Designing Artificial Agents to Detect the Motive Profile of Users in Virtual Worlds and Games

Xuejie Liu
School of Engineering and Information Technology
University of New South Wales, Canberra
ACT, Australia
xuejie.liu@student.adfa.edu.au

Kathryn Merrick, Hussein Abbass
School of Engineering and Information Technology
University of New South Wales, Canberra
ACT, Australia
[k.merrick|h.abbass]@adfa.edu.au

***Abstract*—Understanding the motive profile of users in virtual worlds, computer games or interactive simulation environments promises to complement research on game flow, player experience modelling and game data mining. Traditionally work in these areas examines statistics from users interacting with existing games. This paper takes an alternative approach and explores the design of artificial agents that can aid with detection of a user or player's motive profile. We demonstrate these agents in a decision-making scenario that requires the opponent to trade off social and risk-taking goals. We conclude by identifying a group of four agents that we hypothesize will be able to distinguish between users or players with different motive profiles.**

Keywords—game theory, motivation, non-player character

I. Introduction

Gameplay is a voluntary problem-solving process. Participants engage in game play because of the feeling of fun that arises during gameplay. Understanding and modelling players helps us design entertaining games. This includes understanding player experience from perspectives of emotion, cognition, behaviour and motivation. This provides insights into why and how players enjoy a game, which can facilitate the design of diverse or adaptive games that satisfy a broader range of player needs.

In fact, games have been treated as an essential tool to study player personality, play preferences and behaviour in psychology, neuroscience and other fields [1]–[4]. This paper is concerned with the design of games for detecting motivation.

Many contemporary commercial games are complex in terms of their terrain, maps, levels, stories, quests, music and non-player characters (NPCs). This makes them difficult to use 'as is' for detecting motivation because it becomes difficult to limit and control the experiences of the player to collect data on variables of interest.

This paper describes how simple, abstract game scenarios can be drawn from game theory literature, and explains how, through the use of different NPCs, we can use such scenarios to collect data that can provide us with insights into the motive profile of players. In this paper we focus on the identification of three influential motives: achievement, affiliation and power motivation, through the dimensions of risk-taking behaviour and social attitude [5].

The remainder of this paper is organised as follows. Section II first examines the literature on profiles of achievement, affiliation and power motivation, and links this to literature on risk-taking and social attitude. We then examine existing literature describing games that have been used to detect player attitude to risk-taking and social interaction and select one example—the prisoners' dilemma (PD) game—for our study.

Section III proposes the design of NPCs as opponents in a PD game that can assist with the differentiation of player motives. In Section IV we examine via simulations how these NPCs will respond differently to different play strategies, and hypothesize how these differences can be used to determine human motive profile. We conclude in Section V with a discussion of the next steps we propose for work in this area.

II. USING GAMES TO DETECT MOTIVATION

Modelling player types has been an area of recent interest among computer game academics. Computational models of player types can permit dynamic adaptation of games to suit player interests and keep players in the 'flow zone' for longer [6]. Recurring themes in player type models suggest a common underlying model of human behaviour. One view on motivation that is reflected in literature on player types is incentive-based theories of achievement, affiliation and power motivation [7]. This section briefly examines these motivations then examines how games have been used to identify other cognitive phenomena, as a precursor to the design of NPCs that can be used to distinguish motivation.

A. The 'Influential Trio': Profiles of Achievement, Affiliation and Power Motivation

While many theories of motivation exist, the 'influential trio' that occurs in three needs and three factor theory [8], [9], is particularly relevant to the study of game and virtual world users [7]. We consider each of the three motives that comprise this theory in the following sub-sections, and why they are relevant to game-play.

1) Achievement Motivation

Achievement motivation is defined as an enduring striving to compete with standards of excellence and to increase one's competence [5]. Achievement motivation is involved in achievement-related task, activities and skills. In achievement-motivated behavior, a standard of excellence is applied to evaluate one's actions, and the outcomes of those actions are associated with one's own competence.

These standards of excellence may be personal (mastery oriented) or social (performance oriented) [10]. For mastery oriented people who compare their current performance with their own experience instead of with that of others, self-evaluation emotion is relevant. The emotions of joy and sadness in response to the acquisition and loss of a desired object, are an expression of achievement-motivated behaviour. Pride and shame, which link to dominance and submission, are not only an evaluation of the outcome of people's actions, but more importantly, the evaluation of their own competence against a standard of excellence [5].

Studies have shown that achievement motivated individuals may prefer to work alone and may prefer goals of moderate risk [5].

