Artificial Intelligence: Memory-driven decisions in games

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Abstract

Developing AI (Artificial Intelligence) for games can be a hard and challenging task. It is sometimes desired to create behaviors that follow some sort of logical pattern. In order to do this, information must be gathered and processed. This bachelor thesis presents an algorithm that could assist current AI technologies to collect and memorize environmental data. The thesis also covers practical implementation guidelines, established through research and testing.

Keywords: Artificial Intelligence, Memory, Environment, Emotions, Games

Abstrakt

Att utveckla AI (Artificiell Intelligence) i spel kan vara en hård och utmanande uppgift. Ibland är det önskvärt att skapa beteenden som följer något sorts logiskt mönster. För att kunna göra detta måste information samlas in och processas. I detta kandidatarbete presenteras en algoritm som kan assistera nuvarande AI-teknologier för att samla in och memorera omgivningsinformation. Denna uppsats täcker också riktlinjer för praktisk implementering fastställda genom undersökning och tester.

Nyckelord: Artificiell Intelligence, Minne, Omgivning, Käslor, Spel
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1. Introduction

Artificial Intelligence is an important part in most of today’s games. When hearing the word AI, one might think of the simulation of behaviors, but there are also a lot of other algorithms and subjects that have been categorized together with AI. In this thesis we will only focus on AI as behavior and simulation of intelligence through memorization. Throughout the upcoming sections the human memory will be referred to as memory.

AI is greatly discussed and covered in a lot of articles because of its ineffectiveness and the large amount of subjects it involves. The reason for this is because there are still a lot of problems to tackle within the subject in order to generate any gratifying result. There is no generic way to program or design AI in order for it to work well in all games. All that exists today is base algorithms and behaviors that is somewhat generic and works in most cases, but these things alone or together is far from a complete AI.

The effect of this demands that the AI has to be custom made for the game and therefore needs to be reworked. Thus it cannot be reused in future productions. The time spent on this hinders the development of more, new and old, advanced techniques. With the low performance budget that AI often has in a game they make up the two major reasons that there is still a lot to gain from researching this area.
2. Problem Description

Background

Today’s games may simulate different sorts of intelligent behavior, sometimes in a way that is trying to hinder the player. We have seen that this kind of behavior can be implemented in a very simplistic manner which sets the scene for creating visible and predictable patterns. The player can use these patterns to estimate and abuse their opponent’s actions and skip a part of the game’s thought-out challenge.

There might be a common misconception that AI in games also is the same as AI in academia. Academic AI includes simulating true intelligence where the AI entity can learn and adapt to situations to solve a specific task (Artificial Intelligence (Video Games), 2014). This is not the case when it comes to AI in games. AI in games merely tries to simulate the true intelligence and not necessarily achieve it. The AI entity only needs to know about the context it has been given by a designer and can apply different “cheats” to simulate an expected reaction to the player’s actions. For performance reasons AI in games often can’t simulate a full neural network required for more life-like interaction between the AI opponent and the player. However the recent advances in computing power enables more resources for AI simulation than previously. Therefore more factors from the academic AI are starting to become more relevant for AI development within games.

The AI in games that exists today can already be made difficult to avoid and impossible to beat. Because of this there is no need for harder opponents, only deeper patterns and logical actions that makes it harder for the player to predict the AI’s moves. Due to the large number of logical exits that interpretation of information can have in games, there is often a lack of a deeper kind of decision-making with the information gained from the environment.
One might say that the AI lacks “intelligence” when encountering a bad AI in a game and this is the big challenge. How do we simulate intelligence? The root of the problem is the lack of definition what intelligence involves. Jon (Radoff, 2011) points out three mayor types of intelligence Emotional, Social and Physical. Since Emotional (e.g. reading body language) and Social (e.g. how to communicate in a group) are more distant from movement and environment, this thesis focuses on the third one, Physical Intelligence, which is “associated with learning, controlling and adjusting” (Radoff, 2011).

The research starts with acquiring the determining factors enabling the simulation of a deeper understanding about the environment in AI-driven opponents. Later we will present how these factors can be used in combination with the stored environmental information gained from sight and hearing, to simulate an opponent with a human-like behavior.

**Question**

How can AI comprehend and adapt to remembered environmental factors in relation to real-life expectations to help make complicated decisions in games?

**Purpose**

This thesis aims to create a better understanding of how AI can relate to information in the environment and how this information can be used to simulate complicated decisions with human logical patterns as reference.

