SEA Model and Fuzzy Logic Based AI Player Design

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Abstract. This paper introduces the concept of the SEA Model: Skill, Experience, and Aggression - which serves as a way of defining the behavior of game's Artificial Intelligence (AI) in a Linguistic manner. The SEA Model is a variation of the OCEAN Model, which is a fuzzy logic apparatus used to describe the personalities of Human Beings. However, the OCEAN Model cannot be used to determine the personalities of Game AI - which cannot talk or express emotions. The SEA Model instead observes the behavior, movement and tactics of Game AI to create a linguistic method of describing AI's personality.

Keywords: Artificial Personality; Fuzzy Logic; Video Game AI; OCEAN Model; Five Factor Model; SEA Model.

1 Introduction

One of the main reasons why AI has got so popular is because it makes a computer controlled agent more realistic. The field of artificial intelligence has taken a significant lift from where it started. However, the use of advanced AI is still not very common. Even today, many games use AI that is simple to implement and mostly consists of a collection of conditional statements [1]. The most popular in game AI currently being used is known as *Finite State Machine(FSM)* which is an if/else algorithm to determine different types of states and block of codes the program executes depending on the scenario. One major challenge we face during coding our thoughts is how we can define a way that represents our complex and context sensitive way of thinking to a machine. *"We often fail to realize how little we know about a thing until we attempt to simulate it on a computer."* – Donald Knuth, 1968. FSM does not deal with representations that graphically show diagrams through which we can get a clear view about the characteristic of a computer controlled agent. In this paper, we minimize our focus to create a model designed to provide an easy and simple interfacing solution between a human and a computer control agent.

We begin with describing five major sides of human behavior. The big five characteristics of human behavior are defined by - Openness, conscientiousness, extraversion, agreeableness and neuroticism known as OCEAN model [2]. The explanations of these attributes are provided in details in background section of this paper. Note that the features used in the OCEAN model is directly related to the side of the characters that defines the behavioral impact a person makes on others. Features like these help us to visualize or decide what kind of response a person is likely to make on a specific situation. The attributes can have numerical values to quantify a person's membership in a group, e.g. how well he fits in the group. Now, in case of AI, these major characteristics cannot provide too much information as the features like agreeableness and openness is directly dependent on human behavior. So we create a new model based on the idea of identifying individual through OCEAN, but in this case, the individual is a computer agent.

The method we are proposing is called the SEA model where S stands for skill, E for experience and A for aggressiveness. The model is represented as a triangular form where each line of the triangle defines a behavior. The intersection of the three lines provides an area that defines the behavior or characteristic graph of the AI agent. The detail explanation of SEA model is provided at the methodology section of the paper.

We can use the game of air hockey to illustrate the use of SEA model. The air hockey game is played between two competitive parties with the objective of sending the ball through the goal of the opposition. The Figure 1 shows a court of air hockey. The puck in one side is controlled by a human while the other puck at the opposite side is controlled by the computer. Now a game generally comes with different versions of difficulty levels. Let us create this difficulty levels by using SEA model. A player who is less skilled, less experienced and less aggressive will come across as easy opponent to a person in comparison to a player who has high skill, experience and aggression. The SEA model is created through the idea of fuzzy logic. The purpose of fuzzy logic is to generalize the crisp sets and control the degree of membership of an element of that set, e.g. how strongly does the element belong in that set. The membership of the elements of a set is described by a member function. Values of membership function are fuzzy, meaning they can have any value between 0 and 1. The three inputs of the SEA model are three fuzzy values. Since the number of values between 0 and 1 can be infinite, the combinations that the SEA model forms can be infinite as well, which gives us the opportunity to create a large number of characters as well as describing the nature of these characters through a triangle shape only.

The usefulness of this kind of representation can be understood well when we try to create a new character in the game, a character with a different skill set. We can think of easy, medium and hard player as primary values of a fuzzy linguistic system. The fascinating part of this is that we can now use linguistic terms like VERY, NOT, RATHER, INDEED etc and use the corresponding membership function of these linguistic variable on the primary values in order to generate new characters with new skill, experience and aggression level. The design of new character saves a significant amount of time. However, we focus on the representation of AI agents characteristics in this paper and leave the part of using linguistic description to create new characters of a game for future work.