Achievement motivation is relevant to game play because it is associated with earning points and prizes, or in-world 'money'.

2) Affiliation

Affiliation refers to a class of social interactions that seek contact with formerly unknown or little known individuals and maintain contact with those individuals in a manner that both parties experience as satisfying, stimulating and enriching [5]. The need for affiliation is activated when an individual comes into contact with another unknown or little known individual. Particularly, affiliation motivation is satisfied by forming friendships and associations; greeting, joining and living with others; cooperating and conversing sociably with others; loving and joining groups. The emotions associated with affiliation motivation are trust, empathy, love and liking.

There is evidence that affiliation motivated individuals prefer low-risk goals, and may avoid public competition and conflict that may lead to the acquisition of resources that are desirable to others [5].

Affiliation motivation is relevant to game play because it is associated with relationship building, socialising and cooperation that occurs in games.

3) Power

Power can be described as a domain-specific relationship between two individuals, characterized by the asymmetric distribution of social competence, access to resources or social status [5]. Power is manifested by unilateral behavioral control and can occur in a number of different ways. The taxonomy of power includes six sources of power that are reward power, coercive power, legitimate power, referent power, expert power and informational power. There are also two sides of power motivation: hope for power and fear of loss of power.

Five components of fear (avoidance) of power have been identified: fear of the augmentation of one's power source, fear of the loss of one's power source, fear of exerting power, fear of the counter-power of others and fear of one's power behavior failing [5]. Some analysis shows that the expression of power is linked to positive emotional experience, and a participant's sense of control plays a major role in power behavior. Power motivated individuals will often prefer high risk or high payoff goals, as success at such goals may give them social status or access to desirable resources [5].

Power motivation is relevant to game play because it is associated with gaining control of resources, influencing others and winning.

4) Discussion

We see two themes emerging from the discussion of achievement, affiliation and power motivation above. The first theme concerns social attitude: that is the number of relationships an individual may choose to initiate and maintain. The second theme concerns risk attitude: that is the degree of risk that an individual will tolerate when selecting goals.

Accordingly, we propose a model of motivation that positions achievement, affiliation and power motivation on two dimensions of risk and social attitude in Fig. 1. We propose that power-motivated players prefer high risk tasks and have neutral social attitude, while achievement-motivated players tend to select medium risk tasks and enjoy working alone. Affiliation-motivated players have a high social tendency and prefer low risk tasks.

In order to measure motivations during game-play, we suggest risk-taking behaviour, strategic and social attitude should be considered. The next section reviews a range of games that have been used for detecting cognitive and emotional phenomena, and selects one to use in our study as a basis for identifying a player's motive profile.

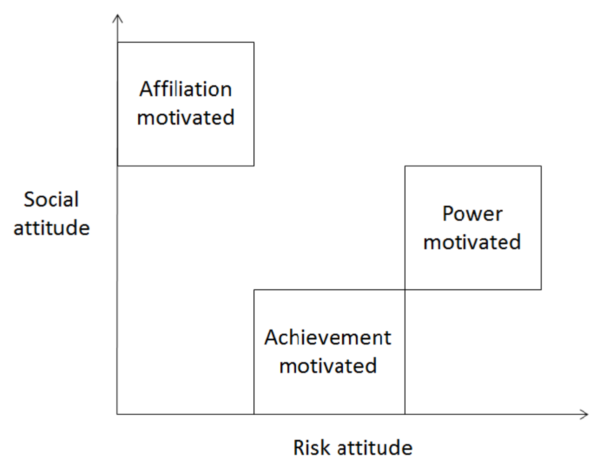

Fig. 1. Our proposed model places different motivations on axes of risk and social attitude.

B. Use of Games in User Profiling

Computer games facilitate the study of human behaviour and psychology, particularly in user cognitive and emotional profiling. The use of games in psychological and neuroscience studies varies from using games to study human behaviour [1] to using games to understand player temperament [3] using games to understand player cognition and emotion [2], [4]. Games have been justified as an optimal tool for examining player psychology from risk-taking to social attitude.

In order to model risk-taking disposition, gambling games have been considered. Table II includes existing gambling tasks used in neuroscience studies. Even though there are a variety of forms between these gambling games (e.g. card games, boxes, balloon, cups and numbers), they essentially share the same risk representation, which is that higher risk accompanies higher gain, while lower risk accompanies lower gain. Players need to make strategic decisions to deal with the trade-off between risks and gains in the game.