**Participants**

This study was carried out by Charlie Forsberg Hedberg and Alexander Pedersen both responsible for the researching, implementing, testing and writing during this study.
Previous Research

Earlier Solutions and History

During the late 80s games started to evolve with more sophisticated gameplay mechanics. One of the early games during this era, which pioneered in the field, was SimCity that allowed the player to take control of grand city simulations. The large amount of factors required to allow a compelling control of a city’s environment demanded a more aware AI then previously (Champandard, 2007).

The next big breakthrough came in 1996 with the game of “Creatures” that presented the first game AI with neural networks, enabling the AI to learn how to behave and react to different situations dynamically. This was seen as a breakthrough in AI and was soon followed by the First Person Shooter game of Halo, which introduced opposing AI that for the first time used the environment wisely to combat the player. The AI entities was treated as individuals and reacted in greater detail than before to fellow AI entities. The algorithm enabling this detailed behavior was called a behavior tree and has since then become a common practice within the game development community (Champandard, 2007).

The game Black & White successfully attempted to simulate AI behavior through algorithms rooted in cognitive science, also known as BDI (belief, desire, intention). The player is allowed to teach an animal through reward and punishments to follow commands. This enables deep interesting behaviors to evolve from interaction with the animal. Actions and non-actions can result in different outcomes directly or indirectly depending on problem the player is faced with.

In 2005 the text-based AI experiment “Façade” introduced complex conversions where the AI entities responded according to how the player chose to communicate. Façade was challenged with handling a great number of outcomes to whatever information the player chose to communicate. It’s
regarded as one of the first successful attempts to create a more human like AI in games, which adapt and respond to different inputs from the player.

The history of AI in games is rather young and one may observe that there are very few important events. This is both because of the areas low priority and budget in past game development but also because of its great size and inability to be generic and dynamic.

Simulating Senses

In order to combine previous technologies with newer and modern technologies, that have come available in recent hardware, it is required to think about what would be needed for simulating senses. By building upon previous games successes and failures these senses would help gather information about the current situation and environment to make the AI seem more human-like in their behavior. “The term “senses” in game development is a useful metaphor for understanding, designing, and discussing that part of the AI that gathers information about items of interest in the simulated environment of the game.” (Leonard, 2003). This sentence emphasizes the importance of having an advanced and a highly focused sensory system within our research. It covers a lot of the subjects surrounding our question (e.g. gathering information and understanding the environment).

How does this so called sensory system work? Tom (Leonard, 2003) writes that in order to cover the main senses you will at least need hearing and sight as a minimum since this is where we gather most of our information as humans. He says that, in a game, this will not work as real-life vision or hearing where the senses are “active” all the time, but instead the AI will have to check its simulated vision and hearing with a set interval that may or not be altered depending on how important or focused the AI is at the moment. The book AI Game Engine Programming (Schwab, 2009, ss. 37-38) writes that the optimal is to have as low interval as possible but that also means that things like the human reaction-time will become more and more relevant.
Schwab and Leonard also mention different variables apart from the interval that could be included in these “sense checks” to get more human-like behaviors. They claim that the hard part is finding the right balance between realistic and optimized AI.

Since there are so much variables that affect our senses it is hard, in a low performance budget, to cover them all and this is one of the reasons that the AI needs to be custom built for the game. In one game the AI’s fatigue may play a big part in how its hearing and vision works, but in another it is more important with perfect vision by using more advanced algorithms for how different objects are visible in distinct angles at different distances.

Tom (Leonard, 2003) mentions that when designing an AI sensory system one would need to gather a list, (“a good core”), of what is needed of the AI and which, both environmental and human, factors that could affect it during the game.

**Learning and Adapting**

When the sensory system has been able to collect the information needed to analyze and read the surroundings of an AI, that information needs to be adapted to and memorized. This would be where systems regarding learning and adapting, in a human-like manner, come into play.

“Each AI entity requires the intelligence to determine the right thing to do, given the limitations of the game. But being human also means making mistakes” (Schwab, 2009, s. 31). The book AI Game Engine Programming mentions that the need to seem realistic isn’t the same as making the correct decisions, it is also about sometimes failing to do so. Since an AI entity only does what it is programmed to do, it needs to implement the ability to fail and consider the delay that comes with being human.