2 Background

The goal of this paper is to suggest an approach to define complex personality traits for artificial agents using fuzzy logic. This paper takes inspiration from a widely accepted personality model, first theorized in 1961, by Tupes and Christal [4]; which later came to be known as the "Big Five", or the "OCEAN model" [5]. The Background Section briefly outlines the OCEAN model and this paper's adaption of the model is detailed in the Methodologies Section.

The emotional complexities, cultural differences, and personal beliefs of individual humans make it difficult (and sometimes unethical) for them to be categorized into aggregate groups; but that has not stopped psychologists from classifying "personality traits". One of the earliest approaches to classifying personality is by Tupes and Christal in [4], who noticed similarities in behavior of different people and identified "five factors" that could be used to describe an individual's personality [3]. These five features were later polished and renamed: the OCEAN model – Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism [2].

Each of the 5 factors describes a separate attribute of a character's personality. "Openness" (more broadly: Openness to experience) describe a person's "tendency to be intellectual, interested in the arts, emotionally aware, and liberal" [2] – a creative or intellectual person has high openness to experience [5]. "Conscientiousness" is about aspiration and responsibility – a person with high conscientiousness is ethical and diligent [5]. High "Extraversion" is the feature that best describe people who are optimistic and those who prefer to socialize more [5]. High "Agreeableness" is synonymous with being straightforward, modest and trusting of others [5]. Finally, "Neuroticism" is the trait associated with negative emotions high neuroticism describes people who worry more or are anxious [5].

Ghasem-Aghaee and Oren suggest in their presentation [6] how these five factors can be represented in the milieu of fuzziness: by assigning fuzzy values to each of the five factor; e.g. low, medium, or high extraversion, such that, a person with low extraversion is considered an introvert, a medium extraversion person an ambivert, and a high extraversion person an extrovert. An individual's personality can be described using any combination of these fuzzy values [2][6].

Furthermore, Oren and Aghaee describe in [2] that each of the five factors in the OCEAN model can be broken down into six individual "facets"; i.e. there are (5 * 6 =) 30 facets in total and they are all fuzzy variables that can be described using low, medium, or high. An example, the facets of Extraversion are: Warmth, Activity, Assertiveness, Gregariousness, Excitement-seeking, and Positive Emotions. The combination of the level of the facets determine the level of their parent factor [2][6]. So if all the 6 facets of extraversion are high for a person, then that person is described to be an extrovert.

3 Related Works

Several works on game AI development have been conducted, especially on 21^{st} century. Many of them proposed fuzzy logic approach to improve existing AI. In this section, we present some of the related works done in this field.

In the paper [2] Oren and Ghasem introduced 5 major characteristics that can be used to describe human behavior which is known as the OCEAN model The ocean model and its transformation to sea model which we designed to fit our experiment have been discussed in the background and methodology part of the paper respectively and thoroughly.

In 2012, Michele Piravano [1] described benefits of using fuzzy logic in game AI in order to encourage the development of advanced AI algorithm in game field. The author pointed out the fact that using fuzzy logic provides us with a way of describing a scenario in a more realistic manner by controlling the likelihood of an event's occurrence. The paper also demonstrated that fuzzy logic enables us to define a relationship between input and output in a simplistic manner than using complicated mathematical models.

Li et al. [10] pointed out that fuzzy control is a quality generator that can entertain perceived complexity and reduce the cost of further modification. The authors provided a way to use fuzzy logic incorporated with agent technology and showed how it can be used in game development by using a number of fuzzy if/then rules and agent-oriented method.

In this paper, we want to propose our own model for representing the fuzziness of AI agents in computer games.

