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Creating Human-Like Agent for a Fighting Game

by

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Abstract

While the game's primary goal is entertainment, it can be also treated as a testbed of fundamental research of AI. In our research we chose environment as a fighting game, using Unity-based Universal Fighting Engine, and focus on making "human-like" AI with two separate projects. During the first project, we created an affective non-player character (NPC) with Gamygdala, an emotional appraisal engine. We model the emotional states of the computer-controlled opponent and use findings from psychology to translate emotions into actions. For the second project, we made an automated procedure to identify players' behavior styles, using cosine similarity analysis. It identifies the same player in the score of more than 80 % on average for every player examined when they play with different opponents.

Chapter 1

Introduction

According to Mihaly Csikszentmihalyi, an authority on the study of flow, major components of enjoyment are as follows [1]:

1. Tasks with a reasonable chance of completion
2. Complete concentration on the task
3. Clear goals
4. Immediate feedback
5. Deep but effortless involvement that removes from awareness of the frustrations and worries of everyday life
6. Sense of control over our actions
7. No concern for the self
8. Alteration of the concept of time, hours can pass in minutes and minutes can look like hours

Since all of these components have the possibility to satisfy during playing games, studying for gaming can be studying for enjoyment which leads to human happiness.

Additionally, the field of the game has contributed to advance of Artificial Intelligence (AI) for more than 50 years. In 1966, Alexander Kronrod claimed chess as Drosophila of AI [2]. At the time Drosophila (fruits-flies) proved to be a superb animal for research by Thomas Hunt Morgan, who got Nobel Prize for Physiology or Medicine in 1933, with the experimental research with Drosophila, established the chromosome theory of heredity. The words are selected for an accessible, familiar, and relatively simple experimental technology that nonetheless can be used productively to produce valid knowledge about other, more complex systems [3].

For chess, IBM's Deep Blue [4] reached the level of pro human player in 1997. The next most notable testbed was Go, In 2016, when AlphaGo [5] won a professional Go player Lee Sedol. Both of this news gave a big impact on various field of research and industry.

Like many other games, the arcade fighting game environment can be another Drosophila of AI. The rule seems to be easy. There is only two player participating, no need for teamwork, you only need to try to attack others and try not to get damaged. However, the moves are various and you have to control four arrow keys and six action keys, and you need a good reaction and expectation of how the opponent would move. So far, it is still difficult for AI to be stronger than the pro human players.

In this study, we are not focusing on strength. Strong AI is not only one answer for "Good AI", because the primary goal of a game system is to entertain the player. We are focused to make "human-like" AI. There is evidence that in games like one-vs-one fighting people enjoy playing against AI that behaves like a human [6]. Also, it would mean avoiding the NPC to be a non-natural, predictable, mechanical way, which has been caused by scripted by the game AI developers.

For this subject, we have done two separate projects. The first project is making the NPC affected with emotion-driven decision-making system Gamygdala [7]. Emotion is one major trait of humans. NPC with emotion will make less machine-like moves and the game is more enjoyable for human players. In practice, it means that some actions of NPCs will be triggered by changes in their simulated inner emotional state.

The other project focuses on identifying playstyle. During our research, we realize how hard to define the "human-like" move. We decide to understand the difference before building one. Which is a useful study for building, not only for "human-like" AI, for all kinds of AI, because no matter what your goal is you need to know what is your goal and the difference of own developing AI. In this study, we make the system to compare the playstyle using cosine similarity analysis [8].

Chapter 2

Related Work

2.1 Enjoyability

A game is generally for entertainment so it is important to study for answers to "what makes a game fun?" for the game field.

There are various of study about defining the fun factors. Malone listed factors, namely challenge, curiosity, and fantasy [9]. Hunicke, LeBlanc, and Zubek suggest eight types sense-pleasure, make-believe, drama, obstacle course, social framework, uncharted territory, self-discovery, and pastime [10]. Sweetser and Wyeth make a model, based on the theory of flow [1], called GameFlow, which consists of eight elements, concentration, challenge, skills, control, clear goals, feedback, immersion, and social interaction [11]. Our main focus of "human-like" also regard as fun factor [12] [13].

2.2 Human-likeness

Human-likeness is our main focus. However, the concept may be a little confusing, while there is a similar concept like imitation. Swiechowski listed three advantages of Human-like AI as follow [14]:

- They can act as believable NPC characters. This greatly increases the immersion in the game. More immersive and interesting games lead to more amount of time spent by people playing them and better overall reception.
- They can take part in multi-player matches if there are not enough human players available at a given moment or they can take over when one of the human players disconnects from the game.
- Human-like bots can be used as virtual testers specialized to predict interactions real (human) players will make. If a goal of the AI challenge is to develop methods and techniques that can accurately capture the style of play of humans, then the property of human-likeness is an inherent part of the challenge.

Moreover, the evaluation for human-likeness is difficult. There was a competition called BotPrize challenges from 2008 to 2014 [15]. The goal of the competition is to convince human judges that the bots are human in a first-person shooter (FPS) game environment. However, as the result of competition actual human players are often judged below the humanness barrier of 50% [16]. This result indicates the difficulty of the Turing test in the modern digital game environment.

