Production of Emotion-based Behaviors for a Human-like Computer Player

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ABSTRACT

The current performance of computer game players is highly promising and efficient in terms of strength, but the behavior of such strong computer players is not promising for the entertainment of human players. For example, in a famous video of a computer player for Infinite Mario Bros., the Mario character shows highly precise movements and no hesitation in his decisions. Such a behavior looks too mechanical; in other words, it is too strong and not entertaining. Human behavior is easily inspired by emotions, such as fear of an enemy or enjoyment in collecting a reward. Behaviors often change, even in the same game and same match. Thus, we propose the design of a human-like computer player with five emotional behaviors: "Safety," "Hurry," "Greedy," "Enjoy," and "Habit." These behavior models reflect human behaviors, which are inspired and affected by an emotion, such as fear, anxiety, or enjoyment. According to these models, we propose simple rule-based switching to handle the transition between models.
This article mainly presents the implementation of the Safety behavior model, which reflects human fear and anxiety. The model was evaluated using the Turing test.

INTRODUCTION

The ideal goal of the academic study of computer games is to make a suitable computer opponent for humans. To achieve this goal, strengthening the computer player is the first and major aim of the research. Currently, the triumph of computer players, such as "Deepblue" (Campbell et al. 2002) and "AlphaGo," (David et al. 2016), over human professional players proves their performance. In addition, in modern computer games, such as Starcraft, computer players have become strong enough to win against intermediate human players. These successes show it is perhaps time to focus on other issues related to computer players, such as education or entertainment.
There are various uses of a computer player in video games. Sometimes computer players are developed to control another character, such as a partner or an opponent, to entertain human players. The design of a computer player with suitable behaviors or strategies is difficult, and it becomes a heavy burden for developers. Thus, efficient algorithms, such as the path-finding algorithm A* and the learning algorithm TD learning, are introduced to generate behaviors or strategies to reduce the load of developers' work. Currently, the performance of computer game players is highly efficient, but the behavior of strong computer players is not promising for the entertainment of players. For example, a famous video of a computer player for Infinite Mario Bros. (the public domain clone of Super Mario Bros. of Nintendo) was published in 2009 on the website YouTube (https://www.youtube.com/watch?v=DlkMs4ZHHr8). The video shows an excellent Mario character, which is controlled by a computer. Each of its actions is highly accurate and instantaneous. Such a behavior looks remarkably mechanical. In this case, a human observer only acknowledges that the player is controlled by a machine. However, in the case of two-player games (e.g., fighting games like Street Fighter http://www.capcom.co.jp/sfv/) or multiplayer games (e.g., shooter game like Unreal Tournament 2004), where a computer player simultaneously plays with human players, humans might suspect they are being cheated, and the entertainment of the game will be harmed because of the unnatural behaviors of the computer player. Hence, the production of behaviors that look natural to humans, called human-like manner, is essential to enabling computer players to entertain human players.
Many approaches have been taken to produce human-like behaviors, such as directed learning in a first-person 3D shooter game (Schrum et al. 2011). In 2013, Fujii et al. introduced a new approach to producing human-like behaviors based on biological constraints. The player exhibits actions that are similar to human players' actions. However, to produce human-like behaviors for computer players, changes in behaviors during the game due to emotions are needed to be concerned.
For example, in Super Mario Bros., the main goal is to clear a stage within a limited time. In the beginning, the player tries to reach the goal as fast as possible. Nevertheless, after some coins are found and the player acknowledges there is still enough time, he or she might ignore the main mission and try to collect coins, which is a sub-objective of the game. He or she might be inspired by greed or enjoyment. Such a change in behavior is inspired by human feelings or emotions. Hence, the production of behavior transitions is important to produce a human-like behavior.
We propose an idea to represent the behaviors of human players, who are affected by their emotions, in several behavior models, as well as a simple transition to produce human-like behaviors. Behavior models are proposed to provide different play styles, and they can be explained as follows:

- "Safety" reflects the anxiety and fear of the player when on guard.
- "Hurry" reflects careless speedy actions, when the player worries about the remaining time.

- “Greedy” reflects the enjoyment of humans when they find rewards.
- “Enjoy” reflects enjoyment and interest, such as killing enemies continuously.
- “Habit” reflects unintended behaviors, such as pressing repeatedly the jump button.

This article presents the implementation of the Safety model, which is based on the A* algorithm. We also present a sample of the Greedy model and the Hurry model, and the guidance of switching between these models using simple rules is considered. The research evaluation was conducted by applying the Turing test, which conforms to the evaluation method of the Mario AI Competition 2010.

