O' Game, Can You Feel My Frustration?: Improving User's Gaming Experience via StressCam

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ABSTRACT

One of the major challenges of video game design is to have appropriate difficulty levels for users in order to maximize the entertainment value of the game. Game players may lose interests if a game is either too easy or too difficult. This paper presents a novel methodology to improve user's experience in computer games by automatically adjusting the level of the game difficulty. The difficulty level is computed from measurements of the facial physiology of the players at a distance. The measurements are based on the assumption that the players' performance during the game-playing session alters blood flow in the supraorbital region, which is an indirect measurement of increased mental activities. This alters heat dissipation, which can be monitored in a contact-free manner through a thermal imaging-based stress monitoring and analysis system, known as *StressCam*.

In this work, we investigated on two primary objectives: (1) the feasibility of utilizing the facial physiology in automatically adjusting the difficulty level of the game and (2) the capability of the automatic difficulty level adjustment in improving game players' experience. We employed and extended a XNA video game for this study, and performed an in-depth, comparative usability evaluation on it. Our results show that the automatic difficulty adjustable system successfully maintains game players' interests and substantially outperforms traditional fixed-difficulty mode games. Although a number of issues of this preliminary study remain to be investigated further, this research opens a new direction that utilizes non-contact stress measurements for monitoring and further enhancing a variety of user-centric, interactive entertainment activities.

Author Keywords

Human-Computer Interaction, video games, game difficulty adjustment, stress monitoring, thermal imaging.

ACM Classification Keywords

H5.2. Information interfaces and presentation: User Interfaces – Evaluation/methodology, Input devices and strategies, Prototyping, Interaction styles.

INTRODUCTION

In most video games these days, the game players are asked to select only one level of difficulty before the beginning of the game play or the beginning of each stage of the game. Once the selection is made, the players must play it only in a monotonous level of difficulty throughout the game or each stage of the game, because the game does not provide any additional opportunity to change the difficulty level in the middle of the game-playing session. However, on occasions, players want to change the difficulty level in the middle of the game. For instance, beginners would like to play a game in an easy mode to learn the game mechanics. Once they gain expertise, they tend to play the game in a more challenging level to maintain their interests. However, transitions from the beginner to the intermediate to the expert level could be frustrating as the game is unaware of the players' psychological state and therefore it fails to intelligently adjust the difficulty level in order to optimize the players' involvement. Ultimately, this can cause the players to be disassociated and then dissatisfied with the game.

There are only a small number of games in the market that provide the players with capabilities to adjust the game difficulty in the middle of the game-playing session. Among them, only a small number of these games automatically adjust their difficulty levels for the players. For example, the Saga Frontier 1 (1998), one of Squaresoft's Role Playing Games (RPGs) for Sony PlayStation 1 console system, is a limited automatic difficulty level adjustable game where the difficulty is adjusted based on the performance of the players. In the Saga Frontier 1 game, the players control the main characters to gain experience points by winning fights against enemy monsters. As the main characters' level increases, this game automatically increases the monsters' level accordingly. Therefore, even the same type of monsters becomes tougher to defeat when the main characters are at a higher level (e.g., level 20) than they are at lower level (e.g., level 2). The increase in the difficulty level is intended to provide more entertaining experiences as the game progresses. However, the game becomes too difficult even for expert players as the main characters' levels are raised to a higher level and, consequently, the players are often forced to start over the game from the beginning or completely stop playing it because they have given up any hope of winning the game. In addition, this concept of automatically adjusting the level of difficulty has a potential to disregard the players' satisfaction of playing the game at a current difficulty level regardless of their performance. For instance, a player satisfied with the easy mode is now forced to play the game at the intermediate mode simply because of performing well at the easy mode. On the other hand, a player could lose interest in the game by being continuously exposed to a too difficult mode. Therefore, automatically adjusting the game difficulty level based only on the performance of the player alone could potentially dissatisfy the player.

In this paper, we propose a system that adaptively and automatically adjusts the game difficulty level based on measurements of the players' facial physiology. When the combination of the game events demands critical decisions and rapid responses from the players, their alertness will be raised, which elevates the blood flow in the supraorbital vessels and frontalis mussel. This increase in the blood flow, consequently, raises the supraorbital region temperature, which can be captured through a highly sensitive thermal camera. We use the rate of change of the temperature as a stress descriptor to quantify the players' interests. The increase of the blood flow in the supraorbital region indicates that the players have sustained stress and frustration. Identifying the stress/frustration via a thermal imaging-based stress monitoring and analysis system, known as *StressCam,* is a non-invasive way of recognizing the players' interest in the game. We propose to create game software that automatically adjusts the game difficulty level from the players' real-time physiological state captured by a StressCam. By continuously monitoring the stress level of the players, the game software can adjust or maintain the level of the difficulty throughout the game playing session.

User-centric game design is another dimension of the proposed system which deviates from the traditional concept of a game-centered system. Traditional systems based on the gradual and consistent augmentation of the difficulty level treat all users equally and ignore the broad diversity of their gaming skills, and preferences. The users have to play the game for a certain or fixed period of time at lower difficulty levels before they are allowed to move to higher difficulty levels. This is a game-centered design. By intelligently adjusting the difficulty level of the game, our system essentially customizes the gaming experience for any individual player and attempts maximize the user's experience, which is a user-centric design.