Chapter 3

Environment: Universal Fighting Game

Both of our projects use Universal Fighting Engine (UFE) [17], a development tool for one-vs-one fighting games in Unity, as a testbed. It supports a large variety of attacks and special moves as well as the ability to create new action types on a per-character basis. UFE aims to provide classic combo-heavy 2D fighting gameplay, associated with games such as Street Fighter or Mortal Kombat. (see Fig. 3.1)

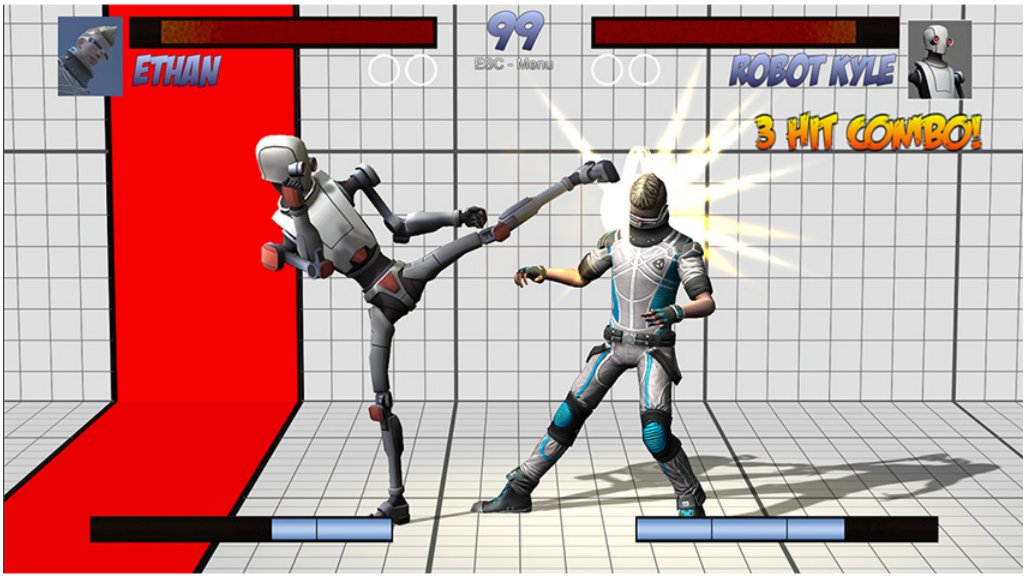

Figure 3.1: Image of a game on Universal Fighting Engine.

3.1 Basic rules

The game consists of three rounds, and the one winning two rounds first is the winner. One round has 99 seconds, and both fighters have 800 to 1100 life points each depending on the character you select. If one of the character's life points reaches 0 within 99 seconds, the opponent player is the winner of the round. If both characters' life points have not reached 0 at the end of the 99 seconds, the player with the least damage is declared the winner.

3.2 Moves

For a fighting game, unique and various moves are the advantages. Table 3.1 shows the Move of Robot Kyle's, the UFE character we mainly use. We picked up 7 unique moves out of 30.

Table 3.1: Example of Robot Kyle's moves in default setting.

Move Name	*Move Type*	*Range Distance*	*Hit Type*	*Hit Confirm Type*
Counter	Neutral	Any	-	-
Throw Attempt	Normal Attack	Very Close	Mid	Throw
Throw Confirm	Normal Attack	Close	Mid	Hit
Throw Reaction	Neutral	Any	-	-
Dash Forward	Forward Launcher	Mid	-	-
Focus Cancel	Anti-Air	Close	-	-
Fire Ball Light	Projectile	Far	-	-
Crouching Heavy Kick	Normal Attack	Close	Sweep	Hit

Move Type has seven options as Neutral, Normal Attack, Forward Launcher, Back Launcher, Dive, Anti-Air, Projectile. *Range Distance* is the best range or distance for this move. *Hit Type* and *Hit Confirm Type* only available when the move has active frames. Active Frames are set when this hit becomes active during the move. (In other words, opponents are able to block this move during the active frame). *Hit Type* has seven types, Mid, Low, Overhead, Launcher, High knockdown, Mid knockdown, Knock back, Sweep. *Hit Confirm Type* has Hit, and Throw. Hit is a Regular attack, which allows for the standard hit options such as damage, hit stun, force, etc. Throw is for only Throw Attempt. Throw move creation is special, it needs Throw Attempt and Throw confirm to attack. The Throw Attempt is the move with the throw's input and is what the player executes. The Throw Confirm is the move that is cast once the Throw Attempt is considered successful. Also, it needs to Throw Reaction to receive the attack from the opponent.

In addition to "Move", UFE also includes "Basic Moves" which are categorized into Standard Animations, Blocking Animations, and Hit Animations. Table 3.2 shows listed all the Basic moves for Robot Kyle.

Table 3.2: Basic moves for Robot Kyle.

Categories	Basic Move Name
Standard	Idle, MoveForward, MoveBack, Crouching
Block	Standing Pose, Standing High Hit, Standing Low Hit, Crouching Pose, Crouching Hit, Air Pose, Air Hit
Hit Reactions	Standing High Hit, Standing Low Hit, Crouching Hit, Air Juggle (Launcher), Knock Back (Knockdown), Standing High Hit (Knockdown), Standing Mid Hit (Knockdown), Sweep (Knockdown), Crumple (Knockdown)

3.3 Debug option

You can easily turn on the debugger and display it on the live game. Table 3.3 shows the list of information you can get.