RELATED WORKS

The topic of the human likeness of machines is an interesting topic in the field of philosophy of the mind and cognitive science. The research in this field has been discussed widely since Alan Turing proposed the Turing Test in his article “Computing Machinery and Intelligence” (Hingston 2010). Until now, the definition was unclear. In the field of computer games, the study of human-like behavior (also known as believability) has interested many researchers. As far as we know, the definition of human-like behavior is still ambiguous, even in the special case of computer games. Considering the word “believability,” the literal meaning is that something can be reasonably believed by someone. Togelius et al. defined player believability as when “someone believes that the player, who controls the character/bot is real, i.e. a human is playing.” This is related to the case of video games, such as Starcraft and Super Mario Bros., where either a computer player or a human player can control a character in the game. The player observes the behavior and judges whether a human player is playing (Togelius et al. 2012). The effects of believability/human likeness can be classified into two levels. In the case where humans do not participate in the game (i.e., in one-player games), such as Infinite Mario Bros., the unnaturalness of the computer player may be harmless. On the contrary, in two-player or multiplayer games, where a human player simultaneously plays with a computer player, and when the computer player is assigned as a partner/opponent of the human, unnaturalness will directly harm the entertainment of the game.

Fujii et al. proposed a human-like computer player with biological constraints. These were applied to Q-learning and the A* algorithm in the Infinite Mario Bros. test-bed game. It was shown that the proposed agent could be more human-like than both the novice and expert human players.

However, human behaviors are easily affected and inspired by emotions, such as fear, anxiety, or enjoyment. For example, in a situation where the Mario character is in an invisible state (the effect of a game item for a short period), the player enjoys killing as many enemies as possible. In contrast, if the character is surrounded by a large number of enemies, the player might hesitate to move forward or backward due to fear and anxiety. Some approaches introduce emotions to machines; for instance, Canamero presents a paper on emotion for behavior control, which discusses the importance of including emotion in machines so the system has a better communication ability and flexibility (Canamero 1997).

We aim to produce computer players with transitions between behavior models that appear to be inspired by emotions. The usual practice in this area has been focused on the human likeness of behaviors in overall game play, whereas our approach produces transitions between multiple behaviors. Each behavior model produces a specific human-like behavior inspired by human emotions or feelings (e.g., anxiety, fear, etc.), and the transition model afterward decides an appropriate moment to change the behavior to make it looks like a human transition.

PROPOSED METHOD

In a modern-style game, not only a single goal but also many sub-goals are given and available for challenge. In the case of the Super Mario Bros. series, the major goal is to reach within a time limit the stage’s goal located at the rightmost of the stage. Players have other optional tasks of collecting coins or beating enemies, though they are not necessary to clear the stage. The player is able to challenge any goal that he or she prefers, but the player must respect the major goal. Thus, the player will exhibit transitions between several local behaviors. For example, at the beginning of the stage, the player’s movements are at ease, so he or she can enjoy collecting coins, or the player can control Mario carefully when he encounters many enemies. After a while, when the time has almost run out, Mario’s movements become faster and riskier to clear the stage in time. Our research interest is in creating a human-like computer player with transitions between emotional behaviors. The usual practice in this area has been focused on the human likeness of behaviors in overall game play, whereas our approach produces transitions between multiple behaviors. Each behavior model produces a specific human-like behavior inspired by human emotions or feelings (e.g. anxiety, fear), and the transition model then decides the appropriate timing to change the behavior, which looks like a human transition.

We propose a research framework, as described in two layers: the “Behavior Model” and the “Transition.” The research is conducted using the Mario AI benchmark as a test bed. The implementation was conducted in the Java environment. The Behavior model includes five elementary models (i.e., “Safety,” “Hurry,” “Greedy,” “Enjoy,” and “Habit”). Each was designed to simulate a specific behavior, which is likely influenced by an emotion. However, the naturalness of each model is significant to produce human-like transitions. Thus, in this article, only the Safety model and the guidance of the Greedy and Hurry models will be described. The implementation of each behavior model is hand-coded, in other words, unsupervised, and based on the A* algorithm.