Today’s AI in games may have some kind of learning behavior. The AI may adapt to the player’s actions while taking into account what the AI entity did
in the past, to avoid repetition. Taking this one step further, which is needed in order to find an answer to this study, learning about changes within the environment and the preconceptions of nearby objects is required in order to build upon the common systems that already exist today. With this type of greater amount learning we would need a more advanced system for managing the memory. This system could implement both the same learning already used in games, but also algorithms for simulating how a human learn, forget and process information.

The article ‘Reflections of the environment in memory’ (John R Anderson, 1991) talks about how human learning is translated into several algorithms with different variables like delay between learning, time spent learning and learning per event that is needed to be considered in the mimicking of human behavior. This is something that becomes more important with a larger base of information and memories with different degrees of importance.

In the game Thief: The dark project, AI store relevant data with variables like time, location, line-of-sight to help in both future decisions and to decide the importance of the information (Leonard, 2003). If this is combined with how one learns and forgets it could result in the AI gathering more detailed contextual memories of the environment.

**Human Memory and Attention**

There are many factors that influence the strength of our memories e.g. age, emotions and physical state. “In general, older adults have particular difficulties remembering information in vivid detail or with contextual associations” (Kensinger, Piguet, Krendl, & Corkin, 2005, s. 241). Emotions associated with danger and fear tends to enhance the memory of certain situations. Scenarios where a subject is threatened for her or his life with a weapon, also known as the *weapon focus effect*, may invoke such emotions which results in a better memory of the particular event (Kensinger, 2011).
Kensinger points out that negative experiences tend to be more strongly encoded in memory than positive experiences. In general, memories associated with strong emotions tend to be better remembered by a subject than emotionally neutral experiences. This effect is often referred to as the emotional enhancement effect (Kensinger, Piguet, Krendl, & Corkin, 2005, s. 241). Without this effect subjects would more rapidly lose the memory of an event.

Emotionally associated memories are likely to derive from a subject’s perception of an emotional situation. The emotions cause the subject’s senses to be more alert and therefore gather more information about the current event (Dzulkifli & Mustafar, 2013, s. 5). However in order for this kind of memory to be constructed a subject’s attention must lay on a factor that can invoke emotional arousal. Such factors may include differences in color, motion and shape relative to the subject’s context.

According to Dzulkifli and Mustafar, who investigated the correlation between shape and color and how these factors influence attention in general (Dzulkifli & Mustafar, 2013, s. 5), the response time and identification process of information improves when the subject is exposed to distinct colors more than shapes. Their study showed that the participants could more easily differentiate colors and especially warm colors from shapes by showing them both different and similarly shaped and colored primitives.

Other factors may also influence someone’s current attention. As Lin, Franconeri and Enns points out, our visual perception of objects in motion and rapid change in size, focuses a subject’s attention to that object (Lin, Franconeri, & Enns, 2008, s. 686).

**Decision Making**

With a good sensory system and a greatly detailed memory of the environment, all that remains is making decisions based on the information.
Artificial Intelligence for Games (Millington, 2006, s. 301) implies that this is one of the first things people think of when hearing about AI in games, despite it just being a very small part of the whole system surrounding AI.

Millington also mentions that the decision making-system is only a converter which takes memories along with the state of the AI and converts them into actions. It is in this system the variety in the AI's behavior is created and it is also where any human errors could occur.

Throughout our research we have recognized the existence of two popular structures for decision-making in games, decision trees and neural networks. They are used in different types of AI and for different type of reasons.

The decision tree seems to be the most common one because of its more simple structure and implementation. Artificial Intelligence for Games also defines decision tree as: “A decision tree is made up of connected decision points. The tree has a starting decision, its root. For each decision, starting from the root, one of a set of ongoing options is chosen” (Millington, 2006). It is simply a tree structure that processes information based on the AI and its memory and can be followed until you reach an end node that contains an action. The decision tree and the, as previously mentioned, behavior tree have a lot in common. But the behavior tree accounts for more than just decisions and a decision tree could exist within a behavior tree.

Neural network is more advanced algorithm, where behaviors are learned and created dynamically. It tries to simulate decision-making and memorization in a realistic manner in order for it to appear more like our brain in real life. Both could be useful in the creation of the AI needed for this study. Due to the fact that the decision making does not need to be as complicated as the memory and senses, it seems that it would be enough just to use a simpler decision tree in most cases.
With this information as a starting-point, we recognize that previous advances within AI usually simulate memorization within a static context, adapting to a few factors directly invoked by the player. This creates an opportunity to investigate how a more generic and dynamic solution can be applied to assist current technologies. The following sections will go through how to build upon these current technologies and collect information in order to simulate an understanding for how an AI entity can comprehend and adapt to its environment.