RELATED WORK

There are several studies devoted to understand the effects of the psychological or physiological states of players while they play computer/video games. Schneider et al. investigated how the existence or absence of the game storyline can affect the players' emotional, motivational, and physiological responses [12]. This study measured the skin conductance of the players by utilizing two Beckman standard Sliver/Silver-Chloride (Ag/AgCl) electrodes on their feet. Ravaja et al. used a questionnaire to measure the players' emotion (i.e., valence, arousal, joy, relaxation, anger, fear, and depression) during the game play and the degree of presence after playing four different games (Tetris, Monkey Ball, Monkey Bowling and James Bond 007). They found that the emotional response patterns and the degrees of presence varied among different games [9]. In another paper, the same group measured cardiac inter-beat-intervals (IBIs) and facial electromyography (EMG) to measure spatial presence and emotions of the players when they were playing against a computer, a friend or a stranger. They found that the players had highest spatial presence, engagement, anticipated threat, post-game challenge appraisals and physiological arousal when they were playing against a friend and lowest when they were playing against a computer [10]. Nenonen et al. used the heart-beat of the players to control the difficulty of a few exercise (or physical) games such as skiing and shooting [13]. Here, the difficulty level of the game was adjusted automatically in real time based on the elevation and the declination of the heart-beat. Physiological parameters have also been used to understand the effects of violence video games on the human cognition and behaviors [1,2,3,4,5,6,7,8].

Lin and Hu demonstrated a correlation between stress and game difficulty [15]. They showed that task performance and difficulty levels affect stress levels significantly. Players' Galvanic Skin Response (GSR), Blood Volume Pulse (BVP), and Heart Rate (HR) were recorded while they were playing a 3D video game called Super Mario 64.

However, the major limitation of these methods is that they use contact sensors for the measurements. The contact sensors introduce noise in the data whenever players move their body parts. Thus data with a poor signal-to-noise ratio may alter the difficulty level erroneously. Moreover, the attached body sensors obstruct players from playing a game freely. Therefore, the contact sensor-based measurements are not practical approaches optimized for interactive gaming applications.

Nosu et al. used a real-time facial emotion recognition system to approximate the emotional state of the players [11]. Based on the emotional state, different pre-recorded voice feedback was provided to the players in a fixed time interval (i.e., 30 seconds) aiming to alter their emotional state. Although computer vision-based facial expression recognition technique could be used as a potential approach for the purpose of automatic adjustment of the difficulty levels, it is not practically effective because current facial expression recognition algorithms are not robust and accurate enough, specifically, in gaming applications where large-amplitude body motions are obvious.

StressCam monitors stress signals from facial physiological states via a thermal imaging camera. It was first proposed by Pavlidis et al. [17]. Their work aimed to understand the role of the supraorbital area in challenging mental activities. In addition, they used offline data analysis to support their general methodology.

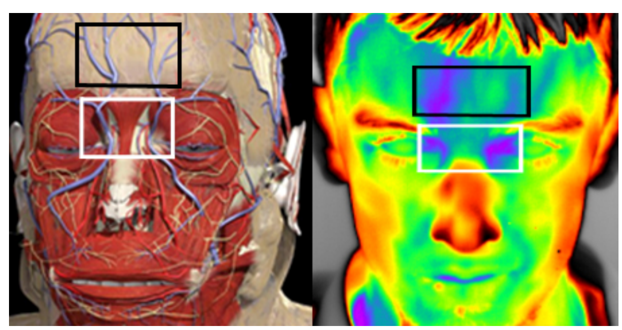
In this paper, we present a gaming-oriented study where *StressCam* is used as a real-time feedback mechanism. The novelty of our work comes from the fact that a contact-free, thermal-based facial physiology monitoring system can be effectively incorporated into gaming applications to improve players' gaming experience. Via this real-time monitoring system, we propose to establish an optimal entertainment ground for a player where he/she can seamlessly maximize the enjoyment of his/her game-playing. Thus, unlike the traditional game-centered design, our proposed system is founded on the user-centric design.

We use the supraorbital skin temperature as a physiological parameter in this study. Because of its higher measurement sensitivity and the ease of measurement, skin temperature based stress monitoring has been a popular approach [20,23,25]. The major advantage of this approach is that it is very difficult to manipulate or fake physiological parameters by an individual during 'flight or fight' situations as it is controlled by sympathetic division of the Autonomic Nervous System (ANS). It is noteworthy that contact sensor based physiological measurement methods restrict participants' motion and increase users' awareness of being monitored [23,24,25]. Therefore, it is not a very effective way for continuous physiological monitoring. Our system, in contrast, monitors facial physiology through the thermal camera which is a passive and contact-free measurement sensor. Therefore, it is suitable for continuous physiological monitoring.

PHYSIOLOGY AND STRESS

Pavlidis and his colleagues have demonstrated that the increased blood flow in the periorbital region is a ubiquitous manifestation of instantaneous stress [20, 22]. A person experiences 'flight or fight' syndrome under stressful situations. In these situations, the sympathetic division of the autonomic nervous system (ANS) prepares the body to cope up with upcoming threats. This requires the eyes to collect accurate visual information and the brain to process the information in order to make rational decisions quickly. Consequently, increased muscle activities require more energy (metabolic fuel), which is carried by the increased blood flow. The ophthalmic and facial vessels, which are the predominant supply of blood to the orbicularis oculi muscle, are superficial to skin in the periorbital region (see the region in the white colored rectangle in Figure 1 (a)). Therefore, heat dissipation from the periorbital region due to the change in blood flow can be monitored through the thermal camera (see the region in the white colored rectangle in Figure 1 (b)).