Social attitudes have been studied via mixed-motive games. The mixed-motive game is defined as a game that is neither a purely cooperative game nor a purely competitive game. Two-player mixed motive games have the structure shown in Table I. Each player, has a choice of two actions: *C* or *D*. Depending on the combination of actions chosen by both players, Player 1 is assigned a payoff value V_1 and Player 2 is assigned a payoff V_2. V_1 and V_2 can have values of *T*, *R*, *P*, or *S*. The value *R* is the reward if both players choose *C*. In other words, *R* is the reward for a (*C*, *C*) outcome. *P* is the punishment if both players defect (joint *D* choices leading to a (*D*, *D*) outcome). In a mixed-motive game, *P* must be less than *R*. *T* represents the temptation to defect (choose action *D*) from the (*C*, *C*) outcome and thus, in a mixed-motive game *T* must be greater than *R*. Finally, *S* is the sucker's payoff for choosing *C* when the other player chooses *D*. In mixed motive games the highest payoff is gained at the expense of one's opponent.

Two person mixed-motive games in game theory include the prisoner's dilemma (PD), leader game, chicken game and the battle of sexes [11] (see Table II). The PD game has been particularly widely studied in this regard, and we use it in our work.

TABLE I. PAYOFF MATRIX FOR A MIXED MOTIVE GAME. PAYOFF FOR PLAYER 1 IS LISTED FIRST IN EACH CELL.

		Player 2	
		Cooperate (C)	*Defect (D)*
Player 1	*Cooperate (C)*	*R, R*	*S, T*
	Defect (D)	*T, S*	*P, P*

TABLE II. EXSITING GAMES USED IN PROFILING RISK-TAKING AND SOCIAL ATTITUDES

Gambling Tasks	**Description**	**Measures**
Investment Game [12]	Participants are asked to invest a certain amount in a risky project. The probability to win is 1/3, whereas the probability to lose the entire investment is 2/3.	Risk-taking
Iowa gambling task [13]	Participants select a card from one of four decks in each trial; two disadvantageous desks have a higher reward but also a higher possible loss, while two advantageous desks offer a lower reward but a lower possible loss.	Risk-taking
Blackjack gambling task [14]	Also known as twenty-one, the goal of the game is to approach 21 points as closely as possible but to avoid getting over 21 points.	Risk-taking
Devil's task [15]	There are seven boxes with money in it and one of the seven boxes contains the devil that will cause players lose all their potential gains in the game. Participants decide how many boxes to open and whether to continue to earn their points with risk.	Risk-taking
Cambridge Gambling task [16]	A token is hidden under one of six boxes that are each one of two colours. Different trials have different ratios between box colours. On each trial, participants select a colour to bet. The colour with a higher probability (more boxes) is associated with lower potential gains and a lower probability is related to higher potential gains.	Risk-taking
Balloon Analogue Risk task [17]	Participants pump a simulated balloon without knowing when it will explode. Each pump increases the potential reward to be gained but also the probability of explosion, which leads to loss of all potential gains in the trial.	Risk-taking
The Cups task [18]	Participants choose between a risky and safe option, which are presented through several cups. The risky option involves two to five cups with a gain or loss of $2, $3, or $5, and the others contain $0. The safe cup offers a sure gain or loss of $1. If the risky option is selected, the payoff from one of the cups is selected at random.	Risk-taking
Gambling task [19]	There are two numbers in two squares, one containing the small number that has a higher probability of winning and a lower probability of loss, and the other has the larger number with a lower probability of winning and a higher probability of loss.	Risk-taking
Prisoner's dilemma [20]	Prisoner's dilemma derives from a situation that two people are arrested and charged with a crime. They held in the different room and are faced with choices between confessing or remaining silent.	Social attitude
Chicken game [21]	The chicken game originates from the situation in which two drivers are driving towards each other on a single-lane street. The driver who stops first is called a chicken, meaning a coward. However, if none of them stop, there would be a serious car accident.	Social attitude

C. The Prisoners' Dilemma Game

The Prisoner's Dilemma (PD) game derives its name from a hypothetical strategic interaction in which two people are arrested for involvement in a crime. They are held in separate cells and cannot communicate with each other. The police have insufficient evidence for a conviction unless at least one of the prisoners discloses certain incriminating information. Each prisoner has a choice between concealing information from the police (action *C*) or disclosing it (action *D*). If both conceal (the (*C*, *C*) outcome), both with be acquitted and the payoff to both will be $V^1 = V^2 = R$. If both disclose, both will be convicted and receive minor punishments: $V^1 = V^2 = P$. If only one prisoner discloses information he will be acquitted and, in addition, receive a reward for his information. In this case, the prisoner who conceals information will receive a heavy punishment. For example if Player 1 discloses and Player 2 conceals, the payoffs will be $V^1 = T$ and $V^2 = S$. Player 2 in this situation is sometimes referred to as the 'martyr' because he generates the highest payoff for the other player and the lowest payoff for himself.