Fig. 1 This image shows the flow of how information is converted into actions. It starts with information in the environment that is picked up by our senses/perception. After that it goes into memory and with a timer it makes a decision that ends up as an action.
3. Approach

Introduction

In order for the AI to be able to comprehend and adapt to remembered environmental factors it was important to find a sustainable solution that could preferably work in most cases. Therefore it was needed to produce an algorithm that could meet these requirements but still be scalable for more advanced behaviors.

The upcoming sections will cover how such algorithm was developed and tested in a real production.

Problems

The human memory is a hard aspect to replicate when it comes to developing conventional AI and it includes so many factors that it is problematic to simulate all in real-time without performance issues. Some sacrifice must be made by simplifying the construct of the human memory to make it profitable in real-time.

One of the major problems when it comes to simulating AI with human qualities is gathering appropriate information of the environment to make logical decisions. In order to get such information one or more data-streams are required to simulate senses.

As mentioned in previous sections performance may quickly become a problem, therefore it is important to narrow down the amount of senses and factors affecting the senses by prioritizing the most relevant information within the context of the AI. Such prioritizations may differ on a case by case basis due to design choices within a simulation.

Even though senses may be scaled down and be less costly, the amount of information that could be obtained may still be too significant to be processed
in real-time. In order for the simulation to be sustainable when it is populated by one or more AI entities, the input data (also known as memorable events and/or objects) must be kept to a minimum chosen by their contextual significance. Such decisions may also vary due to choices made during the design process of the environment.

Due to the performance limitations of simulating memorable information in real-time, updating such information must be kept to a minimum. The context in which a memory is created may change and reach a deprecated state because of physical changes within the environment. These changes must be saved and processed in order for later comparison with their previous state, held by the AI entity.

**Potential Solutions**

The first step simulating AI in real-time with the perception of memory and a comprehension of environment is to greatly simplify the different aspects that influence such a behavior, but while still sustaining some of the expected patterns seen in real-life.

As the earlier research points out, emotions play a big role in deciding what memories should be emphasized. Therefore a decision could be made to generalize emotions into three categories, negative, neutral and positive, negative being emphasized the most. Because of this, associated emotions must be saved in order for AI entities to analyze and draw conclusions from previous experiences, thereby building an understanding of their surrounding environment.

Due to that objects may be associated with certain emotions, these emotions must be established before proceeding to memorize a local context. The ultimate solution would be to in real-time, visually analyze the environment and gather an emotional footprint for the memory currently being built. Understandably this is not feasible in real-time due to the performance implications that comes with it. The most efficient solution to this problem
would be to allow objects to manually be defined with an emotion. This approach would require knowledge about the common perception of an object and what emotion that should be associated with it. Such an approach would also allow game designers to deviate from these common perceptions and create unique experiences. These emotional tags could also be changed in real-time to simulate objects meaning during a change of context.

To simplify the targeted behavior further and enable gathering of contextual information, it is required to also associate memories with a physical location. In turn this simplification also requires an outer bound to be set. The context of a memory cannot be infinite out of a data-management standpoint even though the size of different contexts may vary. The size of these contexts will be left as a design decision.

Due to the reach of the information that can be gathered through the lifespan of an AI entity it is desired to find an easy to integrate yet scalable data-management solution. Such a similarly desired solution has been explored with Light Probes in simulating indirect 3D lighting. A Light Probe-approach enables per-probe data-management and processing of local information. A solution of such kind would also provide substantial benefit when it comes to debugging and visualization of memories.
A probe-like solution would solve most of the problems previously mentioned however due to the spherical shape of probes some areas may be excluded from processing. As fig.3 shows, under perfect circumstances the spherical shape of a probe would result in a packing-density of 52%. This is best resolved by allowing some overlapping between probes to make the packing denser. However in some situations where the height covered by a probe can be of a fixed size a standing cylinder shape might be more appropriate, which has a lower loss in volume vertically than a spherical shape. This is desired in order to cover as much area as possible. With such a solution the AI entity would continuously place probes when moving through the environment to save local information for memorization.
Placed probes would then, with a set interval, gather local information in the area in which it was placed. The information would be stored and an overall state would be computed for the probe by comparing previous and current information. These states may include objects being removed, added, repositioned or having its emotional perception changed.