In recent years, Pavlidis and his colleagues have successfully demonstrated the importance of the supraorbital region in sustained stress measurement [17,18]. The sustained stress results from intense mental engagement in a challenging task. During the intense mental engagement, the brain is overloaded with information receiving and processing tasks. Like the Central Processing Unit (CPU) in a computer, the brain drains more energy if it is overloaded for a considerable amount of time. Another salient feature of the sustained stress is the increased frequencies of the upper facial expressions that stimulate the supraorbital region muscles. Specifically, the frowning expression activates the corrugator muscle, and the surprise expression activates the frontalis muscle. Increased muscle activities demand more energy that is supplied via increased blood flow in the supraorbital vessels. The supraorbital vessels are located superficial to the skin in middle of the supraorbital region (see the region in the black colored rectangle in Figure 1 (a)). Thermal imprints of the vessels appear very clearly in the supraorbital region highlighted by the black colored rectangle in Figure 1 (b). Thus, tracking the region over time in the thermal domain provides an indirect measurement of the users' mental engagement and psychological state. We quantify the sustained stress by computing the rate of the supraorbital temperature change over a certain period. Thus, its unit of measurement is °C/sec (degree centigrade per second).



(a) (b)

Figure 1. Anatomical and thermal images of the face. (a) Facial anatomy [29] (b) Facial areas of sympathetic importance: The supraorbital (highlighted in black colored rectangle), periorbital (highlighted in white colored rectangle) regions.

STRESSCAM

StressCam was first developed in 2005 [17]. It is a high quality Thermal Imaging (TI) system designed and built by the Computational Physiology Lab at the University of Houston. The centerpiece of the TI system is a

ThermoVision SC4000 Mid-Wave Infrared (MWIR) camera [26]. The camera is a cooled type which uses an Indium Antimonide (InSb) detector. It records electromagnetic energy between 3-5µm wavelengths with temperature accuracy of hundredth of a degree centigrade. StressCam captures heat signature at a rate of 40 frames per second (fps) with a 320x256 pixels spatial resolution. It outputs 14bits digital data via a Gigabit Ethernet connection. StressCam is equipped with a pan-tilt and motorized focus mechanism to locate the target. The pan-tilt features a ±217.5° pan, 8°/sec pan speed, ±90° tilt, 3°/sec tilt speed and a RS-232 interface [27]. It uses a differential blackbody for temperature calibration [28]. The differential blackbody features a -25°C to 75°C temperature range and a RS-232 interface. It has a temperature sensitivity of 0.01°C, which matches the temperature sensitivity of the camera. StressCam uses a MWIR 100mm lens to have a closer view of the face. It was using a Dell PowerEdge 1800 server computer when this experiment was conducted. Recently, we have upgraded the PC to a Dell Precision T3400 computer.

The predecessor of StressCam is ATHEMOS (Automatic THErmal MOnitoring System) that was designed in 2003 by Pavlidis and his group at the University of Houston. ATHEMOS went through many software revisions and hardware upgrades before it became a mature and sophisticated system. Specifically, it now uses a high quality thermal camera with a Gigabit Ethernet cable rather than a bulky RS-232 cable. It uses a lightweight black body and pan-tilt. It uses a webcam to record visual information. The manual focus adjustment has been replaced with motorized focus. The system is lightweight and sturdy. Hence, it is portable. In terms of software revision, StressCam uses sophisticated tracking and segmentation algorithms, and an improved GUI.

EXPERIMENT DESIGN

We selected a Microsoft XNA game, *Robot Game* (http://creators.xna.com) in this work. We chose this game because it has reasonably high entertainment and challenge values. It is a third-person 3D shooting game where a participant plays as a robot to defeat various enemy opponents. The objective of this game is to defeat all enemy robots in the first stage and defeat an enemy captain in the second stage. It runs on a PC environment. Experiment participants play with a Microsoft Xbox 360 controller that provides enhanced user-interaction with the game. We categorized the game into three modes based on its difficulty level: easy mode, moderate mode and difficult mode. In the easy mode, the participants' robot is stronger than the enemy robots, which requires only few shots to destroy an enemy robot. In the moderate mode, both the participants' and the enemy robots have equal strengths. In the difficult mode, the participant's robot is weaker than the enemy robots, which requires a higher shooting power to destroy the enemy robot. The game can be played in any of the above modes by adjusting its internal parameters.

We modified the game in order to accommodate the automatic difficulty adjustable feature. We used two computers for memory intensive applications: one for the game (PC-1) and the other for StressCam (PC-2). PC-2 computes the stress descriptor (unit °C/sec) based on the thermal data and sends it to PC-1 via the TCP socket functionalities. PC-1 receives the descriptor, analyzes the descriptor values and alters the game difficulty level accordingly.

The XNA based game was running on the Windows Vista platform while the StressCam software was developed and running on the Windows Server 2003 platform. In the near future, we plan to run both applications on one PC after we complete software migration of the StressCam software to the Windows Vista platform.