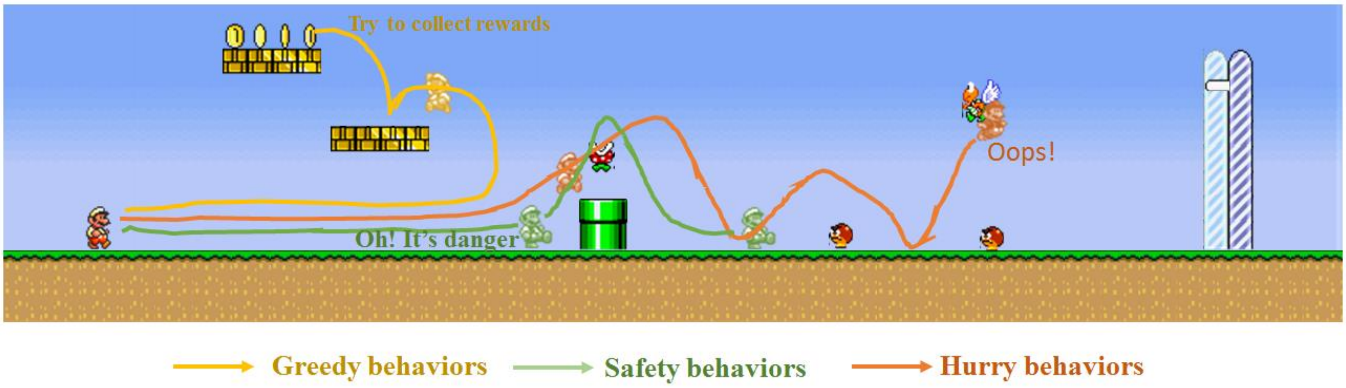

Figure 2: Safety, Greedy, and Hurry models

A algorithm in Mario*

The A* algorithm is a well-known path-finding algorithm. By using the best-first search, A* finds the path with the lowest cost from a start node to a goal node. To compare traversal paths, a cost function for A* is defined and used:

$$f(current, goal) = g(start, current) + h(current, goal) \quad (1)$$

Where $f(current, goal)$ is an estimated total cost of a current node, which is the sum of $g(start, current)$; the actual cost from the start node to the current node; and $h(current. goal)$, the heuristic estimation from the current node to the goal.

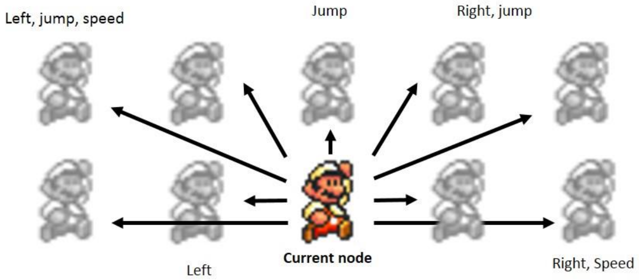

Figure 1: Possible nodes for A*

In the Mario AI competition, Baumgarten presented an efficient controller using a modified A* algorithm, which computes possible trajectories of Mario. The video of the controller was published and has been viewed over 600,000 times in a short period because the performance is excellent, and the behavior is far more from human players.

The algorithm expands the path by nine actions, as shown in Fig. 1 (i.e., left, right, jump, dash/fire), where $g(start, current)$ is defined as the time that the controller used to reach the current position and $h(current, goal)$ is the estimated time from the current node to the goal with the current speed (Togelius et al. 2010).

Our idea of the Safety model and two samples, one being the Greedy model and the other being the Hurry model, is shown in Fig. 2.

The first and the most important behavior is the Safety behavior. Most of the time, human players try to play safe, so their character can survive and move toward the goal. Based on this kind of behavior, our Safety model is created, and it allows the character, in this case Mario, to move steadily and carefully. In addition, the character is able to recognize dangerous areas, and it hesitates to move forward until the dangerous turn into a safe area. The area changes from dangerous to safe if the enemies are killed or they disappear.

The second behavior model is Greedy. While the Safety model forces the character to pay attention to the enemies, the Greedy model leads the character to the locations of coins. Instead of moving toward the goal, the character moves to the location of a coin. This is only one example related to the Greedy model, where the character will only move to the coin's position.

Similarly, an example of the Hurry model would be making Mario move as fast as possible to reach the goal without paying any attention to enemies or coins. We explain the mechanism of each model in the next part.

Safety Model

Maslow explained the motivation of humans in a hierarchy of five layers of needs. The term "Safety" has been used to describe the needs of health, well-being, and safety against adverse impacts. Moreover, the need for safety can influence a player's behavior. While playing a game, movements can be affected by anxiety or fear. For computer players with perfect control and information, precise actions, such as evasion from an enemy by one pixel, are possible. Nevertheless, beginner and intermediate players are aware of their imperfect controls and perceptions. Thus, a safer movement, such as keeping distance from each enemy, is preferred.