The PD game has been used as a model for arms races, voluntary wage restraint, conservation of scarce resources and the iconic 'tragedy of the commons' (see [11] for a review). In computer games, the PD game can represent arms races, such as might occur in strategy games. In this paper we use the PD game as a money-earning exercise. Players can earn money either by cooperating with their opponents or by exploiting them. We examine how they choose to earn money as indicators of their motive profile, including whether they choose to do this at the expense of other players.

We can use Table I to summarise the payoff of the PD game, if we consider the following constraints. The PD game requires $T > R > P > S$. In addition, if more than one round of the PD game is to be played, the iterative version of the game requires $2R > T + S$. This prevents players from 'cooperating' by alternating between the (*C*, *D*) and (*D*, *C*) outcomes. For the remainder of this paper Player 1 in Table I is the human 'player character', while Player 2 in Table I is the computer controlled 'non-player character'.

III. Design Of Non-Player Characters to Aid Detection of Motivation

NPC design is a multi-faceted topic, including the design of the visible avatar, as well as the design of the algorithms that control the behaviour of the avatar. A range of different approaches are taken to this latter topic. This includes rule-based, state-machine, learning and evolutionary approaches to controlling behaviour. In this paper we are interested primarily in aspects of decision making that force players to reveal their risk attitude and social attitude. We propose to do this through examination of their behaviour. As such we do not consider the design of the visible avatar, but focus on the design of the character's mental attributes and decision-making behaviours.

Specifically, we propose an abstract character in Fig. 2 with dimensions for money and satisfaction. The money dimension is so named to represent a tangible, valuable item from day-to-day life. It is included to assist with the differentiation of achievement and power motivation. The satisfaction dimension is associated with social satisfaction about interactions between players and NPCs, which reflect the need for affiliation we experience in our daily life. Thus the satisfaction dimension is included to assist with the differentiation of power and affiliation motivation. The following sections describe how we link these two dimensions with common strategies for the PD game.

Fig. 2. Our abstract non-player characters have dimensions for money and satisfaction.

A. Play Strategies for the Money Dimension

A strategy in game theory is a plan of play. Formally, suppose we denote the probability that Player 2 will choose action *C* as $P^2(C)$, then the utility of the pure strategies (always play *C* and always play *D*) available to Player 1 are:

$$U^1(C) = P^2(C)R + [1 - P^2(C)]S$$

$$U^1(D) = P^2(C)T + [1 - P^2(C)]P$$

Theoretically, the total money earned by a player after *I* iterations can be expressed as:

$$V_I^1 = \sum_{i=1}^{I} U_i^1(C) + U_i^1(D)$$

We use this to examine total money earned by NPCs with different strategies in the next section. We examine the following common strategies for the NPCs.

1) Always Cooperate

The always cooperate (ALLC) strategy [22] states simply that the NPC always plays *C*. That is $P(C)=1$.

2) Always Defect

The always defect (ALLD) strategy [22] states that the NPC always plays *D*. That is, $P(C)=0$.

3) Random Strategy

In this strategy the NPC has $P(C)=0.5$ [22].

4) Tit for Tat

The Tit for Tat (TFT) strategy [22] states that the NPC's action is based on its opponent's last move. Specifically, the NPC always chooses the opponent's last action as its next action. This means that it will cooperate if the opponent chooses *C*, but punish the opponent if they choose *D*.

On the first round, because the opponent's action is unknown, the NPC chooses *C* [22].

5) Suspicious Tit for Tat

The suspicious TFT strategy stipulates that the NPC always defects on the first move, then replicates the opponent's last move. This strategy outperforms TFT in monetary terms when the opponent's first move is defection [22].

6) Tit for Two Tat

This strategy is almost the same as TFT, but it stipulates two consecutive defections by the NPC in response to a defection by their opponent. This strategy begins with cooperation on the first two moves, then, if facing defection twice, defection is chosen as the next move. The performance of Tit for Two Tat (TF2T) is better than TFT when defection is the opponent's first action [22].