A total of 14 participants (12 males and 2 females) volunteered in this study. Their ages ranged between 19 and 34 (Average = 25.36, Standard Deviation = 5.24). Since the thermal camera cannot penetrate through hair, we only recruited those participants whose supraorbital regions were not covered by hair. The participants sat approximately six feet away from the StressCam (Figure 2). Before the experiment began, the participants were asked to complete demographics and gamer questionnaires. The questionnaires were used to collect basic information about the participants including their game experience, expertise level, and interests. Based on the collected participant information, we categorized them into four classes: beginner, intermediate, advanced and expert.

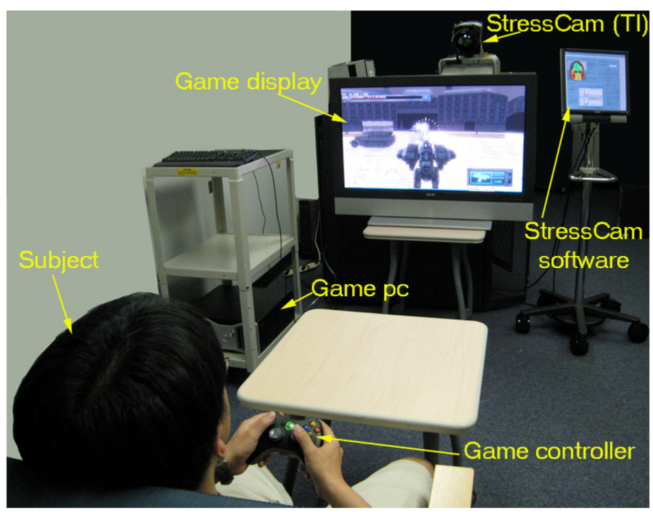


Figure 2. Experimental setup; participant, imaging equipments, gaming equipments.

After completing the questionnaires, the participants were asked to relax for 3 minutes. We let participants listen to soft/calm music during every relaxation phase. This helps to isolate effects of other stress factors that the participants may have carried from the past events. The participants' facial thermal signature was recorded during this relaxation phase. After the relaxation phase, the participants were given an opportunity to explore the game in the easy mode for 10 minutes before the experiment was begun. This gave the participants a hands-on feeling about the gaming environment. The participants' facial thermal signature was not recorded during this test run.

After the test run, the participants were asked to relax for 3 minutes. Next, in the first trial, the participants were allowed to play the game in the easy mode. The participants' facial thermal signature was recorded during this trial. After every one minute interval, the following subjective attitudinal questionnaire popped up on the game display:

1. Too easy, but I am enjoying the game
2. Too easy and I am begin losing interest in the game unless it gets more difficult
3. Moderate in difficulty and I am enjoying the game
4. Moderate in difficulty but I want the game to be easier to have more fun
5. Moderate in difficulty but I want the game to be more difficult to have more fun
6. Too difficult, but I am enjoying the game
7. Too difficult and I want to give up the game unless it gets easier

The participants were required to choose one of the above options. The game was paused at the end of every minute until the participants entered a response. Thus, they did not lose any part of the game while entering their response. The concept of this attitudinal questionnaire was inspired by the Microsoft TRUE design [14]. The questionnaire did not contribute to the difficulty adjustment. Although pop ups every minute could annoy some participants to a certain extent, the responses later provided a useful insight on how the participants responded to a particular level of game difficulty (see Experimental Results).

The participants were asked to complete the following post-game survey after they completed the first trial:

1. How was the difficulty of the game?
2. Did the game provide adequate challenge in overall?
3. Did the game provide adequate entertaining experience in overall?
4. How immersive was the game?

Unlike the minute-by-minute attitudinal questionnaire, the post-game survey allows the participants to evaluate the overall gaming experience. Subsequently, the participants were asked to relax for 3 minutes. We did not record thermal data during this relaxation period.

After the relaxation, the participants had the second trial of the game. The game was running in the difficult mode during this trial. We repeated all the steps that were performed in the easy mode. The participants' facial thermal signature was recorded during this trial. Next, the participants were asked to relax for 3 minutes. Again, we did not record thermal data during this relaxation phase.

Finally, the participants were asked to play the game for a third time. The game was operated in the auto-difficulty mode during this trial. We repeated all the steps that were performed in the previous two trials. The participants' facial thermal signature was recorded during this trial. The participants were not told about the difficulty levels of the game during the experiment.

Each relaxation and game-playing session lasted for approximately 3 and 10 minutes, respectively. The periods of relaxations and game-playings were determined based on a previously conducted pilot experiment (n=3). Too short a relaxation period would not allow the participants to sufficiently cool down while too long a relaxation period let them fall asleep. The length of the game-playing sessions was optimized by considering the following two practical trade-offs: data sufficiency to conclude the experiment and the participants' busy schedule. Every participant spent on average 2 hours for our experiment.

The thermal signature of every participant was recorded four times: while resting, playing the game in the easy mode, difficult mode, and auto-difficulty mode. Thus, we collected a total of 56 thermal clips (14 participants x 4 clips/participant).

METHODOLOGY

We have observed considerable skin temperature alteration in the supraorbital region of all 14 participants during the game period. This temperature change is an outcome of altered blood supply to the supraorbital, which is an indirect measurement of mental activities [17]. In the past, the periorbital region was used to quantify instantaneous stress in the startle experiment and mock crime experiment [20,22]. In this experiment, we focus our attention to the skin temperature of the supraorbital region because we are interested in monitoring sustained stress during the game play. Moreover, the participants' continuous eye movement during the game-playing session introduces noise into the periorbital signal. Therefore, the contribution of instantaneous stress to the game difficulty level adjustment is not explored in this experiment.

