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HEART RATE VARIABILITY OF ADOPTA VIDEO GAME PLAYER TYPES: COMPETITOR AND STRATEGIST

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ABSTRACT

Video game players may be categorised according to their preferences and play style. Competitors are known to enjoy active and often aggressive challenge whereas strategists prefer calmer tests of planning and intellect. Knowing a given player's type may be useful in developing games that adapt to their preferences in real time in order to maximise enjoyment. Heart Rate Variability (HRV) is a physiological measure that may be able to transparently determine both a player's type and their current level of enjoyment. This exploratory work attempts to identify patterns in the HRV of two significant player types associated with enjoyment and dislike of the playing experience. 10 Players were categorised as either competitor or strategist using the ADOPTA play styles questionnaire. HRV of these players was measured when playing games that they like and dislike and clear patterns in the NN20 and NN50 measures of HRV were seen. Both profiles demonstrated significantly lower HRV when playing games they dislike, which is consistent with the literature where low HRV is associated with stress. Competitors, being a more spontaneous and flowing type of gamer, displayed generally higher HRV than strategists. These findings will be utilised in an adaptive gaming system in the near future.

KEYWORDS: Player Types; Player Styles; Heart Rate Variability; HRV; Adaptive Games.

INTRODUCTION

Video games generate more income than the music and movie industries combined. Annually, 100 billion dollars are spent on games because people enjoy playing them (NewZoo 2018). Traditionally, game structure and content has largely been fixed by the designer and therefore the player must adapt to these confines or choose another game. More recently, the possibility of adaptive games has been explored (Karpinskyj et al 2014) for their potential to maximise player enjoyment by using approaches such dynamic difficulty adjustment (DDA) or varying game parameters such as story development and the reactions of non-player characters (NPCs) (ibid).

Any adaptive game must make two crucial decisions during play: when to adapt, and what to adapt. Deciding when to adapt depends on the player's current state of enjoyment, which varies in realtime and must somehow be detected. In principle, this decision is straightforward: the game should adapt whenever the player is not sufficiently enjoying themselves. Deciding what to adapt is a more difficult question which depends on many factors, some of which will be discussed presently. Although all adaptation should be to promote player enjoyment, a given change in game structure and content may not please all players because our preferences vary. At extremes, a game might attempt to adapt to please every individual player but achieving such unconstrained flexibility is a tremendous amount of work, and is beyond the capability of any current system. However, clusters in preference have been observed among players that may provide a workable level of generality for adaptive games. Player motivation and style have been extensively studied and a small number of general player types have been identified (eg Bartle 1996, Bontchev et al 2018). For example, some players are warriors who enjoy direct competition and fast paced action, whereas logicians prefer to solve puzzles. If a player's type is known then adaptation can be tailored to the known preferences of that type.

Crucially, the information gathering process required for adaptation should be as transparent to the player as possible. Directly asking players how they want the game to be is likely to degrade their experience and is to be avoided (Bontchev and Georgieva 2017). For this reason, much previous work on adaptive games has sought to understand when and what to adapt based on in-game analysis of a player's progress and playing style, with some limited success (Bakkes et al 2012). Another approach is to make decisions based on measuring the player's state directly. For example, some researchers have tried to estimate player state from facial expression (Bontchev and Georgieva 2017), which is innovative but difficult and error-prone. Physiological measurements offer another option for directly understanding player state during play. Heart Rate Variability (HRV) is a physiological measurement known to be related to emotions and can be acquired using a simple and cheap sensor or wristband (Shaffer and Ginsberg 2017). The sensor is essentially transparent to the player after fitting. HRV is known to reflect certain emotional aspects of player experience (Nunez Castellar et al 2015) but it is not currently known how HRV relates to distinct player types and their levels of enjoyment. If HRV was found to demonstrate identifiable patterns among enjoyment levels and player profiles then it could be used to decide when and how to adapt game parameters for maximum enjoyment. The work described here is a simple first step in that direction.

BACKGROUND

Player Types

Games and their players have long been the focus of considerable study. By their nature, the rules of games dictate certain goals and constrain possible actions. In doing so, they provide opportunities for some activities and not others. It uncontroversial that people play games with different positive motivations and do so with different styles (Karpinskyj et al 2014; Magerko et al 2008). This combination of game constraints and personal preferences therefore strongly influence which games an individual enjoys and does not. This can be considered to be the player’s type and may be more or less narrow among individuals. It should be noted that the term 'play style' is often used interchangeably with player type but type can be considered a more consistent internal tendency whereas style can vary even within individuals and within the same game. As Magerko et al. say: “players may adopt different play styles in different games or at a different time” (ibid).