Due to the fact that a memory probe is the physical representation of an AI entity’s perception of the local context, probes cannot fully overlap. Most likely this would generate conflicts later down the simulation. To achieve a good packing result between probes it is required to perform accurate placing of probes. This can be accomplished by testing if the AI entity’s position is contained by the volume of any nearby probes. The test must be performed before placing any new probes within an environment to avoid full overlaps.

As previously mentioned memories may vary in strength and degrade over time. To simulate this aspect probes must be deleted after a certain time thereby losing its local information, emulating that the AI entity has forgotten something. Even though this approach may not be completely accurate with the human memory, the generalization enables some flexibility throughout the design process.

When an AI entity moves through the environment it will eventually encounter one of its probes and delay its time until deletion. This would replicate a subject being reminded of a local context. If the local context has changed the AI entity need to recognize this change and take appropriate action depending on the type of change that has been made.

The previously described solutions make up for what we would like to call “Memory Probes” and we will refer to this in the upcoming sections.
Implementation

In order to test Memory Probes in practice, we chose to use a well established game development tool to prove that the technique can be implemented in a real production. We chose the *Unreal Development Kit* for this task as it is a commonly used development tool for games (List of Unreal Engine games, 2014).

When starting to test the algorithm we first developed an AI with a set of basic behaviors. These behaviors include moving to a position, freely navigate, investigate an environment and also attack and chase the player if seen or heard. This was important to do in order to make sure that the algorithm would be adaptable to current techniques, which would greatly increase its usability.

When developing the algorithm in code we used an object-oriented approach because of two reasons. The Unreal Development Kit with the UnrealScript programming language favors an object-oriented approach. Secondly we estimate that an object-oriented approach is a well established programming convention which fits well with the structure of the algorithm.

The code can be generalized into two separate object classes, one collecting data (Memory Probe) and one analyzing the data (the “brain” of the AI). The brain class of the AI continuously analyzes nearby probes and places new probes if none exists. This emulates the behavior previously explained, but in order to further improve performance we applied numerous data-collecting timers to make probe updates less taxing on the CPU (Central Processing Unit). Such an approach makes probes ignore sudden passing and irrelevant changes due to the time span between updates, which may or may not be a desired outcome. The timer solution does not prevent passing objects changing a probe’s state information completely. A requirement for having the AI entity within the bounds of the probe before allowing any updates was added to avoid this problem.
4. Result and Discussion

The previously described implementation resulted in a behavior where the AI roams and memorizes objects within an area. If a conflict in memory is recognized the AI proceeds to investigate and look for the cause. This proves that the previous explained algorithm works in practice and can be used to extend existing AI implementations with a layer of environmental memorization.

Though our implementation of AI, using Memory Probes, only responds to changes by an investigating behavior, we recognize that the information held by probes can justify deeper and more complex behaviors. For example sometimes it might be more appropriate to respond with a curious behavior rather than an aggressive one.

![Fig. 4 Demonstrates visual debugging of Memory Probes in action.](image)

As we recognize AI may be hard to analyze and debug. Visual assistance is key in order to decrease the amount of time spent on solving errors. This can easily be achieved thanks to the simplification of probes representing memories at a location in the environment. Probes and their outer bounds are very well suited for debugging purposes by drawing their wireframe models. By also drawing data-links to associated objects we can build a complete picture of how data is related to the probe within its local environment. We
also recommend rendering symbols representing the probes status at their individual positions.

Though Memory Probes are relatively easy to manage and maintain, one of the flaws with a probe-like design is that they may not completely cover the area visited by an AI entity. We see that a more exact grid-like data-structure could help to increase the precision of the area covered, which can also be used simultaneously by several AI entities to store information. Other solutions such as Navigation Meshes may also help to create a more precise data-structure. We chose not to extend on these solutions because of their complex structure and maintenance requirements. Memory Probes can easily be incorporated with existing AI as we have proven through our implementation. Solutions such as Navigation Meshes may not even be a possible option due to the access limits of the technology chosen for the development.

The Memory Probe algorithm developed has its roots in the observation of human behavior and perception; though this design choice may sound restrictive, the algorithm’s simplification enables it to be used for simulating the memory of other beings. The humanlike behavior is established by manually applying the correct emotion associated with the objects being memorized. Changing these perceptions allows for simulating other beings with a different perception and understanding of its environment.