4 Methodology

Let us begin by creating a distinction between the "Player Agents" and the "AI Agents". In video games, the "Player Agent" is any entity that represents the human player in the game world, e.g. in role-playing-games: the game's protagonist is the player agent – as the human player has full control of the protagonist's actions and motives. The human player basically puts himself/herself in the shoes of the Player Agent.

In contrast, the "AI Agent" are entities that seem intelligent from a human player's perspective, but are not under the control of the human player, e.g. in role-playing-games: individual villagers, animals, soldiers, villains, etc. are AI Agents. The human player can interact with them, talk to them, and at best influence their actions, but ultimately, the AI Agent's actions are controlled by the algorithm in the game. Note: It is important that the human player "perceives" the AI Agent as intelligent – this improves the game world's realism.

For the purpose of this paper, the Player Agent in the air-hockey game is the "bottom paddle" controlled by the player, while the AI Agent is the "top paddle" controlled by the Artificial Intelligence of the game; and the main focus of this paper is on the AI Agent – specifically on how the human player perceives the "personality" of the AI Agent.

Reasoning – Summary

The AI Agent – being only a paddle – cannot talk, cannot make facial expressions, and cannot display emotions. Attempting to linguistically describe such an agent's personality using the OCEAN model would be futile. However, we can identify other aspects of the AI Agent: the way it moves, the speed at which it reacts, the type of shots it plays, etc. We will call these observable aspects the "Facets" of the AI Agent. They are: "Accuracy", "Reaction", "Position", "Cunning", "Speed", and "Power".
These Facets are also the core functionality of the air-hockey game's AI Agent: they have values, are programmable and are chosen by the game's developers. This paper has 6 facets for the AI Agent in an air-hockey game (this game is simple – more complex games would require more facets). All of these facets are observable by the human player through the actions of the AI Agent.

Furthermore, these 6 Facets can be grouped into 3 clusters – we will call these three groups the "Factors". They are: "Skill", "Experience", and "Aggression". Inspired from the OCEAN model, we call this the "SEA model". The 3 Factors are fuzzy functions of the values of the 6 Facets, such that:

Skill ← S (Accuracy , Reaction)
Experience ← E (Positioning , Cunning)
Aggression ← A (Speed , Power)

Just like the OCEAN model's factors, the SEA Model Factors are abstract in nature – the values they hold do not make sense to the game's programming. However, they serve an important role in conveying a concise "message" to the human players: How "skilled" is the AI Agent? How "experienced" is the AI agent? And how "aggressive" is the AI Agent?

Here in, lies the fundamental concept of this paper: human beings easily understand behavior of agents in terms of few, linguistic, abstract terms (the Factors); and are confused by multiple, specific, values (the Facets). The SEA model provides a way to convert the developer's input values that the game utilizes, into linguistic terms that the game's consumer can easily understand.

Inputs - Explanation

When developing the air-hockey game, we included the 6 Facets in the game's programing. Each Facet has a specific value and control / limit / influence the AI Agent's behavior. They are: "Accuracy", "Reaction", "Position", "Cunning", "Speed", and "Power".

Accuracy: The AI Agent is programmed to target the opponent's goal. So by default, the AI Agent always hits the puck in such a way that it is shot at the center of the opponent's goal. The Accuracy modifier is a probability that the default action is performed; i.e. if set to 100% Accuracy (MAX), the AI Agent performs the default action 100% of the time; and when set to 50% Accuracy (MIN), the AI Agent performs the default operation 50% of the time and intentionally misses (it targets the bars of the goal) 50% of the time. An AI agent with "perfect aim" has Accuracy set to 100% , and one with "terrible aim" Accuracy set to 50%.

Reaction: To make the game easier to play, the AI Agent has a time delay (delay in reaction) which it must suffer before reacting to a shot from the Player Agent. Reaction is a value from -1.5sec to 0sec: describing how long the AI Agent waits before making a move against the Player Agent's attack. An AI Agent with "lazy reaction" has the variable set to -1.5sec (MIN), and one with "instant reaction" has the variable set to 0sec.