In early work, Caillois (1961) identified games that offer four main types of experiences: Agon (competition), Alea (chance), Mimicry (role-playing) and Ilinx (affect altering/vertigo), with the implication that the players that would find each of these enjoyable would constitute types. A more recent incarnation of these game properties is from Lazzaro (2008) whose four 'Keys of Fun' comprise hard fun (challenges in achieving goals), easy fun (exploratory playful behaviour), serious fun (playing for rich game experience and escaping from the real world), and people fun (collaborative or competitive play in multiplayer mode). In 1996, Bartle explicitly identified four player types which continue to be influential today: killers (whose dominant play experience is to defeat other players), achievers (collectors of game assets through challenges), explorers (of the in-game world) and socialisers (eager to make close relationship and socialising with others). However, Bartle's taxonomy and associated questionnaire have been criticised as being too tied to a certain type of game (MMORPGs), driving more recent attempts at a player taxonomy to be more general. In an attempt to embrace educational as well as entertainment-oriented games, Bontchev et al (2018) devised the ADOPTA taxonomy of Competitor, Strategist, Logician, and Dreamer, which will be used in this work.

Competitors enjoy action and shooting, and are focused on the competition. They usually have good hand-eye coordination, can take risks and are good at thinking on their feet. Competitors rely on their natural instincts and intuition more than theoretical analysis and succeed by spontaneous action and intense drive to improve performance and to discover new things. Strategists are motivated to resolve complex problems in the most efficient and effective way possible. They dislike taking actions that are not guaranteed to yield a reasonable of reward, and strive to find more practical ways to fulfill the game rules. Planning ahead is their primary trait, relying on long-term thinking, decision-making, and hypothesis testing, and observing the consequences of their actions. Dreamers prefers roleplaying and thrive in avatar-based fantasy worlds where they enjoy observing the game rather than controlling it. Guided gameplay is usually their favorite play mode and they prefer to stay at a certain level of the game until they have fully mastered it before moving on. They demonstrate superb communication skills and often prevail in collaborative play. Dreamers prefer to immerse themselves into the game scenario, and are fond of social interaction, diplomacy and negotiation. True to their name, Logicians enjoys logic and analytical gameplay using pattern-based approaches for executing in-game tasks. They possess good spatial awareness and contextual thinking, combined with numerical knowledge and verbal skills. They enjoy exploring the in-game world, discovering and assimilating gameplay facts in a precise and systematic way.

ADOPTA player types are based on Kolb's experiential learning theory which observes the four stages of the learning cycle: concrete experience, reflective observation, abstract conceptualization and then to actual experimentation. Based on these four stages, Kolb identified four learning styles which are the accommodator (gaining experience through experimention), diverger (reflective observation based on experience), assimilator (conceptualisation based on reflective observation), and converger (turning conception into actual experimentation). The parallels between playing and learning styles were first developed by Honey & Mumford, who in 1992 proposed an 80-item questionnaire to identify four different learning styles which are the Activist (learns by experience), Reflector (learns from reflective observation), Theorist (learns from studying and analyzing relationships) and the Pragmatist (learns by acting to achieve a practical goal). More recently, Magerko et al. (2018) claimed that play motivation is closely correlated with learning styles, forming a parallel between playing styles and learning styles. Although their origin is in learning theory, the ADOPTA player types can still be mapped to Bartle's orginal taxonomy in the domain of entertainment. ADOPTA also has the advantage of possessing an empirically-validated 40-item questionnaire (the ADOPTA PSQ).

Finally, it should be noted that identifying player type is only one component of the larger domain of player modelling. In much previous work, players have been modelled in terms of properties such as in-game behaviour, tactics, and strategy, and focusing on these more objective properties of gaming and can be useful. However, player types also covers subjective aspects of game playing such as inner motivations for play and preferences. This concern for emotional states suggests that physiological measures have the potential to capture it.

Heart Rate Variability

Heart rate variability (HRV) is a measure of the variation in the time between consecutive heartbeats, also called interbeat intervals (IBI) (Shaffer and Ginsberg 2017; Campos 2017). It is not to be confused with the simpler measure of heart rate. Figure 1 should serve to illustrate the concept.

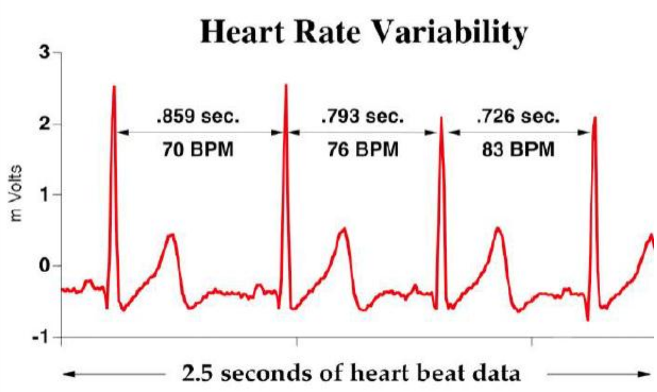

Figure 1: Interbeat Intervals (IBIs) used for calculating HRV.