Table 3.3: Information enable to get from debug option.

	Definition
Move Info	The move being played at the moment
Position	The position of the character (Vector3)
Life Points	The current life points
State	The current player state (Stand, Crouch, StraightJump, ForwardJump, BackJump, Down)
SubState	The current player sub-state (Resting, MovingForward, MovingBack, Blocking, Stunned)
Combo Hits	A live feed from the current combo
Combo Damage	The current damage being dealt in a combo
Input Held Time	A direct feed on how long each input is being held for
Move Execution	The resulting input after successfully executing a move (console)
Fuzzy AI Weight List	The movement decision weight made by the A.I. during its gameplay

Probably the tricky part is the difference of “Move”, “State” and “SubState”. “Move” is the one I explain in the previous section with Table 3.1. “State” and “Substate” are defined as PossibleStates and SubState respectively on the MoveInfo. They are the condition each player must be in order for the move to be executable. For example, Forward + Button moves can be created by having only Moving Forward toggled, or blocking maybe avoid an attack. The selection may seem to be similar to “Basic Move”, which is explained in the previous section, however, while the “Basic Move” concentrates on animation, the “State” and “SubState” only focus on how it affects the movement. “State” represents whether the character must be standing (idle, moving back, moving forward), crouching, jumping straight, jumping forward, jumping back or down. “SubState” represents additional conditions.

3.4 Fuzzy AI

UFE comes with a built-in customizable rule-based AI engine called “Fuzzy AI”. According to UFE documentation, Fuzzy AI “uses Fuzzy Logic to evaluate the information of the scene and calculate the desirability of each given action, translating the AI decisions directly into user input” [18]. During our research, we record games for normal level fuzzy AI and four human players, 10 games for each human player in a total of 40 games. The winning rate of the AI was 58%. We can say, this AI is similarly strong as a human.

Fuzzy AI is the presence of numerous tunable settings that can be modified in real-time to adjust the behavior of an AI-controlled opponent. It is desirable for project 1 (Chapter 4) for translating the emotional reactions of an NPC into changes of Fuzzy AI parameters.

For project 2 (Chapter 5), we use five different levels of Fuzzy AI character. The setup parameter presets are shown in Table 3.4.

Table 3.4: Fuzzy AI settings for five different skill levels.

	Very easy	easy	normal	difficult	very difficult
Time between decisions	0.4	0.3	0	0.1	0
Time between actions	0.1	0.1	0.05	0.05	0.05
Rule compliance	0.9	0.9	0.9	0.9	0.9
Aggressiveness	0.1	0.3	0.5	0.6	0.6
Combo efficiency	0.1	0.2	1	1	1

The choice of Fuzzy AI parameters and their values, described in the documentation as follows:

- Time between decisions (sec): minimum time taken to formulate a decision.
- Time between actions (sec): time between executing each decision.
- Rule compliance: controls the balance between the systematic appliance of rules and randomicity (higher values correspond to lower randomicity).
- Aggressiveness: controls the balance between basic moves such as walk, crouch and jump, and attacks. Higher values correspond to a higher contribution of attacking actions
- Combo efficiency: controls the probability of attempting combo actions.

Chapter 4

Project 1: Affective Fighting Game AI System

Our first focus was making NPC emotional with a unique action selection. The affective (emotion-driven) decision-making is one major trait of human-like behavior. In our project this is done via Gamygdala, an emotional appraisal engine that enables game developers to easily add emotions to their non-player characters.

4.1 Gamygdala

Broekens, Hudlicka, and Bidarra proposed Gamygdala, an emotional appraisal engine implemented in the proof-of-concept system [19] [7], which is currently available as an open-source JavaScript library. Gamygdala is designed for use in complex multi-agent environments where the goals of different agents can be indirectly linked. Agents can be friendly, hostile, or neutral to each other, and the information passed between agents (such as rumors) can be uncertain. Therefore, from this point of view, fighting represents a very simple game world. There are only two agents involved, they are hostile to each other, their goals are the opposite, and there are no hidden or uncertain events. When requested, Gamygdala performs an emotional assessment of a particular agent and returns a list of numbers that correspond to the strength of the individual emotions. This list contains 16 of the 24 emotions defined in the OCC model [20]. It is helpful to understand how beliefs affect emotions. For example, success in a desired goal or failure in an undesired goal increases joy, and the desired event occurs in a disliked agent, which increases resentment.

4.2 Integrate with Universal Fighting Engine

Figure 4.1 shows how Gamygdala works with an external system. Firstly, we have the environment as Universal Fighting Engine, from our environment, we take state as time and the health points for both players, as state, and we need to define the inputs as beliefs and goals for the NPC. Goals are the states that a character wants to achieve, and they may have different utility values, indicating their desire, and negative utility corresponds to unwanted goals. Beliefs are annotated events that move a character closer to or farther from a goal, affecting their emotional state. (detail at Section 4.3) With these inputs, Gamygdala calculates to produce emotional state according to OCC model, to the psychological model of the cognitive structure of emotions with utility values. To use emotion as input for the environment, we can make difference in NPC's move with emotional change.