On the initial frame of every thermal clip, we manually select a Tracking Region of Interest (TROI) such that it encompasses the supraorbital region as shown in Figure 3. The TROI is then tracked over time via the coalitional tracker [21], which is specifically designed for the facial tissue tracking. This tracker can handle various head poses, partial occlusions, and inter-tissue region temperature variations. The tracker estimates the best matching blocks in the next frame of the thermal clip. We compute the mean temperature of the Measurement Region of Interest (MROI) for every frame in the thermal clip. The MROI is intentionally selected to be smaller than the supraorbital region to reduce the noise introduced due to minor oscillations of the tracker (see Figure 3). TROI is selected such that it covers a wide range of temperature values including the colder eyebrows and hair, and hotter periorbital region. This ensures a higher stability of the tracker and, therefore, one manual selection of the TROI per game-play is generally sufficient.

Thus, a 1D supraorbital temperature signal is extracted from the 2D thermal data. However, due to imperfections in tissue tracking and systemic noise, the measurements from this area carry substantial noise. We suppress the noise to a large degree by utilizing the Fast Fourier Transformation (FFT) based noise reduction technique [22]. Finally, we model the noise-cleaned signal by fitting a linear polynomial to every 20-seconds signal segment. Although the parameter value 20 was determined heuristically and experimentally, the rationale behind the selection is that the linear fitting on a shorter period segment is affected by local temperature variation due to the noise while the linear fitting on a larger period segment may overlook or smooth out the facial physiological changes. Therefore, the stress descriptor is computed every 20 seconds on PC-2 and sent to the PC-1. PC-1 takes three samples of the stress descriptor every minute, computes the mean of these values and then alters the difficulty level of the game. We compute the stress descriptor for all three trials: the easy mode, difficult mode, and auto-difficulty mode. However, we change the game difficulty level only in the auto-difficulty mode. The stress descriptor values of the easy mode and difficult mode are just used for comparative analysis.

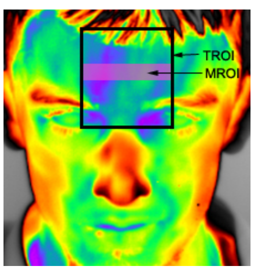


Figure 3. The supraorbital signal was extracted from the mean thermal footprint of the pink colored region (MROI).

The design of our auto-difficulty mode is as follows: it begins with the moderate level difficulty and lets the participants play the game in this mode for one minute. After a minute when the attitudinal questionnaire pops up to mark the participants' response, the game program changes the game difficulty level based on the last one minute stress level. If the stress descriptor is higher than an upper threshold (T_u), the program considers the last one minute period as a stressful period for the participants and it changes the difficulty level of the game to the easy mode. On the other hand, if the stress descriptor is smaller than a lower threshold (T_l), the program assumes that the game is too easy for the participants and therefore, the participants are losing interests in the game. Thus, it increases the difficulty level to the difficult mode. If the stress descriptor is within the two thresholds (T_u and T_l), the game difficulty level remains unchanged. Based on the experimental test data, we computed the upper threshold (T_u), which is +0.01°C/sec and the lower threshold (T_l), which is -0.01 °C/sec.

If the stress level is lower than T_l while the participants are playing in the easy difficulty level, our program assumes that the participants are not very interested in the game and therefore, the difficulty level is switched to a more difficult level (i.e., the moderate level). On the other hand, a high stress level in the easy mode forces the participants to remain in the easy mode because the current setup does not have options to further lower down the game difficulty level.

The game difficulty level is lowered down to the moderate mode whenever the participants experience extensive mental stress in the difficult mode. On the other hand, a low stress level in the difficult mode forces the participants to remain in the difficult mode because the game is already in the highest difficulty level.

We also compute the participants' performance based on the type and quantity of the enemy robots they destroyed during each mode. The scoring scheme is designed to accommodate the difficulty level, i.e., the participants get fewer points for destroying an enemy robot in the easy level as compared to destroying the same enemy robot in the difficult level. The cumulative performance per trial is the sum of all the points accumulated during the trial. Whenever the participants' robot is destroyed, the game takes a few seconds to start a new game. Thus, the participants lose game-play time and hence opportunity to collect more performance points. Therefore, we did not penalize the participants for losing the game battle. The scoring scheme is mainly used for the follow-up comparative results analysis.

EXPERIMENTAL RESULTS

In this work, we used the rate of change of the temperature as the stress descriptor. We also used subjective data (minute-by-minute participants' feedback and post-game survey) in our analysis. The subjective data were collected to validate our hypothesis that the thermal-based facial physiology can be used to improve the users' gaming experience. Figure 4 shows a visualization of the thermal signature of the supraorbital region while the participant played the game in the easy mode. Since the participant has a low expertise (beginner) in terms of playing video games, his stress level was high during the easy mode. The mean stress descriptor during the easy mode was high (+0.05°C/sec). This result is in par with his subjective feedback, which infers that the participant was having difficulty in playing the game in the easy mode.