Shaffer and Ginsberg (2017) state that the value of HRV is highly correlated with the body's neurocardiac function and is generated through the interactions of heart brain interactions and dynamic non-linear autonomic nervous system (ANS) processes. As HRV values are also closely linked to the heart beat, it is highly reflective of a person's physical health (blood pressure, gas exchange, gut, heart, vascular tone). Importantly for our purposes, Shaffer and Ginsberg state that HRV also reflects psychological condition and that generally, higher HRV values indicate a relaxed or resting state, whereas lower HRV values indicates a state of stress. Marcelo also states that a person with higher HRV is in a more relaxed state and may be in a healthier, favourable cardiovascular condition and more resilient to stress, while a person with low HRV might be under stress. Notably, boredom and being forced to do things we may not enjoy may also considered stressful. Low HRV values have been associated with depression and anxiety. In a gaming context, Nunez Castellar et al (2015) studied HRV for assessing player experience and found that it can effectively identify emotions if referenced to a player's activity log which contains various and sufficient complimentary information in evaluating player physiology.

There are a number of ways to characterise HRV and an appropriate measure for the context must be chosen. Shaffer and Ginsberg (2017) separate the measurements of HRV into three separate domains, namely the time-domain, frequency-domain, and non-linear measurements, which can be further categorized into 24-hours, short-term (> 5 minutes), and ultra-short-term HRV measurements (< 5 minutes). Each have their own properties and must be selected according to context. Long term measures may not be appropriate for situations where fast, realtime response is important. Popular time-domain measures which are often used long-term are SDNN and SDRR, which calculate the standard deviation of the IBI values over the measuring period, in ms, differing only in that SDNN uses normal sinus beats only with the abnormal beat and noises removed, while SDRR takes into account all sinus beats. The standard measurement period for SDNN and SDRR is 5 minutes. However, the accuracy of these metrics for health assessment could increase with the length of time for measurement. SDNN is said to be the standard method in the determination of cardiovascular related diseases when measured over a 24 hours period, and is able to predict the morbidity and mortality of a person.

Alternatively, the xNNxx faily of HRV measures count the number of adjacent NN interval pairs with IBI values that differ from each other by more than xx ms. pNN50 is the percentage representation of NN, which requires a minimum 2 minutes time frame. According to Mietus et al (2002), pNN50 is the standard measure but a lower time threshold, such as pNN20, could improve the discriminative capabilities of HRV for classification and differentiating people of different groups. Therefore, these will be the measures employed here.

MATERIALS AND METHODS

10 Malaysian undergraduate students (2 females, 8 males) were used as test subjects. They were aged between 18 and 26 and were active game players. The ADOPTA learning styles questionnaire was used to identify the profiles of these subjects. Based on this questionnaire, 5 of the subjects were identified as competitors and the other 5 were found to be strategists. Each subject was asked to play a game that they enjoyed and a game that they disliked playing for 10 mins each. The specific choice of game varied even between subjects of the same type. During play, raw IBIs were measured using a Xiaomi MiBand 3 wristband sensor, with auxiliary software used to capture the raw data.

RESULTS AND DISCUSSION

After data collection, NN20 and NN50 measures of HRV were calculated for each playing session. With two player types (competitor and strategist) and two playing states (like and dislike) there were thus four conditions to consider.

Table 1: NN50 HRV for competitor and strategist under like and dislike conditions.

	Competitor	**Strategist**
Like	**21.6**	**14.2**
Dislike	**14.0**	**11.0**

Table 2: NN20 HRV for competitor and strategist under like and dislike conditions.

	Competitor	**Strategist**
Like	**77.4**	**38.6**
Dislike	**49.6**	**34.4**

Two observations can be made. First, it is clear that within both profiles, playing enjoyment is associated with higher HRV than when the playing experience is not enjoyable. If one accepts that being forced to play a game that one actively dislikes is stressful then this is consistent with known findings that low HRV is associated with stress. Second, it is clear that overall, competitors have higher HRV than strategists. This finding is less easy to explain. But if we accept that to play as a strategist is to concentrate hard then this can be objectively stressful (in terms of physiological demands) even if it is subjectively enjoyed. This is a state known as eustress. We know that competitors are generally more flowing and spontaneous in their play style and do not tolerate long periods of heavy resistance without movement. These differences are more pronounced when using the NN20 measure.

CONCLUSION

These findings are encouraging in that they suggest that identifiable differences in HRV exist among player types. Larger scale studies must be performed in order to confirm these patterns and if confirmed, using them in practice will require consideration.

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