7) Adaptive strategy

Adaptive Tit For Tat (ATFT) is a strategy that uses an adaption rate to compute a continuous variable *x* according to the history moves of the opponent [23]. This strategy should have an estimate of the opponent's move, whether cooperate or defect, then play it in a TFT manner. The *x* variable ranges from 0 (always disclose) to 1 (always conceal). Intermediate values will represent degrees of cooperation and defection. The adaptive TTF model can be formulated as a simple linear model:

```
If (opponent played C in last
    iteration) then
    x = x + r(1-x),
else
    x = x - rx
If (x > 0.5)
    play C,
 else
    play D
```

r is the adaptation rate between 0 and 1, and *x* is initialized as 0.5. The typical TFT model is the case of $r = 1$. The use of smaller *r* will lead to more gradual change in behaviour, and large *r* will increase the learning rate.

B. Defining Satisfaction

We also require a way to define the satisfaction dimension of our NPCs. Existing commercial computer games, such as *Civilisation*, *The Sims* and *SimCity*, have used satisfaction or emotional factors to define their NPC. These are generally calculations made on domain specific attributes, like enough entertainment, low pollution, good transport etc. In this paper we want a definition of satisfaction based on abstract psychological concepts so that our characters are transferable between specific games. To do this, we propose models of satisfaction based on achievement motivation. Recent work has examined achievement motivation from an approach-avoidance perspective [10] and distinguishes between two types of approach goals: performance-approach and mastery-approach goals. Mastery-approach goals are grounded in an intrinsic desire to improve one's competence at a task. They generally imply either a self-based or a task-based evaluation of one's competence. Achievement in the context of a mastery-approach goal means 'making progress' or learning. In contrast, performance-approach goals are grounded in a desire to demonstrate or prove competence, especially in the presence of an audience. Performance-approach goals generally imply a norm-based evaluation of one's competence, that is, a demonstration of ability relative to that of others. Achievement in the context of a performance-approach goal means doing better than others. Similarly, two types of avoidance goals are hypothesized: mastery-avoidance and performance-avoidance goals. Achievement in the context of mastery-avoidance means not doing worse than one has done before. Achievement in the context of a performance-avoidance goal means not doing worse than others. In this paper we consider each of these approaches to satisfaction. In the following sub-sections we propose three models of satisfaction based on mastery-approach and performance-approach motivation.

1) Mastery-approach

a) Self Based

We propose a self-based mastery oriented view of satisfaction E_I^1 that compares the money the NPC just earned to its average money earned over the last *I* iterations. A value less than 1 indicates performance below one's own average, and a value greater than 1 indicates above average performance.

$$E_I^1 = \frac{IV_i^1}{V_I^1}$$

And conversely for E_i^2.

b) Task Based

Next, we propose a task-based mastery oriented view of satisfaction that compares the money of the NPC's total earnings to the maximum attainable earnings over the last *I* iterations. The result is a number between 0 and 1, where 1 implies the NPC has earned the maximum amount of money possible over the last *I* iterations.

$$E_I^1 = \frac{V_I^1}{IT}$$

2) Performance-approach

Finally, we propose a performance-approach view of satisfaction as follows, where satisfaction is computed as proportional to the percentage of the winnings pool accumulated by both players:

$$E_I^1 = \frac{V_I^1}{V_I^1 + V_I^2}$$

This value ranges between 0 and 1. A value of 1 implies that the agent has individually earned all the winnings, while a value of 0 implies that the agent gains nothing in the game which lead to the lowest satisfaction. A value of 0.5 implies that winnings have been evenly shared between agents and reflect neutral satisfaction.

IV. ANALYSING NPCS FOR DETECTING MOTIVATION

In this study, we analyse the total money and satisfaction of seven different kinds of NPCs after 20 iterations of the PD game. We use a performance approach definition of satisfaction, because this best takes into account the social aspects of satisfaction that we would like players to trade off when they are making decisions. We analyse each agent against theoretical opponents with different preferences for choosing *C*, ranging from $P(C) = 0$ to $P(C) = 1$. The payoff values chosen for this abstract game are $R=3$, $P=1$, $S=0$ and $T=5$.