Positioning: Is a discreet input for (1 to 6) that defines the AI Agent's knowledge of positioning in the playing field. An agent with Positioning set to 1 (MIN) is thought to be "reactionary": it has no understanding of positioning and only runs after the puck (i.e. reacting to the opponents shots). An agent with positioning set to 2-5 shows varying levels of position adjustments, e.g. an AI Agent with rating of 3 "mimics" the Player Agent after hitting the puck. An agent with positioning set to 6 (MAX) is said to be "predictive", based on the player's movements, it calculates where the Player Agent is going to shoot the puck and readies itself in that position.

Cunning: There are 3 trick-shots in air-hockey, and the discreet input, Cunning, unlocks these. A rating of 1 (MIN) mean the AI Agent cannot perform any trick-shots and must resort to making only "direct" shots towards the goal. A rating of 2, means the AI can perform angled shots, a rating of 3 "tricky" unlocks the ability to perform bank shots, and a rating of 4 (MAX) "deceiving" unlocks the ability to perform double-bank shots.

Speed: The game has a top speed, T, at which any object in the game is allowed to move at. AI Agents move always move at the highest speed they are allowed to. The Speed modifier is a percentage input that acts as a limit to that top speed. An input of 100% (MAX) means the AI Agent can move at T*100% speed – the agent is "explosive" in nature. Where as, an agent with 30% (MIN) is able to move at T*30% - making it "sluggish" in nature.

Power: The Power modifier is a percentage that describes the strength with which the AI Agent hits the puck. We have developed the game to calculate momentum when making shots. To make the game playable we have made the AI Agent "defy the laws of physics" by reducing momentum in an instant. Consider the transfer of momentum to the puck from the AI Agent to be, M. With 100% (MAX), the puck retains M*100% of it momentum; and with 30% (MIN), the puck retains M*30% of its momentum.

Reasoning - Explanation

Skill: From the perspective of a human being, Skill is a trait that describes someone's latent abilities. Linguistically speaking, a "talented" player has: "quick" Reaction and "perfect" accuracy; where as an "inept" player has: "lazy" Reaction and "terrible" accuracy. For our AI Agent, Skill can be defined as a function of Accuracy and Reaction.

Skill ← S (Accuracy , Reaction)

Furthermore, the relationship between the Facets: (“Accuracy”,“Reaction”) and the Factor: (“Skill”) can be represented in a table:

Table I

	Reaction	Lazy	Attentive	Instant
Accuracy	**Skill**			
Terrible		Inept	Inept	Average
Precise		Inept	Average	Talented
Perfect		Average	Talented	Talented

However, the problem in this table is that it shows relationship between “linguistic” variables – whereas, the inputs we have used in the game are both floating numbers. The “linguistic values” of Accuracy: Terrible, Precise, and Perfect. The “linguistic values” of Reaction: Sluggish, Attentive, and Instant. Whereas, in the game, the input range for Accuracy: [50 , 100] %, and the input range for Reaction: [-1.5 , 0] sec.

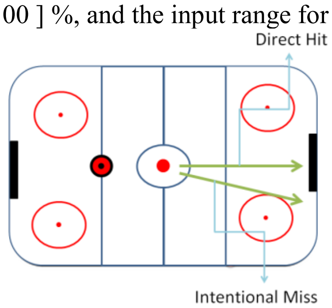


Fig 1. Air Hockey Game

In order for us to represent the relationship between Accuracy and Reaction as Skill, we will have to find a way of representing the floating number inputs in the form of linguistic variables. This is where the Fuzzy Inference System (FIS) plays an important role. The FIS allows us to represent the “linguistic values” of Accuracy and Reaction in the form of membership functions:

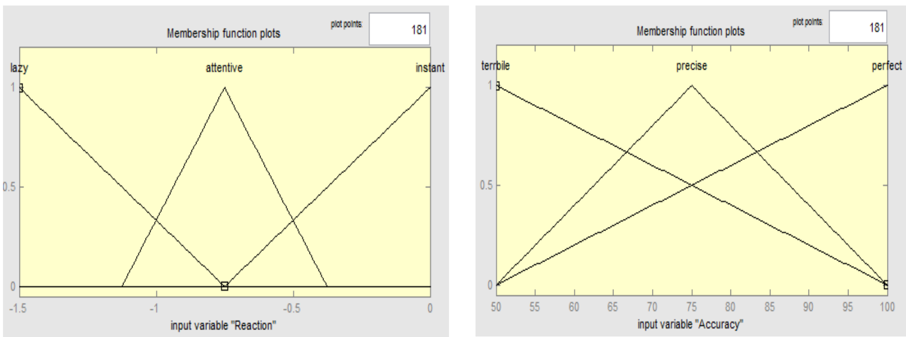


Fig 2. Accuracy of shots

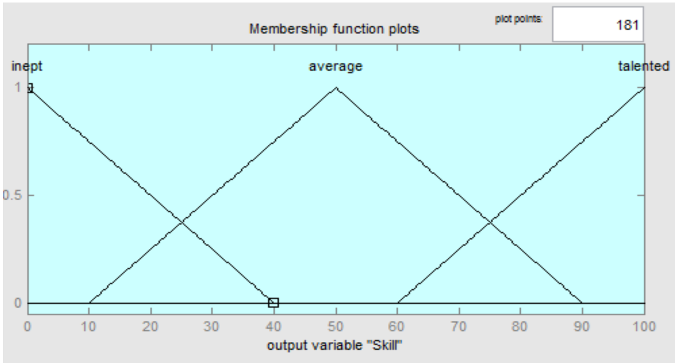


Fig 3. Skill Membership

The input values for Reaction and Accuracy provide a fuzzy membership value (between 0 and 1) for each linguistic value (depending on the membership function of each linguistic value). The membership values are compared with the Relationship Rules in the FIS (which is the Table 1). Finally, depending on the membership functions of the linguistic values of Skill, the results is a value [1 , 100] for Skill, This is simply a generalization of how the FIS works. A full explanation of the membership functions and FIS is beyond the scope of this paper.

Experience: From the perspective of a human being, Experience can only be gained over time and through practice – individuals may learn from through trial and error on where to "position" themselves given the situation, and by observing more experienced players, individuals may pick up knowledge on how to play "cunning" shots. For this reason, the AI Agent's Experience factor can be represented in the form of a function of Positioning and Cunning.

$$\text{Experience} \leftarrow E\,(\text{Positioning}, \text{Cunning})$$

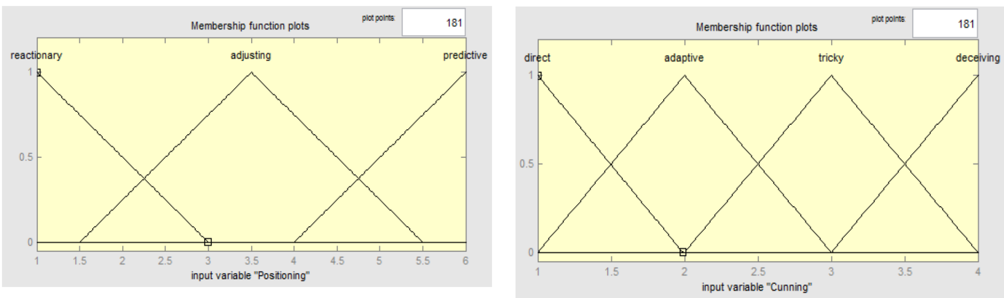


Fig.4 Positioiniong and Cunning Membership

The relationship can be represented in terms of linguistic values in the form of a table:

Table II

	Positioning	Reactionary	Adjusting	Predictive
Cunning	**Experience**			
Direct		newbie	amateur	Moderate
Adaptive		amateur	moderate	Moderate
Tricky		moderate	Professional	Professional
Deceiving		moderate	legendary	Legendary

Aggression: Unlike experience and skill, aggression is dependent on a person's mentality. An aggressive individual moves around the board quickly and plays powerful shots as a display of intimidation. For this reason, the Aggression factor of our AI Agent is a function of Speed and Power.