Since Gamygdala is written entirely in JavaScript while UFE is developed with Unity using C# language, we have integrated Gamygdala into UFE using the .NET JavaScript compiler

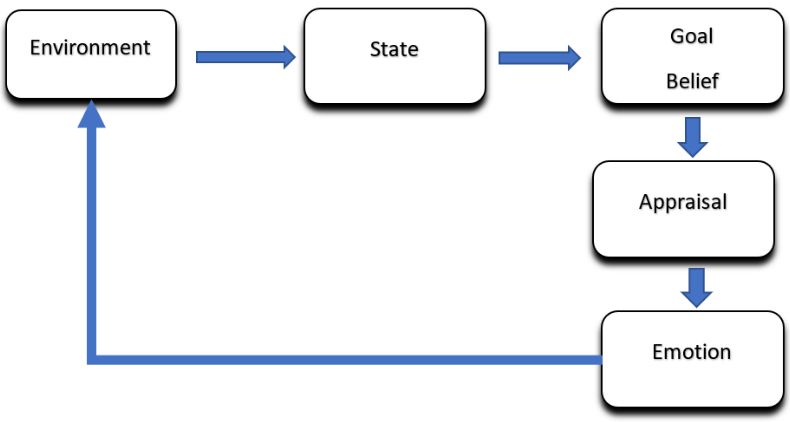

Figure 4.1: How Gamygdala integrate with external system.

Jurassic [21] and established an interface between these engines to facilitate the emotional evaluation of AI-controlled UFE characters. Gamygdala is implemented in a single JavaScript file Gamygdala.js, and our procedures interfacing Gamygdala (such as agent goals setup and event generation) are stored in an additional file GamygdalaUfe.js. Let me explain some codes here:

```
// a fragment of BattleGUI.cs
public class BattleGUI : UFEScreen {
    protected ScriptEngine engine = new ScriptEngine();
    protected virtual void
        OnGameBegin(CharacterInfo player1,
                    CharacterInfo player2,
                    StageOptions stage) {
            BattlePrepare();
        }


    protected void BattlePrepare()
    {
        engine.SetGlobalValue("humanlife",
            (int)player1.totalLife);
        engine.SetGlobalValue("npclife",
            (int)player2.totalLife);
        engine.ExecuteFile("Gamygdala.js");
        engine.ExecuteFile("GamygdalaUfe.js");
    }
    ...
}
```

To make Gamygdala aware of changes in the fighting game world, we translate relevant Unity events into JavaScript code via global functions. The code below shows, global functions for damage caused or received by the players:

```
// GamygdalaUfe.js implements
// global functions OnHit() and getDamage()

// C# code
```

```
protected virtual void OnHit(HitBox strokeHitBox,
            MoveInfo move, CharacterInfo player) {
    if (player.playerNum == 2) {
        int life1 = (int)player1.Life;
        engine.CallGlobalFunction("OnHit", life1);
    }
    else if (player.playerNum == 1) {
        int life2 = (int)player2.Life;
        engine.CallGlobalFunction("getDamage", life2);
    }
}
```

By calling Gamygdala emotional appraisal functionality, the emotional state of the NPC character should be stored in a global variable as a stringified JSON object:

```
// GamygdalaUfe.js
emolen = emotionAgent.internalState.length;
for (var i=0;i<emolen; i++) {
    emo[i] =
        JSON.stringify(emotionAgent.internalState[i].name);
    intensity[i] = emotionAgent.internalState[i].intensity;
}

emoall = JSON.stringify(emo);
intensityall = JSON.stringify(intensity);
```

On the C# side, we read the global variable and convert it from JSON to a conventional List object:

```
// C# code
int length = (int)engine.GetGlobalValue("emolen");
string emoall = (string)engine.GetGlobalValue("emoall");
string intensall =
    (string)engine.GetGlobalValue("intensityall");
List<string> emotion =
    JsonConvert.DeserializeObject<List<string>>(emoall);
List<float> intensity =
    JsonConvert.DeserializeObject<List<float>>(intensall);
```

4.3 Goal and Beliefs

In the current implementation of our system, there are only six goals — all associated with the NPC. (Table 4.1)

All of our goals are related to either or both time and damages, but still distinct each other. For example, if an agent attacks an opponent and lowers its health level, the agent is more likely to win. However, your chances of losing do not change because it depends on your health level, not your opponent's health level. We set the utility value of "Win by Points" as 0.7 lower than "Win by KO" because even Winning points is a legitimate goal, we want agents to prefer knockout wins. Still, losing points is not as desirable as losing a knockout. The "Keep Morale" goals were introduced to deal with certain scenarios that are typically perceived as either pleasant or annoying by people.

The emotional state of a given NPC is affected by the beliefs, as listed in Table 4.2.

Table 4.1: Goals for our agents.

Name	Utility Value	Description
Win by KO	1	The agent wins when the opponent's health level reaches zero
Lose by KO	-1	The agent loses when the agent's health level reaches zero
Win by Points	0.7	The agent wins by points when the round is over, and the agent's health level is higher than the opponent's health level
Lose by Points	-1	The agent loses by points when the round is over, and the agent's health level is lower than the opponent's health level
Keep High Morale	0.6	The agent's morale is affected by several ad-hoc events.
Keep Low Morale	-0.6	This negative goal is handled analogously to the previous one.

Choosing belief/goal congruence values can be tricky since one has to decide to what extent a certain belief blocks or facilitates a given goal on a scale [-1, +1]. Currently, we use the following rules: [Each belief is associated with a list of possible values (used to describe uncertain events), the agents that cause them, and the combined values of the affected goals. There is also the concept of time involved.]