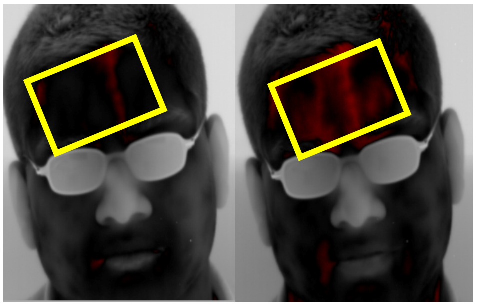


Figure 4: (a) The supraorbital region, delineated in the yellow colored rectangle, was snapped right after the experiment started in the easy mode. It represents normal blood flow in the supraorbital region (b) The supraorbital region was snapped right before the experiment was concluded in the same mode. The bright red region is an evidence of heavy mental activities.

Figure 5 combines the subjective and the quantitative results of the same participant for the easy (blue colored data) and difficult (red colored data) modes. The easy mode signal and associated subjective feedback in the graph shows that the participant was enjoying the first half of the game (feedback option-3) while experiencing stress in the easy mode. When the accumulation of the stress level reached beyond a certain limit in the second half of the game, it changed the psychological state of the participant and therefore, the participant was finding the same game very difficult (feedback option-6). The global ascending trend of the easy mode signal confirms that the participant was engaged in the game.

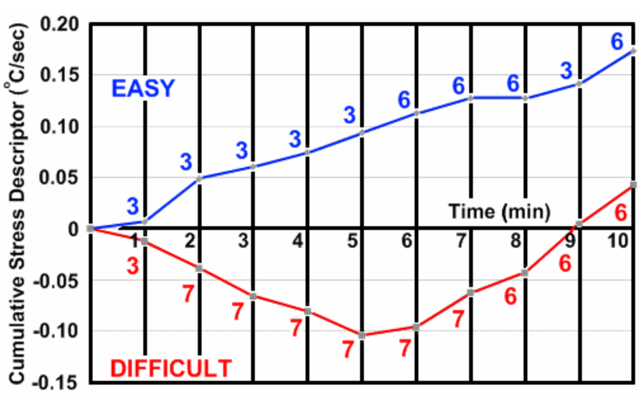


Figure 5. The graph illustrates a relationship between the subjective data and the mental stress level for the easy and difficult modes. The numbers placed next to every data point of the signals show the subjective feedback of the participant's experience. As mentioned under the Experimental design section, the subjective feedback option-3 indicates that the game was moderately difficult but the participant enjoyed the game. The subjective option-6 indicates the game was too difficult but the participant enjoyed the game. The subjective option-7 indicates that the game was too difficult and the participant wanted to lower the difficulty level.

In contrast, the participant's stress level was decreasing during the first half of the difficult mode, which indicates that he was disassociated from the game as it was too difficult for him (see Figure 5). This observation agrees with his subjective feedback for the difficult mode where he wanted to quit the game unless the game difficulty level was lowered (feedback option-7). The participant got acquainted with the game during the remaining half and therefore, his stress level had an inverse trend. The subjective feedback of the second half indicates his engagement in the game. However, the steepness of the rate of change of the temperature indicates that the participant was having a hard time playing the game. This observation again agrees with the subjective feedback that he believed the game is too difficult (feedback option-6).

The most interesting result would be to see how the auto-difficulty adjustment agrees with the subjective feedback. Figure 6 illustrates results of the auto-difficulty mode. The participant played the game in the moderate difficulty level for the first minute. At the end of the first minute, the game difficulty was lowered as the stress descriptor was higher than the upper threshold. The participant's subjective feedback also rated the game too difficult in the first one minute. Similarly, the game difficulty was adjusted every minute to optimize the participant's interest. Due to this adjustment, the stress level was stabilized after a few minutes. The participant played the game in the lowest level of difficulty for most of the auto-difficulty mode session, which is a self-explanatory outcome for the player with novice gaming expertise. The validity of our hypothesis is confirmed by associating each minute's subjective data with the stress level. Specifically, whenever the participant felt the game was too difficult (feedback option-6), his facial physiology also revealed the same psychological state.

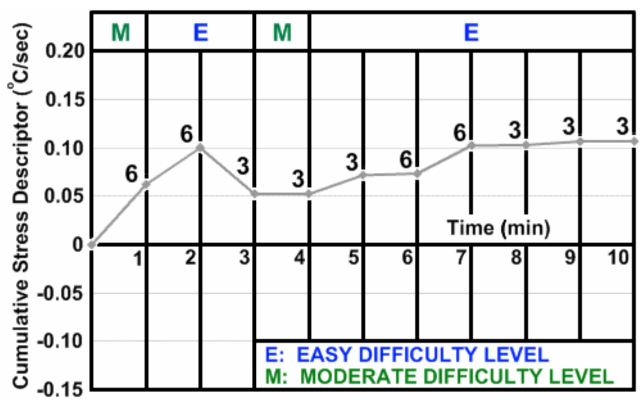


Figure 6. The graph illustrates a relationship between the subjective data and the mental stress level for the auto mode. The numbers placed next to every data point of the signals show the subjective feedback of the participant's experience.