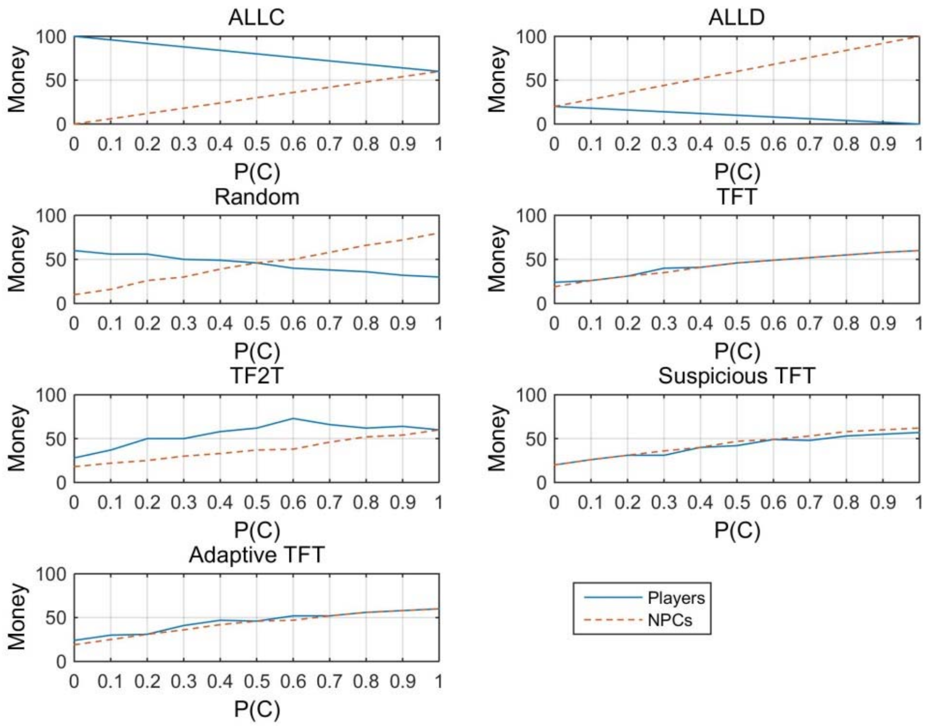

Fig. 3. Money results when NPCs with different strategies play against opponents with different preferences for choosing *C*.

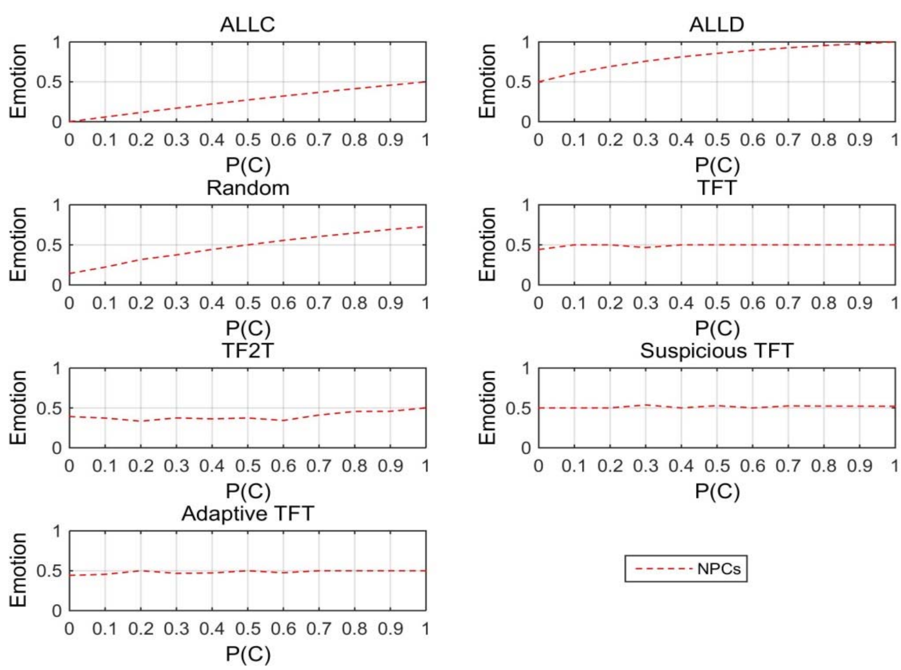

Fig. 4. Emotion results when NPCs with different strategies play against opponents with different preferences for choosing *C*.

We implemented the mechanism of the game between NPCs and agents in *MATLAB*. The money and satisfaction results of NPCs with different strategies playing against different agents are visualized in Fig. 3 and Fig. 4 respectively.

We see from Fig. 3 and Fig. 4 that NPCs with the ALLC strategy will have the highest satisfaction value against an opponent with a similar strategy. This is because both the NPC and opponent will earn a similar amount of money. The NPC will have the lowest value of satisfaction against an opponent with high preference for playing *D*.

In contrast, we see from Fig. 3 and Fig. 4 that NPCs with the ALLD strategy will have the highest money value when they play against an opponent that prefers *C*. These NPCs can achieve higher satisfaction values that NPCs using the ALLC strategy.

NPCs using a random strategy can also achieve higher satisfaction values than NPCs using the ALLC strategy by exploiting cooperative opponents.