1. Caused damage/Win by KO:

$$c[ongruence] = 1–OppHealth/MaxHealth$$

2. Received damage/Lose by KO:

$$c = 1–NpcHealth/MaxHealth$$

3. Any belief facilitating or blocking Win by Points:

$$c = \frac{RoundTime * (NpcHealth - OppHealth)}{MaxRoundTime * MaxHealth}$$

4. Any belief facilitating or blocking Lose by Points:

$$c = \frac{RoundTime * (OppHealth - NpcHealth)}{MaxRoundTime * MaxHealth}$$

5. About to win by KO or by points:

$$c(KeepHighMorale) = 0.7$$
$$c(KeepLowMorale) = -0.7$$

6. About to lose by KO or by points:

$$c(KeepHighMorale) = -0.7$$
$$c(KeepLowMorale) = 0.7$$

Table 4.2: Beliefs of the AI agent.

Belief name	Casual agent	Event Trigger	Goals affected (+/-)
Caused damage	NPC	Occurs when NPC hits the opponent, reducing its health level.	Win by KO (+) Win by Points (+) Lose by Points (–)
Received damage	Opponent	Occurs when the opponent hits NPC, reducing its health level.	Lose by KO (+) Lose by Points (+) Win by Points (–)
Spent time winning	Empty	Occurs every second as long as NPC's health level is higher than the opponent's health level.	Win by Points (+) Lose by Points (–)
Spent time losing	Empty	Occurs every second as long as NPC's health level is lower than the opponent's health level.	Lose by Points (+) Win by Points (–)
About to win by KO	NPC	Occurs when the opponent's health is very low.	High Morale (+) Low Morale (–)
About to win by points	NPC	Occurs when time is running out while the agent has more health than the opponent.	High Morale (+) Low Morale (–)
About to lose by KO	Opponent	Occurs when the agent has very low health.	Low Morale (+) High Morale (–)
About to lose by points	Opponent	Occurs when time is running out while the opponent has more health than the agent.	Low Morale (+) High Morale (–)
Made 3 successful attacks	NPC	Three consecutive attacking moves of the agent were successful.	High Morale (+) Low Morale (–)
Failed to attack 5 times	Opponent	Five consecutive attacking moves of the agent were unsuccessful.	Low Morale (+) High Morale (–)
Opponent is evasive	Opponent	The agent failed to cause any damage for 10 seconds while receiving no damage.	Low Morale (+) High Morale (–)
Opponent is very resilient	Opponent	The agent received damage five times consecutively without being able to cause any damage.	Low Morale (+) High Morale (–)

7. Made 3 successful attacks (incremental event):

$$c(KeepHighMorale) = 0.2$$
$$c(KeepLowMorale) = -0.2$$

8. Failed to attack 5 times, opponent is evasive, opponent is resilient (incremental events):

$$c(KeepHighMorale) = -0.2$$
$$c(KeepLowMorale) = 0.2$$

Congruence values in incremental Gamygdala events are treated as relative contributions towards or against the goal. We also have an emotional decay event ("cooling down"), which is generated once per second.

4.4 Transformation to Action

Numerous studies confirm the impact of affect on decision-making and judgment, e.g. [22] [23] [24] [25] [26]. Positive emotions tend to increase the deliberation, whereby more information is sought and risk avoided, while aroused states and negative emotions result in simpler decisions, increased risk, and polarised judgment [27]. Emotions may further lead to biased decision making; with fear and anger, e.g., having significant (and opposite) effects on risk perception [28]. Generally, positive affect is associated with faster thinking and negative affect with the opposite [23]. Isen [29] argues that positive emotions facilitate systematic and careful information processing, resulting in more efficient and more thorough decision-making. As important motivators, emotions influence action [30] [31] [32].

Figure 4.2 depicts our attempt at matching emotions with a behaviour style, from very defensive to very aggressive (which is easily set with Fuzzy AI), with the horizontal arrows indicating an increase or decrease in aggressiveness. Since only focus on the affects that relate to the overall goal of defeating a disliked opponent, the emotion is limited to nine, namely hope, fear, fearsConfirmed, joy, distress, satisfaction, disappointment, relief, and anger.

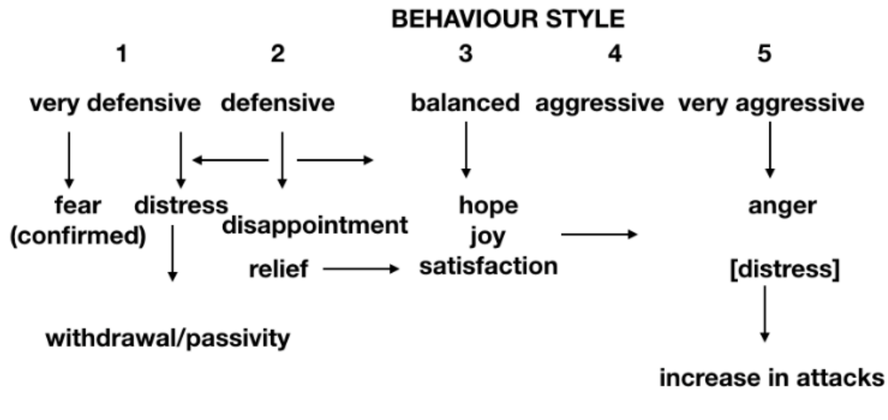

Figure 4.2: Behaviour style continuum.

