins=56.1666667,15.5833333&destinations=56.1814,15.5906&mode=driving&key=*GOOGLE_API_KEY*

*Response*


```
{
   "destination_addresses" : [ "Valhallavägen 1, 371 41 Karlskrona, Sweden" ],
   "origin_addresses" : [ "Järnvägstorget 5, 371 34 Karlskrona, Sweden" ],
   "rows" : [
      {
         "elements" : [
            {
               "distance" : {
                  "text" : "2.1 km",
                  "value" : 2115
               },
               "duration" : {
                  "text" : "6 mins",
                  "value" : 370
               },
               "status" : "OK"
            }
         ]
      }
   ],
   "status" : "OK"
}
```

**Google Maps (Transport Mode - Walking)**

*Request*

https://maps.googleapis.com/maps/api/distancematrix/json?origins=56.1666667,15.5833333&destinations=56.1814,15.5906&mode=walking&key=*GOOGLE_API_KEY*

*Response*


```
{
   "destination_addresses" : [ "Valhallavägen 1, 371 41 Karlskrona, Sweden" ],
   "origin_addresses" : [ "Järnvägstorget 5, 371 34 Karlskrona, Sweden" ],
   "rows" : [
      {
         "elements" : [
            {
               "distance" : {
                  "text" : "2.1 km",
                  "value" : 2122
               },
               "duration" : {
                  "text" : "26 mins",
                  "value" : 1573
               },
               "status" : "OK"
            }
         ]
      }
   ],
   "status" : "OK"
}
```


**Bing Maps (Transport Mode - Driving)**

*Request*

http://dev.virtualearth.net/REST/V1/Routes/Driving?wp.0=56.1666667,15.5833333&wp.1=56.1814,15.5906&key=*BING_API_KEY*

*Response*


```
{
```

```
    "authenticationResultCode" : "ValidCredentials",
    "resourceSets" : [{
        "estimatedTotal" : 1,
        "resources" : [{
            "distanceUnit" : "Kilometer",
            "durationUnit" : "Second",
            "routeLegs" : [{
                "travelDistance" : 2.817,
                "travelDuration" : 356,
                "travelDurationTraffic" : 370
            }]
        }]
    }],
    "statusCode" : 200,
    "statusDescription" : "OK"
}
```


**Bing Maps (Transport Mode - Walking)**

*Request*

http://dev.virtualearth.net/REST/V1/Routes/Walking?wp.0=56.1666667,15.5833333&wp.1=56.1814,15.5906&key=*BING_API_KEY*

*Response*


```
{
    "authenticationResultCode" : "ValidCredentials",
    "resourceSets" : [{
        "estimatedTotal" : 1,
        "resources" : [{
            "distanceUnit" : "Kilometer",
            "durationUnit" : "Second",
            "routeLegs" : [{
                "travelDistance" : 2.132,
                "travelDuration" : 1536,
                "travelDurationTraffic" : 1536
            }]
        }]
    }],
    "statusCode" : 200,
    "statusDescription" : "OK"
}
```

**Here Maps (Transport Mode - Driving)**

*Request*

https://legacy.route.cit.api.here.com/routing/6.2/calculateroute.json?waypoint0=56.1666667,15.5833333&waypoint1=56.1814,15.5906&mode=fastest%3Bcar&app_id=*HERE_APP_ID*&app_code=*HERE_APP_CODE*

*Response*


```
{
    "Response" : {
        "Route" : [
            {
                "Summary" : {
                    "Distance" : 2451.0,
                    "TrafficTime" : 303.0,
                    "BaseTime" : 303.0,
                    "Flags" : []
                }
            }
        ]
    }
}
```


**Here Maps (Transport Mode - Walking)**

*Request*

https://legacy.route.cit.api.here.com/routing/6.2/calculateroute.json?waypoint0=56.1666667,15.5833333&waypoint1=56.1814,15.5906&mode=fastest%3Bpedestrian&app_id=*HERE_APP_ID*&app_code=*HERE_APP_CODE*

*Response*


```
{
    "Response" : {
        "Route" : [
            {
                "Summary" : {
                    "Distance" : 2099.0,
                    "TrafficTime" : 1679.0,
```

```
                    "BaseTime" : 1679.0,
                    "Flags" : []
                }
            }
        ]
    }
}
```


**Mapquest (Transport Mode - Driving)**

*Request*

http://www.mapquestapi.com/directions/v2/route?key=*MAPQUEST_API_KEY*
&from=56.1666667,15.5833333&to=56.1814,15.5906&routeType=fastest&unit=k

*Response*


```
{
    "route" : {
        "distance" : 2.0519,
        "time" : 259,
        "statuscode" : 0,
        "messages" : []
    }
}
```


**Mapquest (Transport Mode - Walking)**

*Request*

http://www.mapquestapi.com/directions/v2/route?key=*MAPQUEST_API_KEY*
&from=56.1666667,15.5833333&to=56.1814,15.5906&routeType=pedestrian&unit=k

*Response*


```
{
    "route" : {
        "distance" : 2.1549,
        "time" : 1926,
        "statuscode" : 0,
        "messages" : []
    }
}
```