$$\text{Aggression} \leftarrow \text{A (Speed , Power)}$$

Similarly, the relationship can be represented in terms of linguistic values in the form of a table:

Table III

	Power	Weak	Medium	Strong
Speed	**Aggression**			
Sluggish		Pacifist	Pacifist	Neutral
Normal		Neutral	Neutral	Brutal
Explosive		Neutral	Neutral	Brutal

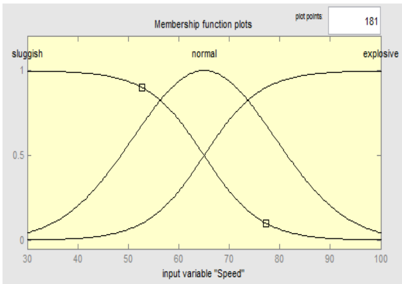


Fig.5 Speed Membership Function.

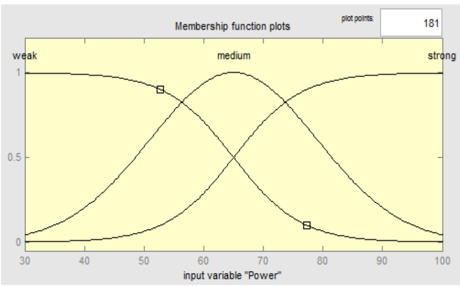


Fig.6 Power Membership Function.

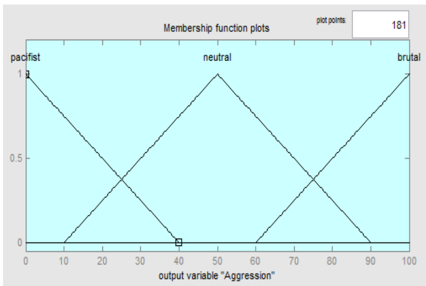


Fig.7 Aggresion Membership Function Ouput.

By itself the values [0 , 100] for the Factors: Skill, Experience, and Aggression is enough to give human players a good understanding of what the "play-style" and in-turn the "personality" of different AI Agents are like. However, we can make it even easier for the human players by displaying the Factors in the form of a 3-armed Kiviat Chart (or RADAR Chart).

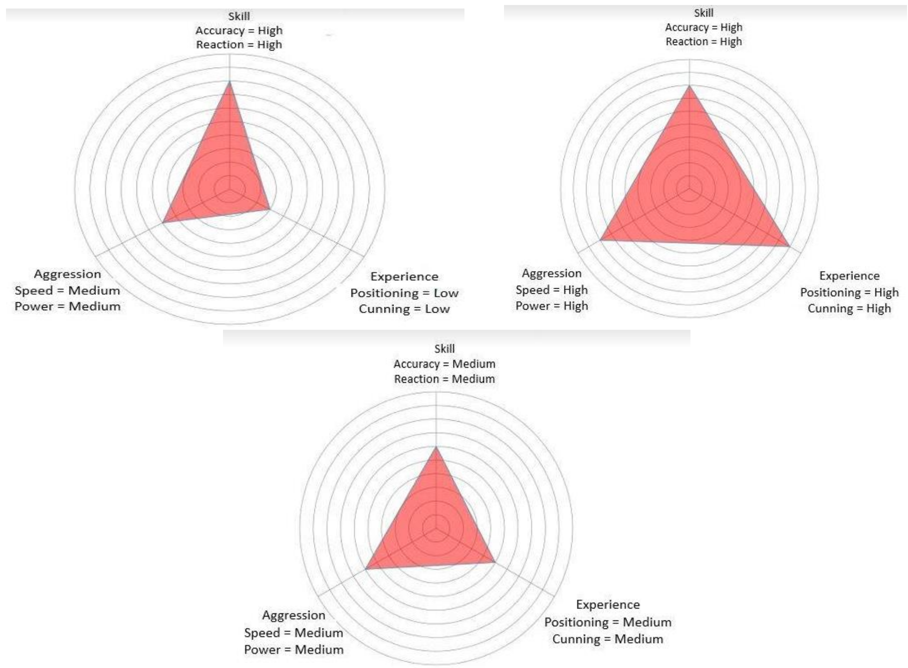


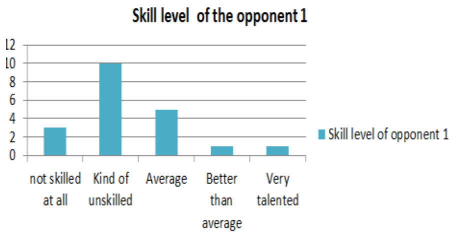
Fig.8 Radar charts with varying parameters