4.5 Emotion Output

Figure 4.3 is one of the results of the Gamygdala. In this game, both players get damage at the same pace. In the beginning, fear, hope resentment, gloating, and anger all of those emotions gradually increase. During this time, the agent's both positive and negative goals increase gradually. At 77 seconds, hope goes up significantly. It means, one of the positive goals, keeping high moral, reach the goal. Also, resentment goes up later because of the achievement of keeping low moral goals.

The five generated emotions here, fear, hope, resentment gloating, and anger seems to be understandable feeling in the fighting game match.

However, I have to note that the value of emotion is not trustable. For example the beginning of the game there is no emotion, also the decay of emotions is too small.

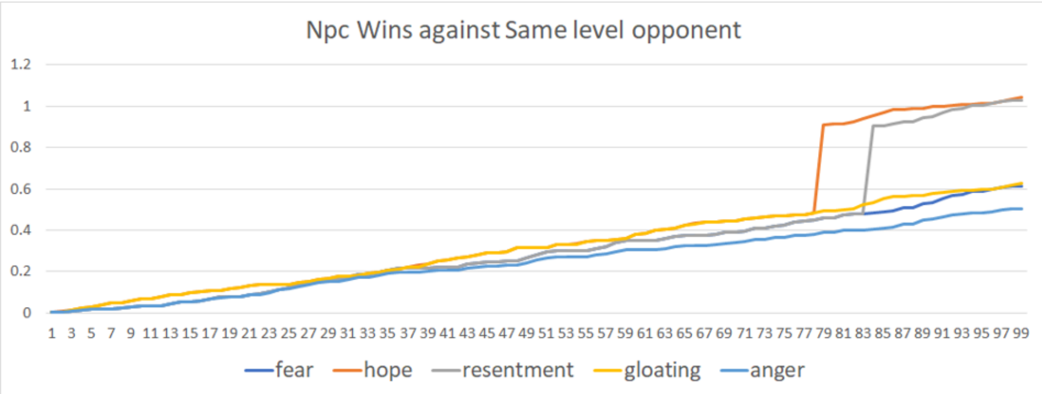

Figure 4.3: Gamygdala's emotion state output with utility value by time in a game.

Chapter 5

Project 2: Identification of Playstyles

In the previous project, we have successfully attached the cognitive appraisal model to the fighting engine character. It can change the character movement interestingly. However, in terms of building "human-like" AI, it is not clear if the agent movement is achieved the requirement. To evaluate human-likeness, we need to have a way to capture behavior patterns.

In this project, we develop an automatic system to distinguish individual players using cosine similarity analysis. It also compares the style of people's play with Fuzzy AI, a built-in AI of UFE. From section 5.3, we also report the results of a study at clarifying whether human observers can find human-like characteristics of game character behavior. In this research, we are focused to deal with the following research questions:

RQ1. Do human- and AI-controlled characters possess distinct, identifiable play styles?

RQ2. Are these styles consistent across matches or change depending on the opponent?

RQ3. Do human-controlled characters possess identifiable "human-like behavior traits"?

RQ4. Can questions RQ1-RQ3 be answered with a certain automated evaluation procedure?

5.1 Method: Cosine Similarity Analysis

To compare the behavior of individual players, we adopted the cosine similarity-based procedure, earlier used in boxing games [8]. It works as follows. We game recordings of interest participants and create its "behavior fingerprint", which is an ordered list of probabilities of all possible tuples (A1, A2, A3) representing three consecutive actions. Actions we selected to consider are three elements, State, Sub State, and Basic Move. (see Table 3.3 and 3.2).

Cosine similarity can be compared between two vectors A and C for two behavior fingerprints, yielding a similarity ratio of [0, 1]:

$$\begin{aligned} Similarity(A, C) &= cos(|A|, |C|) \\ &= \frac{A \cdot C}{|A||C|} \end{aligned}$$

Behavior fingerprint comparison was applied to a dataset consisting of matches, played by four humans and five skill presets of Fuzzy AI as follows:

1) Every human participant played with every other human participant and with an AI system set to a normal skill level.

2) Two human participants played against each AI skill preset.

Every pair played 10 matches of two to three rounds (until one gets two rounds). A round lasts 100 seconds unless a knockout occurs. A separate behavior profile for a particular player is built by processing all 10 matches played against a specific opponent, and it is possible to compare fingerprints of the same player obtained in matches with different opponents.

5.2 Cosine Similarity Result

We have 435 cosine similarity data from 30 different fingerprints in 15 games. Figure 5.1 shows the 28 possible links for four games, played by four human players (Ryoya, Kaori, Ippo, and Riku) and the normal level of Fuzzy AI. The name of the player for comparison is represented by the bold font, and left and right means the initial player position in the game. For example, there are 4 links between Ryoya and the normal level of Fuzzy-AI, the similarity ratio of the time when they have a game together is 0.73, the minimum similarity ratio is 0.70 and the maximum ratio is 0.78.