Fig. 5 The image shows how a Memory Probe links intersecting surrounding objects with different emotional tags.
Our implementation shows that changes of different factors within a memory can invoke responses, in our case a single investigating behavior. However even though memorization of an area might be great in detail, which allows for changes being recognized with a high precision, we acknowledge that a detailed outcome level (large amount of responses to a scenario) is also required to create deeper and more complex behaviors. For example, an AI entity can be created to perceive an environment like a human. But if the entity does not respond like a human would, the data-gathering for memorization would most likely be a waste of resources.

Due to the design characteristics of Memory Probes, the algorithm allows memory-sharing between AI entities. This comes in handy if one would like to simulate multiple entities having a conversation and “verbally” sharing experiences with each other. Such sharing of information would result in a collective memorization of the environment. This could result in memories having a prolonged lifetime or be fragmented by different entities due to miscommunication, which may be desired quality.

In order to justify some behaviors it may be required to have a more detailed memorization of the environment with the help of other senses than sight. This may include simulating hearing and remembering the positioning and direction of local audio sources. Sources may include a radio or a ventilation fan that generates a constant noise. To create a picture of the audio in the local environment one could summarize the volumes of all nearby sources into an average audio level. This would be helpful as another variable that a probe could hold and provide state information about for the AI entity if the audio in the local environment has changed.

Another way to create more detailed behaviors is by implementing limitations to the senses that we also may experience in our day-to-day life. Such limitations may include rejecting information due to the low amount of luminance within a local environment. This would simulate being unable to see certain objects due to the darkness of an area. For example an AI entity may fail to recognize the repositioning of an object due to the low luminance
while if the object would have been somewhat lit, any change to the object would be more easily recognized.

To calculate this factor, preexisting techniques can be used to determine the average luminance. Techniques such as light probes (Unity Technologies, 2013) that hold static environmental luminance could provide sufficient light information. Other sources that could provide such information may include dynamic lights, which could be collected by the memory probe itself when scanning for local objects.

In order to create more emotional variation, which in turn would generate new interpretations of how the environment is perceived and memorized, dynamically changing an object's emotional state according to its current context would yield different perceptions. For example a knife placed in a kitchen drawer might not be perceived as a threat (neutral association) but if the knife is being held by a person it might generate a threatful and negative emotion. Though it is important to note that the interpretation of such emotional objects may vary due to the perspective it is experienced from. The person holding the knife may not see the object as a threat but any bystander might perceive the object differently.

**Conclusions**

As we discovered in our research Memory Probes would be a valid option for collecting and memorizing environmental information for AI in games. The solution proves to be easy to visualize and debug. This makes it a viable option for extending current implementations of AI in order to simulate an environmental perception. The probes provide sufficient information to allow AI entities to comprehend and adapt to any changes.

We recognize that the technique might not be in its final state but the research we have made points to Memory Probes being an applicable solution. We would like to see the algorithm being used in more productions to verify that it
can successfully be used in multiple scenarios. This would confirm that Memory Probes is a true generic and scalable solution.
5. Glossary

- **Academic AI** – *AI that fully tries to replicate intelligence, not just simulate it.*
- **Behavior Tree** – *A logical tree structure of behaviors representing how behaviors are controlled and related.*
- **Data-stream** – *Flow of data from one point to another.*
- **Decision Tree** – *Similar to behavior tree only the difference is a decision tree does not execute in parallel.*
- **Emotional Enhancement Effect** – *The enhancement of memorization for emotionally intense contexts.*
- **First Person Shooter** – *Shooting game genre, played through the eyes of a character.*
- **Light Probe** – *Probe that collects light information from its local environment.*
- **Memory** – *“Memory is the means by which we draw on our past experiences in order to use this information in the present”* (Stemberg, 1999).
- **Navigation Mesh** – *Algorithm for finding walkable paths within an environment.*
- **Neural Network** – *A data-structure replicating the human brain.*
- **Real-time** – *Time during the execution of a game or program.*
- **Unreal Development Kit** - *A software used to develop games.*
- **Weapon Focus Effect** – *The emotional attention given to a threatful object.*
6. Bibliography

*Artificial Intelligence (Video Games)*. (2014, 05 22). Retrieved 06 19, 2014, from Wikipedia:

http://aigamedev.com/open/review/top-ai-games/


http://www.gamasutra.com/view/feature/2888/building_an_ai_sensory_system_.php