The safety model imitates such a behavior by introducing a "dangerous area" to the A* algorithm. The "dangerous area" surrounds each harmful object (Figure 3), so the safety model controller intends to avoid the object and the "nearby area." The heuristic function of the A* algorithm is defined as:

$$h'(s_t) = S \rightarrow R | h'(s_t) = RP_t + MP_t - h'(s_{t-1}) \quad (2)$$

Where s is the state of the game at frame t, RP_t is the penalty from real damage that Mario takes in frame t, and MP_t is the penalty from the virtual damage from the dangerous area, as shown in Fig. 1. There are many kinds of harmful objects, so there are also many kinds of dangerous areas. For example, fast-moving enemies should have a wider area compared to slow or fixed objects. If we compare the two areas shown in Fig. 1, the left has an isotropic area. On the other hand, the right one has no virtual damage over the enemy. This is because some enemies can be stomped on, and in such a case, Mario is not damaged.

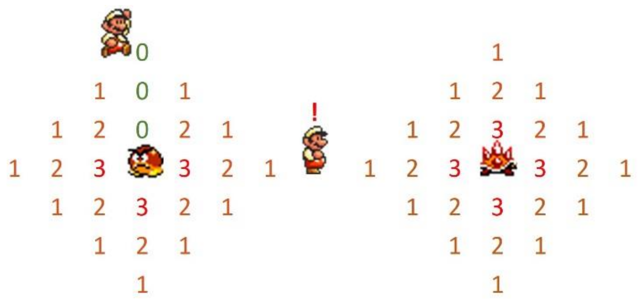

Figure 3: Dangerous area

Hurry Model

The major goal of Super Mario Bros. is to clear the stage by travelling to the rightmost end of the stage without being killed. In each stage, 300 seconds are given, and after 200 seconds have passed, there is a warning sound and the background song will quicken. Afterwards, the player will be aroused and try to clear the stage as fast as possible. Sometimes the player might ignore remaining coins, give up on killing enemies, or even ignore damage that does not kill Mario immediately, such as in the "Fire" or "Big" state. Thus, we proposed the Hurry model to display such behavior. The implementation is based on the A* algorithm of Baumgarten, including the concept of the dangerous area, which smaller than in the Safety model.

Greedy Model

In the Mario game, coins and items are rewards that provide some benefits to Mario. Collecting coins adds to the score of the player, and for every 100 coins, the player gains an additional life. Items give to the player not only a score, but also a status upgrade from Small to Big or to Fire. Sometimes the player's attention might be drawn to these rewards. Our Greedy model imitates such attention to rewards. This behavior reflects the enjoyment of humans when they obtain a benefit. The main idea of the Greedy model slightly differs from the Hurry model. The target of path finding is set to coin locations and item locations, instead of the real goal. For instance, in Super Mario Bros., we assume (x_g, y_g) and (x_{ci}, y_{ci}), where (x_g, y_g) stands for the coordinate of the goal and (x_{ci}, y_{ci}) stands for the coordinate of the coin with the index i. As a result, the Mario character will change its target to the coordinate of coin i, and only when coin i is collected will the target change to the next coordinate of coin $i+1$. When there is no coin left in the area around the character, the target changes back to the coordinate of the goal. Finally, by using the A* algorithm for path finding, we were able to make the character move to the expected target.

Enjoy Model

Sometimes the player might face some challenging situations that are unnecessary to solve to clear the stage. Yet, the player might enjoy such a situation. In the case of the Mario game, if the player is able to stomp continuously on enemies without falling to the ground, the score will double for each kill. The challenge may provide a big score, but it is not necessary to clear the game. We present the interest and enjoy emotions in this model.

Habit Model

We found that for some human behaviors, it is impossible to identify the purpose or even the reason for the behavior. Often, human players produce actions having no aim or benefit, such as the player jumping all the way while running, even though there are no enemies or obstacles in the game scene. The behavior might occur by instinct or sometimes with the player's intention. We defined such a behavior as the Habit model.

Switching Model

Human behavior is more complicated than we can imagine. To illustrate, at a specific period in the game, a human player uses the Safety style, but after a numerous rewards appear, the player changes to the Greedy style and begins to collect as many rewards as possible. Hence, we propose this model based on the idea that human players change behaviors during the game. The mechanism of this model is simple. It is the combined models of two or more individual models, which we already introduced in the previous part. To change between models, a set of rules is used as a switch. If the information in the environment around a character meets the condition, the character is able to change to an appropriated behavior model. For example, if the number of coins is greater than three, the Greedy model is activated, or if the number of enemies is greater than five, the Safety model is activated. When one model is activated, others are disabled.