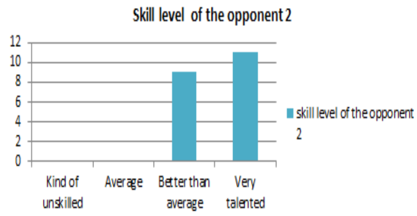
5 Findings

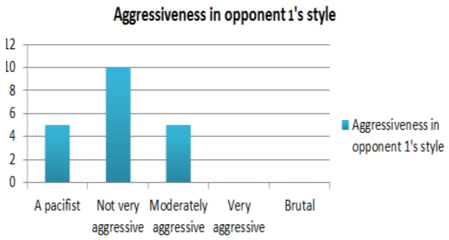
We conduct a survey over 20 people in a gamer community and also non-gamer. 12 males and 8 are females are part of these surveys. We created 2 opponents and named them, opponent 1 and opponent 2.

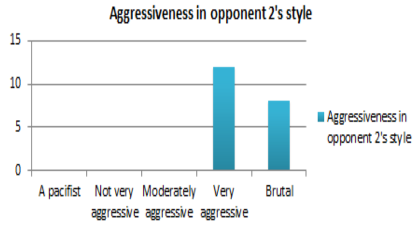
Skill level of opponent 1:
50% of the respondents said that the bot was “kind of unskilled”. 25% replied that the bot was average. 15% replied with the bot “BOT was not skilled at all” 5% saying it’s better than average.5% saying it’s very talented.

Aggressiveness in opponent 1's style:
50% people replied that the bot was not very aggressive. 25% voted into a pacifist and moderately aggressive. None of them responded found opponent 1 as very aggressive or brutal.









Skill level of opponent 2:
55% very talented. 45% better than average. None of them found kind of unskilled or average.

Aggressiveness in opponent 2's style:
60% people found it very aggressive. 40% people found it brutal. None of them voted the bot a pacifist, not very aggressive or moderately aggressive.

6 Conclusion and Future Work

In this paper, we presented a model named “SEA” for describing the behavior of a computer controlled agent in a more pleasant and simple manner. The motivation of the SEA model was extracted from OCEAN model but modified in a way that suits in our game development procedure. The paper also states that using this kind of model will open new ways to create a new character or modify existing AI character in multi character games in a much reduced cost. The SEA model however has its own limitations. For games where the characters need to have many attributes, this type of graphical representation becomes difficult to visualize. Since each of the line in the graph represents an attribute, too many attributes will create a graph with many lines, resulting in a complex and messy graphical representation. While 9-10 attributes may still seem fair, a character having 15 attributes will cause the graph to be generated with 15 lines which makes it difficult to visualize. One proposed solution for this problem can be using three graphs instead of one to represent the characteristics of a same character, each graph representing five of the attributes for a character, resulting in three pentagons to represent all 15 attributes. The model provides a better and easier to understand representation of AI behavior to the game developers.

Introducing new characters using fuzzy linguistic description described in the introduction section of the paper can be a big improvement in the process of making the AI for video games. Games implemented using this model also reduces the cost when we try to modify existing characters than the cost that would have been necessary to modify characters in games implemented through if/then rules. This is especially true if rules applied to a new AI agent conflicts with a rule that is already implemented in an existing AI agent. Also fuzzy logic can be further used to make computer controlled agent that behaves in a more humanoid manner. Work on the following scope can improve game AI that we use in current world of computer games.

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