NPCs using variants of the TFT strategies have generally moderate satisfaction values as a result of their adaptive strategies that permit them to perform well (in monetary terms) against opponents with a range of different preferences for choosing *C*/*D*.

In summary, Fig. 3 and Fig. 4 show that a player defecting against an NPC using the ALLC or random strategies can maximise their money. However a player cooperating against such NPCs can maximise their satisfaction. For an NPC using the ALLD strategy, defection can maximize money. While players opposing a NPC using the TFT strategy, can respond accordingly to earn money and achieve moderate satisfaction.

Based on the results above, we hypothesise that our ALLC, ALLD, Random and TFT are a good choice of strategies to permit agents to distinguish between players with dominant achievement, affiliation and power motivation. This is because these individuals will seek to optimise money and their satisfaction differently. Our hypothesis, based on the literature of motivation theory, is summarised in Table III. Different players will respond differently to different agents, seeking to optimise money or satisfaction subjectively according to their motives.

Furthermore, if players are given the option of selecting their opponents, we hypothesise they will choose different opponents to satisfy their motives. Our hypothesis is shown in Table IV. Players select different opponents for various motive tendencies like exploiting uncertainty and other opponents (as for power motivation), or earn money (as for achievement motivation) and maximize NPC emotion (as for affiliation motivation).

TABLE III. PREFERRED STRATEGIES OF PLAYERS WITH DIFFERNET DOMINANT MOTIVES

	ALLC	**ALLD**	**Random**	**TFT**
Achievement	Defect to maximise own money	Defect to maximise own money	Defect	Cooperate
Power	Defect to maximise own money	Defect to maximise money	Defect to maximise own money	Defect
Affiliation	Cooperate to earn money and maximise NPC emotion	Defect	Cooperate to maximise NPC emotion	Cooperate

TABLE IV. PREFERRED OPPOENTS OF PLAYERS WITH DIFFERENT DOMINANT MOTIVES

	ALLC	**ALLD**	**Random**	**TFT**
Achievement	No, insufficient challenge (too predictable)	No, insufficient challenge (to predictable)	No, high uncertainty	Yes, as can cooperate to earn money and maximise emotion
Power	Yes, as can maximise own money by exploiting opponent	No, cannot exploit	Yes, can exploit uncertainty	No, as cannot exploit
Affiliation	Yes, as can cooperate to earn money and maximise NPC emotion	Maybe, predictable and can maximise NPC emotion	No, high uncertainty	Yes, as can cooperate to earn money and maximise emotion

V. Conclusion and Future

This paper has examined the design of artificial agents to support identification of player motive profiles. We proposed two dimensions necessary for these characters: money and satisfaction. We proposed models of mastery and performance oriented achievement motivation as indicators of NPC satisfaction and payoff from well-known mixed motive game as money.

In future, we envisage that these characters could be used to distinguish player preferences as follows:

- By examining how players choose their opponents if given a choice
- By examining how many points players earn, and how many they permit their opponents to earn

- By examining how players choose to maintain or deny NPC satisfaction emotion

In future work we will incorporate NPCs in a game that permits human players to choose their opponents, before playing against those NPCs. We will validate our models by comparing results from traditional motivation measures, such as the thematic apperception test, against behavioral statistics from the game.

Acknowledgment

This work was supported by the Australian Research Council under Grant DP160102037.

References

[1] B. Cowley and D. Charles, "Behavlets: a method for practical player modelling using psychology-based player traits and domain specific features," *User Model. User-adapt. Interact.*, 2016.

[2] L. E. Nacke, C. Bateman, and R. L. Mandryk, "BrainHex: A neurobiological gamer typology survey," *Entertain. Comput.*, vol. 5, no. 1, pp. 55–62, 2014.

[3] M. V Birk, D. Toker, R. L. Mandryk, and C. Conati, "Modeling Motivation in a Social Network Game using Player-Centric Traits and Personality Traits," in *International Conference on User Modeling, Adaptation, and Personalization*, 2015, pp. 18–30.

[4] M. Elson, J. Breuer, and T. Quandt, "Know Thy Player: An Integrated Model of Player Experience for Digital Games Research," in *Handbook of Digital Games*, John Wiley & Sons, Inc., 2014, pp. 362–387.

[5] J. Heckhausen and H. Heckhausen, *Motivation and action*. New York: Cambridge University Press, 2010.

[6] G. N. Yannakakis and J. Hallam, "Real-time game adaptation for optimizing player satisfaction," *Comput. Intell. AI Games, IEEE Trans.*, vol. 1, no. 2, pp. 121–133, 2009.