Table 1 summarizes the association between the subjective and quantitative results for the entire dataset. The first column of the table shows participants ID (P##) and their gaming expertise level. Cells in the other columns show psychological state (stress descriptor) above difficulty levels above subjective feedback (attitudinal data) of the corresponding participant at every minute. Participants P01, P02 and P08 were beginners and therefore, their comfortable zone was in the lowest difficulty level. The table shows that they played the game in the easy difficulty level for most of the auto-difficulty mode. Their attitudinal data confirms that they indeed enjoyed the game in the auto-difficulty mode. Participants P09, P12 and P13 were intermediate expertise players and therefore their inclination was toward the easy and moderate difficulty level.

	TIME (min)													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	0.062	0.100	0.053	0.053	0.072	0.074	0.103	0.103	0.107	0.107	← Stress Descriptor			
P01	M	E	E	M	E	E	E	E	E	E	← Difficulty Level			
[1]	6	6	3	3	3	6	6	3	3	3	← Attitudinal Data			
	0.031	0.071	0.103	0.118	0.164	0.252	0.153	0.210	0.190	0.200				
P02	M	E	E	E	E	E	E	M	E	M				
[1]	5	2	2	2	1	2	3	3	2	3				
	0.000	0.009	0.057	0.079	0.074	0.088	0.090	0.099	0.114	0.121	0.117			
P03	M	E	E	E	E	E	E	M	E	M	E			
[3]	3	6	3	3	1	3	3	3	1	1	3			
	0.008	-0.007	0.019	-0.008	-0.011	-0.081	-0.079	-0.079	-0.048	-0.115	-0.116	-0.077	-0.044	
P04	M	M	D	M	D	D	D	D	D	M	D	D	M	
[4]	3	2	2	2	2	2	2	2	2	2	2	2	1	
	-0.037	-0.084	-0.147	-0.221	-0.177	-0.016	0.014	-0.008	-0.054					
P05	M	D	D	D	D	D	M	E	E					
[4]	3	3	3	3	3	2	2	2	2					
	-0.017	-0.047	-0.062	-0.099	-0.121	-0.207	-0.199	-0.202	-0.169	-0.158	-0.170	-0.247	-0.232	-0.212
P06	M	D	D	D	D	D	D	D	D	D	E	M	D	M
[3]	3	3	6	3	6	3	6	3	6	3	3	3	3	1
	-0.002	0.023	-0.008	-0.032	-0.073	-0.053	-0.085	-0.110	-0.173	-0.137				
P07	M	M	E	M	D	D	M	D	D	D				
[3]	1	1	3	3	3	3	3	3	4	3				
	0.012	0.018	0.023	0.033	0.050	0.055	0.090	0.110	0.125	0.140	0.152			
P08	M	E	E	E	E	E	E	E	E	E	E			
[1]	3	3	3	3	3	3	3	5	3	3	3			
	-0.044	-0.003	0.012	0.000	0.008	0.017	0.011	0.020	-0.013	0.000	-2.183			
P09	M	D	D	M	M	M	E	E	E	E	M			
[2]	3	3	3	3	3	3	4	4	4	4	1			
	-0.171	-0.548	-0.521	-0.402	-0.660	-0.933	-1.182	-0.905	-0.991	-0.768	-0.825			
P10	M	D	D	M	E	M	D	D	M	D	M			
[4]	5	5	5	5	2	5	5	5	5	3				
	-0.009	0.002	0.015	0.016	0.016	0.031	0.046	0.038	0.060	0.085	0.094			
P11	M	M	E	E	E	E	E	E	E	E	E			
[4]	1	1	1	1	1	1	1	1	1	1	1			
	-0.031	-0.015	-0.011	-0.020	-0.022	-0.004	-0.022	-0.071	-0.092	-0.123				
P12	M	D	M	M	M	M	E	M	D	D				
[2]	5	3	3	3	3	3	5	3	5	3				
	0.042	0.062	0.101	0.103	0.099	0.095	0.109	0.128	0.139	0.157				
P13	M	E	E	E	E	E	E	E	E	E				
[2]	3	1	1	2	1	1	1	1	1	1				
	0.012	-0.021	-0.042	0.015	-0.026	-0.037	0.057	-0.145	0.145	-0.433				
P14	M	E	E	M	D	D	D	M	D	D				
[4]	1	1	1	3	3	4	3	3	3	4				

Difficulty Level	
E	Easy
M	Moderate
D	Difficult

P##	Participant No.
[#]	Gamer Expertise
[1]	Beginner
[2]	Intermediate
[3]	Advanced
[4]	Expert

Attitudinal Data	
1	Too easy, but I am enjoying the game
2	Too easy and I am begin losing interest in the game unless it gets more difficult
3	Moderate in difficulty and I am enjoying the game
4	Moderate in difficulty, but I want the game to be easier to have more fun
5	Moderate in difficulty, but I want the game to be more difficult to have more fun
6	Too difficult, but I am enjoying the game
7	Too difficult and I want to give up the game unless it gets easier

Table 1. This table summarizes every minute stress level (highlighted in yellow color), difficulty level, and subjective feedback (highlighted in gray color) for the entire dataset.