EXPERIMENTS

The assessment of each model incorporated the Turing test method of the Mario AI Championship 2010. We want to confirm the human likeness of the Safety model and the possibility of the idea as an extra. The preparations were done by collecting the replay from a human intermediate player. The player was asked to play the game in 10 stages, with four various instructions.
"Please clear the stage as safely as possible"
"Please clear the stage as quickly as possible"
"Please clear the stage and gather as many coins as possible"
"Please play at will"
In the same set of stages, the replays from the "Safety model player" were collected. We also implement a sample Greedy model that aims to collect coins, a Hurry model that aims to clear a stage as quickly as possible, and simple rule-based switching for these three models.
We employed 15 human subjects whose mean age was around 20–30, who have experience with the game, and who know the rules of Super Mario Bros. The subjects were asked to observe pairs of non-label replays. Then, they have to answer the following question:

"Q1: How expert is this player?"

"Q2: Does the action of this player look natural?"

The answers to each question were based on a 5-point Likert scale. Subjects were asked to compare replays one by one, such as to compare a human player with a safety instruction to a Safety model computer player or a human with a greedy instruction to a Greedy model player. The displayed orders are random and each type appears 37–38 times.

Experimental Results

The results of the experiment are shown in following chart

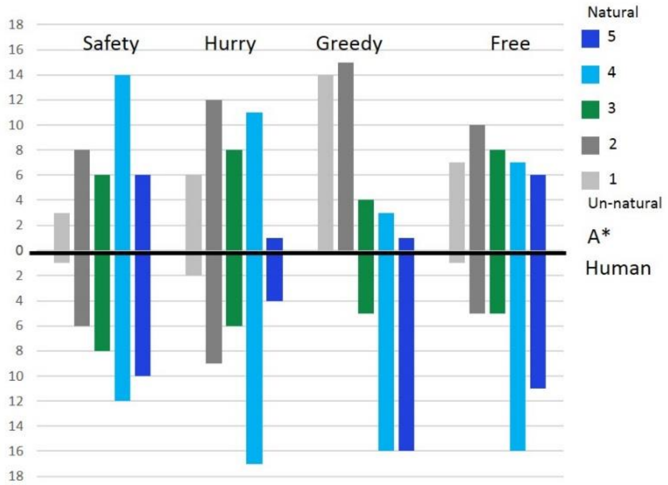

Figure 4: Score of naturalness of a behavior

The Safety model shows behaviors that are believable to the subjects. The frequency of a score of naturalness higher than 3 is almost equal to a human play with a safety instruction. There are some differences between the model and the human player. The most common reason that subjects presented was that "there are nearby coins that should be collected but they are not." Next, the performance of the Hurry model is lesser than that of the human player with a hurry instruction, but the gap between the naturalness scores is not large. However, the Greedy model, which does not consider any risk or danger, showed a significantly lower score compared to the human with a greedy instruction.

We also implemented rule-based switching to switch among the Safety model, the Hurry model, and the sample of the Greedy model to confirm whether believability will increase if a computer player produces many behaviors. The results show improvement in the Switching model compared to only the Greedy model or only the Hurry model, but it is still lower than the Safety model. The main reason is that overall performance depends on the quality of all individual models.

Considering human plays, evaluations are high in the case of the free will instruction and the greedy instruction. The reason is that people tend to play in multiple styles (they play safe even when collecting coins). It might be said that the player with multiple behavior types looks more human-like than those with a single behavior do. Thus, behavior transitions are important for making a believable computer player.

CONCLUSION & FUTURE WORKS

We are able to confirm our hypothesis in the Safety model. Staying safe is a significant behavior among human players, which refers to maintaining distance from enemies and avoiding risky play. This important behavior makes a computer player appear more human. The result of the Turing test has shown that the believability of the Safety model is almost closely equal to a human player. However, there is still a claim from subjects about a lack of some behaviors, such as "searching for coins or items." These are related to our original hypothesis, where the human-like behavior contains multiple behavior types. In this article, we introduced Hurry, which involves risky play, and the simple Greedy model, which ignores all enemies. The quality of their believability in the Turing test is low, but after we combine them all using simple rules, there is an improvement in believability.

We also verified that the player with multiple behavior types looks more human-like than a single-behavior player does. This also conforms to our hypothesis stated at the beginning.

Thus, our future work will concentrate on the believability of the Greedy model and the Hurry model, as well as on a better transition between these models. Additionally, a learning-based transition will be analyzed in the near future.

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