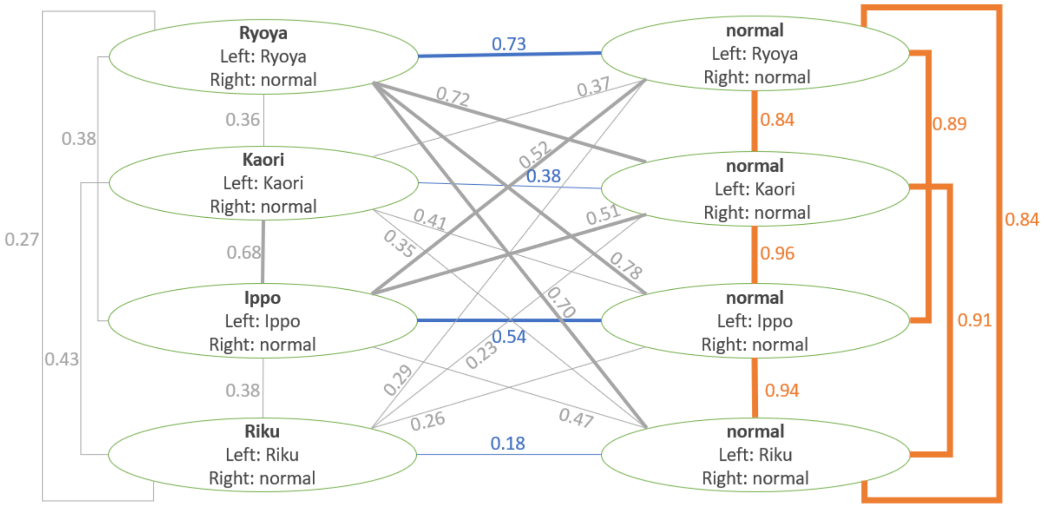

Figure 5.1: Similarity in human vs normal-level fuzzy AI games. Blue for match opponent. Orange for same player. Gray for others.

Our first observation concerns the playstyle diversity of Fuzzy AI. Any two given behavior profiles of AI-controlled characters have a similarity ratio average of 88% and all of them are more than 76%. This way, we can conclude that parameter tuning has very little effect on AI behavior profiles. While the skill level of the AI system can be modified, its playstyle remains virtually the same. Thus, for the sake of simplicity, we will mostly deal with AI set to the "normal" difficulty in subsequent tests. It should be noted, however, that high play style similarity values were obtained with an automated scoring algorithm, it may not fully agree with human perception of a play style.

Figure 5.2 and Table 5.1 are representing the results of the similarity ratio with the match opponents. Instead of dealing with context-sensitive profiles (such as "player A as seen in games against player B"), we can discuss generalized profiles of individual players, representing their typical playstyle across game sessions. Our calculations show that people are indeed closer to other people in terms of their play style. Only one participant (Ryoya) happened to be closer to AI than to other people. It is also clear that individual play styles are distinguishable: as mentioned before, comparison of behavior profiles of the same player obtained in matches with different opponents typically yields values of 90% and above, while the average similarity between different players is only 44%-65%.

Interestingly, human players seem to stick to the same playstyle, even when faced with different opponents. The similarity ratio between two behavior profiles of the same player obtained in matches against a variety of opponents is at least 80% on average (see Table 5.2).

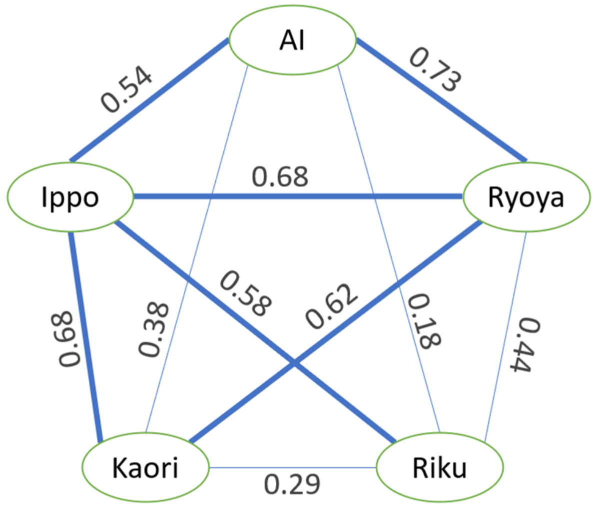

Figure 5.2: Play style similarity of game participants.

Table 5.1: Play style similarity between human-controlled and AI-controlled characters.

	Similarity with AI	Average Similarity with human players	Median Similarity with human players
AI	1.0	0.46	0.46
Ippo	0.54	0.65	0.68
Kaori	0.38	0.53	0.62
Ryoya	0.73	0.58	0.62
Riku	0.18	0.44	0.44

Table 5.2: Similarity scores for profiles of the same character in different matches.

	Minimum	Maximum	Average
AI-normal	0.76	0.98	0.88
Ippo	0.61	0.93	0.82
Kaori	0.70	0.94	0.85
Ryoya	0.69	0.99	0.85
Riku	0.70	0.88	0.80

5.3 Method: Turing Test

The higher similarity scores of human participants suggest the existence of identifiable "human-like features" in their playstyle, but automated procedures alone cannot provide credible evidence of this suggestion. Livingstone [33] describes the possibility of applying variations of the Turing test [34] to assess the human-likeness of computer-controlled characters. In this scenario, believability is judged by a person, not an automatic scoring procedure. Implementing the Turing test in computer games is not an easy process, but certain recommendations have been proposed in the literature [35] [15].