The remaining 8 participants were either advanced or expert players who were supposed to enjoy the game at higher difficulty levels. The stress descriptor values of the table illustrates that their facial physiology allowed them to play the game at the highest difficulty level during most of their playing time. This proves that they were less stressed in the highest difficulty level. Their attitudinal data also showed that they enjoyed the game in the auto-difficulty mode except for the participant P04 who marked option-2 in most feedback surveys. The post-game survey of P04 reveals that he was seeking an even higher level of difficulty which the current game was unable to provide. P11 was an interesting participant. Even though he was an expert player, he played the game in the easy difficulty level most of the time. His attitudinal data confirms that he indeed enjoyed the game even though the game was too easy for him. This is a counter example where the expert player, rather than worrying about a suitable difficulty level, played the game at a level that was customized for his current psychological state. Based on Nicole Lazzaro's *Four Keys to emotion* [16], this player's motives could be classified as seeking Easy Fun (focusing on the enjoyment of the game activities) rather than Hard Fun (focusing on wining conditions).

Table 1 shows that every group of participants found their comfortable gaming environment in the auto-difficulty mode. In other words, most of the participants played the game at a difficulty level that was matched with their gaming expertise level. Moreover, they occasionally, explored higher difficulty levels as well as recovered from the intense stressful period by resting at lower difficulty levels. Since the difficulty levels are automatically computed and determined from the facial physiology, the game is capable of adjusting the game difficulty level without the participants' intervention. Thus, the proposed system provides a seamless way to allow the participants to exploit their current expertise for maximizing the fun factor, to explore higher difficulty levels for learning new or challenging game settings, or to relax at the lower difficulty levels.

Figure 7 illustrates the average performance scores of the participants based on the type and quantity of the enemy robots they destroyed during each mode. The result reveals participants achieved the best average performance in the auto-difficulty mode. This finding validates our hypothesis from a different perspective.

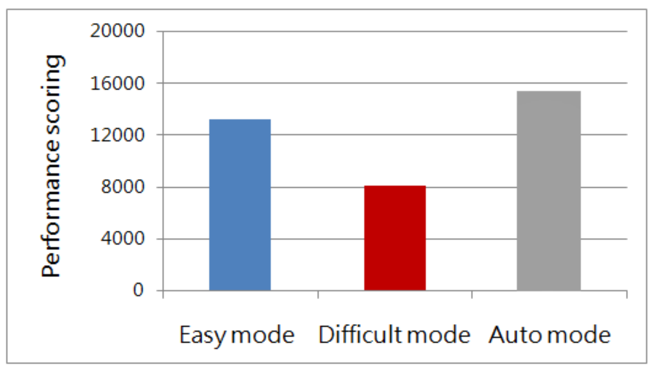


Figure 7. Average performance scores of the game modes. The average score was highest in the auto-difficulty mode.

DISCUSSION AND CONCLUSIONS

Our work demonstrates the feasibility of applying stress quantification technique for the improvement of the users' gaming experience. This methodology is broadly applicable to many instances and applications where the users' facial physiology can be used to quantify their interests in interactive, user-centric activities, e.g., playing games at a level that provides optimal entertainment effects or automatically changing music that gives optimal pleasure to listeners. Our initial experiment with a limited dataset confirmed the applicability of our approach. To the best of our knowledge, this is the first experimental research effort that has been made towards applying the thermal facial physiology to a broad variety of interactive, user-centric entertainment applications.

Users' performance during a game-play alters blood flow in the supraorbital vessels, frontalis and corrugator muscle, which reflects their mental activation level. StressCam continuously monitors these physiological changes and quantifies it into psychological states. The game program exploits this information to adjust its difficulty level. Thus, our proposed feedback system is capable of reflecting the users' psychological state, which is further utilized to seamlessly augment their gaming experience in real-time.

This work opens new potential directions of research in the field of users' entertainment enhancement and optimization. The major limitation of our current work is that we did not separate the impact of participants' mental engagement from the stressful phase whenever the supraorbital temperature increased. Similarly, we did not separate the impact of relaxation from losing interest whenever the temperature decreased. We are currently in the process of improving our algorithms to accommodate these limitations. One possible solution to tackle this limitation is to use more advanced statistical approaches (e.g., Bayesian classifier) or machine learning approaches (e.g., decision tree or Support Vector Machines) for the stress quantification.

Another limitation of the current system setup is that it cannot handle the game-play between multiple players. The current system is designed for single-user games that allow the player to play against the computer program. Extending this setup to multi-user game environments is not meaningful because favoring one player against another may not be desirable and thus will not improve the overall entertainment effects. Thus, automatically adjusting the difficulty level of multi-user games is irrelevant.

The proposed technology requires a manual initiation of the tracker on the supraorbital region. This is a minor inconvenience to the users as the tracking region of interest (TROI) needs to be selected at the beginning of the game-play. In order to eliminate this constraint, we plan to extend our eye blinking detection algorithm for automatic localization of the supraorbital region. This algorithm was originally developed for automatic initiation of periorbital signal extraction process. It is capitalized on detection of involuntary eye blinking in the thermal imagery. By applying anthropometry information of the face, this method can be utilized to automatically localize the supraorbital area on the face as well.

One practical factor of this system is that the thermal camera used is still relatively costly at this point, which might prevent its wide deployment. With the possible decrease of the cost of the thermal camera in the near future, we expect the proposed stress-incorporated entertainment systems will be popularized in many real-world applications.

ACKNOWLEDGMENTS

This material is based upon work supported in part by the National Science Foundation (NSF) under Grant No. # ISS-0812526 entitled 'Do Nintendo Surgeons Defy Stress'. (PI: Professor I. Pavlidis). This work was also supported in part by the University of Houston faculty start-up funds of Professor Zhigang Deng. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the funding agencies.

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