[7] K. Merrick, *Computational models of motivation for game playing agents*. Berlin Heidelberg: Springer Verlag, 2016.

[8] R. C. Davis and D. C. McClelland, *The achieving society*. JSTOR, 1962.

[9] D. Sirota and D. Klein, *The enthusiastic employee: How companies profit by giving workers what they want*. FT Press, 2013.

[10] A. J. Elliot, A. B. Eder, and E. Harmon-Jones, "Approach-Avoidance Motivation and Emotion: Convergence and Divergence," *Emot. Rev.*, vol. 5, no. 3, pp. 308–311, Jul. 2013.

[11] A. M. Colman, *Game theory and experimental games: The study of strategic interaction*, vol. 4. Elsevier, 2014.

[12] S. K. Mesrobian, M. Bader, L. Götte, A. E. P. Villa, and A. Lintas, "Imperfect Decision Making and Risk Taking Are Affected by Personality," in *Decision Making: Uncertainty, Imperfection, Deliberation and Scalability*, V. T. Guy, M. Kárný, and H. D. Wolpert, Eds. Cham: Springer International Publishing, 2015, pp. 145–184.

[13] D. J. Schutter, E. H. de Haan, and J. van Honk, "Anterior asymetrical alpha activity predicts Iowa gambling performance: distinctly but reversed," *Neuropsychologia*, vol. 42, no. 7, pp. 939–943, 2004.

[14] J. Hewig, R. Trippe, H. Hecht, M. G. Coles, C. B. Holroyd, and W. H. Miltner, "Decision-making in Blackjack: an electrophysiological analysis," *Cereb Cortex*, vol. 17, no. 4, pp. 865–877, 2007.

[15] L. R. R. Gianotti, D. Knoch, P. L. Faber, D. Lehmann, R. D. Pascual-Marqui, C. Diezi, C. Schoch, C. Eisenegger, and E. Fehr, "Tonic activity level in the right prefrontal cortex predicts individuals' risk taking," *Psychol. Sci.*, vol. 20, no. 1, pp. 33–38, 2009.

[16] R. D. Rogers, A. M. Owen, H. C. Middleton, E. J. Williams, J. D. Pickard, B. J. Sahakian, and T. W. Robbins, "Choosing between small, likely rewards and large, unlikely rewards activates inferior and orbital prefrontal cortex," *J. Neurosci.*, vol. 19, no. 20, pp. 9029–9038, 1999.

[17] G. Xue, Z. Lu, I. P. Levin, J. A. Weller, X. Li, and A. Bechara, "Functional dissociations of risk and reward processing in the medial prefrontal cortex," *Cereb Cortex*, vol. 19, no. 5, pp. 1019–1027, 2009.

[18] C. W. Lejuez, J. P. Read, C. W. Kahler, J. B. Richards, S. E. Ramsey, G. L. Stuart, D. R. Strong, and R. A. Brown, "Evaluation of a behavioral measure of risk taking: The Balloon Analogue Risk Task (BART)," *J. Exp. Psychol. Appl.*, vol. 8, no. 2, pp. 75–84, 2002.

[19] B. Schuermann, T. Endrass, and N. Kathmann, "Neural correlates of feedback processing in decision-making under risk," *Front Hum Neurosci*, vol. 6, p. 204, 2012.

[20] F. Babiloni, L. Astolfi, F. Cincotti, D. Mattia, A. Tocci, A. Tarantino, M. G. Marciani, S. Salinari, S. Gao, and A. Colosimo, "Cortical activity and connectivity of human brain during the prisoner's dilemma: an EEG hyperscanning study," in *Engineering in Medicine and Biology Society, 2007. EMBS 2007. 29th Annual International Conference of the IEEE*, 2007, pp. 4953–4956.

[21] L. Astolfi, F. Cincotti, D. Mattia, F. De Vico Fallani, S. Salinari, G. Vecchiato, J. Toppi, C. Wilke, A. Doud, and H. Yuan, "Imaging the social brain: multi-subjects EEG recordings during the 'Chicken's game,'" in *Engineering in Medicine and Biology Society (EMBC), 2010 Annual International Conference of the IEEE*, 2010, pp. 1734–1737.

[22] J. Li, "How to Design a Strategy to Win an IPD Tournament," in The Iterated Prisoner's Dilemma: 20 Years On, pp 28-40 2006.

[23] E. Tzafestas, "Toward adaptive cooperative behavior," in *Proceedings of the Simulation of Adaptive Behavior Conference, Paris*, 2000.