Our Turing test was conducted as an online survey using Google Forms. The participants were asked to watch four video clips (ranging from 1m06s to 3m15s in length) of matches between two unknown participants. The task was to guess which characters are controlled by people, and which by the AI system. To reduce random guessing, a third "not sure" choice was also available. In total, 14 subjects participated in the survey. One of them is over 40 years old, and the rest are 20-25 years old. Most of the participants (71%) identified themselves as occasional players of fighting games, while the rest pointed out that they do not play fighting games at all.

5.4 Turing Test Result

Table 5.3 shows survey results for each video clip.

Table 5.3: Turing test results.

	Match participants	Correct answers	Incorrect answers	"Not sure" answers
Match 1	Left: Riku	43%	57%	0%
	Right: Ryoya	36%	57%	7%
Match 2	Left: Kaori	50%	21%	29%
	Right: Ryoya	29%	36%	36%
Match 3	Left: AI	43%	36%	21%
	Right: AI	29%	43%	29%
Match 4	Left: Kaori	36%	36%	29%
	Right: AI	29%	43%	29%
Total		37%	41%	22%

It's not easy to distinguish between human and computer-controlled opponents in a fighting game. Our participants were wrong more often than they were right. The results are slightly better for occasional fighting game players who provided the same number of correct and incorrect answers (45%) and chose the "don't know" option only for 10%. Both participants in Match three are the same AI-controlled character, but for some reason, our observers found more human-like traits in the left-hand side character. Curiously, the most "AI-like" player, Ryoya (according to the cosine similarity method), also had the fewest correct answers in the Turing test.

As a follow-up to this test, we had a discussion of five clips (two human-human, two human-AI, and one AI-AI game) with three experienced gamers who play fighting games at least weekly for over three years. One person could correctly identify whether a certain player is human or AI in eight cases out of ten, another individual correctly identified six players, and the third one made only two correct guesses.

Interestingly, these experts had different ideas about what constitutes a "human-like" style. For example, the best performing individual associated AI movements with "nice" smooth movements. Another correct guess was made by associating a "seemingly intentional" jump with human-like behavior. These statements overlap somewhat with the comments provided in [35], revealing that relatively simple clues are often associated with human-like or AI-like behavior ("fires for no reason, must be human", "stand and wait, AI wouldn't do this", etc). As a side note, the development of AI like humans is usually done through a variety of "ghosting" or "mirroring" strategies aimed at reproducing actual patterns of human behavior rather than to understand and implement specific features considered "human-like" by other players [36] [37] [38]

5.5 Research Question Answers

Results obtained in the course of the present study suggest the following answers to our research questions:

RQ1. Yes, game characters possess distinct and identifiable play styles in a sense that it is possible to cluster players according to their playstyles and find out whether a particular behavior profile belongs to a specific player.

RQ2. Yes, individual play styles are consistent and recognizable even in games against different opponents.

RQ3. "Human-like behavior traits" are seemingly possible to detect with a cosine similarity-based tool described above. At least, this is true for the Fuzzy AI system of UFE, but the answer might be different for other AI engines.

RQ4. Yes, an automated approach can be used to address the challenges listed in RQ1-RQ3.

Chapter 6

Conclusion

In the first project, we show how emotional behavior can be integrated into the fighting game genre to make the artificial opponents more attractive. The emotional state of a computer-controlled character is modeled with Gamygdala, a system specially designed for this purpose. This approach does not require a complete redesign of the game AI system. The knowledge of the characters' emotional states can be used to fine-tune the settings of an existing AI technology, such as Fuzzy AI of Universal Game Engine.

One of the difficult aspects of this task is translating emotions into actions. First, we need to understand how different types of emotions affect real human behavior. We relied on discoveries from psychological studies to design the presented rules. However, even a solid foundation does not guarantee a clear perception of emotional behavior by the player, extensive testing and fine-tuning of the system is the next goal. From a technical point of view, this project provides an example of practical experience connecting a JavaScript-based module (Gamygdala) to a Unity-based game engine. This result can be interesting to the broad community of game makers given Unity's popularity as a game development instrument.

For the second project, our behavioral comparison tools based on cosine similarity provided consistent and reliable results in most cases. However, it should be noted that the "similarity score" should not be obtained at face value. Since this tool captures only certain basic behavioral characteristics, its output can be used to create statements such as "player1's playstyle is closer to player2 rather than player3", but the numerical evaluation is rough.

The Turing test results are difficult to interpret. First, let us note that it is difficult for people to rate a large number of video clips and compare the playstyles of players acting in non-adjacent game sessions. Therefore, we have to limit our surveys to a small number of short clips. The ability to evaluate playstyle seems to improve with experience, but even hardcore fighting game players have difficulty distinguishing between AI-controlled characters and human players.

The high "human-likeness" scores of AI systems may indicate that fuzzy AI is a high-quality system and can mimic the patterns characteristic of human players. Also, some short video clips may not be able to assess the credibility of the action, and necessary to be deeply immersed in the game world.

This research is dedicated to creating human-like AI. At this moment, no one has succeeded to make a complete one, if I consider the human-like should be believable and follow an understandable cognitive model. If someone succeeds to make one, people deeply understand how humans behave, or how humans are diverse. I believe it will help us in the different fields of study like education or medical science and lead us to live better.

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