Modulation of Physiological Responses and Activity Levels During Exergame Experiences

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***Abstract*— Exergames are exercise-oriented games that offer opportunities to increase motivation for exercising and improving health benefits. However, Exergames need to be adaptive and provide accurate feedback for physiologically correct exercising, sustaining motivation and for better personalized experiences. To investigate the role of physiological computing in those aspects, we employed a repeated measures design exploring changes in physiological responses caused by the gaming and exercising components of an Exergame intervention. Seventeen older adults (64.5±6.4 years) interacted with a videogame in two modes (Control, Exergaming) in different difficulty levels. Electrocardiography, Electrodermal and Kinematic data were gathered synchronously with game data. Findings show that Exercise intensities and heart rate changes were largely modulated by game difficulty, and positive feedback was more likely to produce arousal responses during Exergaming than negative feedback. A heart rate-variability analysis revealed strong influences of the interaction mode showing that Exergaming has potential to enhance cardiac regulation. Our results bring new insights on the usefulness of psychophysiological methods to sustain exercising motivation and personalizing gameplay to the individual needs of users in Exergaming experiences.**

Keywords*— *Game user research; exergaming; psychophysiology; older adults; physiological computing, positive reinforcement; EDA; ECG.

I. INTRODUCTION

Psychophysiological methods are becoming popular in games user research not only as a passive recording tool to assess affective player experience [1], emotions [2] and cognition [3], but also as a way to create new adaptation strategies and input channels for interaction [4]. While conventional game metrics such as self-reports, surveys and user observation provide insights on the experience of players, they can miss emotional responses [5]. These can be apparent responses but also non-apparent such as body posture, facial expression or psychophysiological changes. The latter ones are not visible to the naked eye and require specific biomedical equipment to measure signals such as electrocardiography (ECG), electromyography (EMG), electroencephalography (EEG) or electrodermal activity (EDA) [5]. There are three main advantages in using physiological metrics in game user research: i) they are more objective and direct compared to conventional methods because they are language independent and do not rely on memory; ii) they can be covertly assessed continuously, without interfering with the interaction and thus providing a high level of temporal precision (useful to detect event related responses) [2]; and iii) can detect unconscious emotional and attentional responses [6].

Exergames are exercise-oriented games that aim at wrapping physical activities into computer gaming [7]. Exergames can address general fitness for healthy individuals as well as age and/or health specific needs [8]. For this reason, Exergame design requires a precise understanding of the physiological mechanisms of exercise and target population in order to guarantee safety and clear short and long-term health benefits. Traditional approaches to evaluate Exergames include observations of codified human movements during interactions [9], automatic recognition of body movements through motion capture technologies [10], specific assessment scales such as the Borg's perceived exertion scale [11], behavioral logs to record activities of users when interacting [12], think aloud protocols [13] and physiological measurements. The particular case of usability in Exergames for elderly care and rehabilitation is generally limited to qualitative studies focusing on users' perception towards systems and controllers [14].

The use of physiological sensors to measure exertion is not new [15]. The analysis of multiple body changes that, to some extent, reflect user's behavioral states emerged as a powerful

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tool for quantitative game user research. In this case, the regulation of emotions is assessed by measuring the activity of sympathetic (fight and flight reactions) and parasympathetic (rest and digest reactions) nervous systems [4]. Hence, developing a better understanding of the psychophysiological responses to Exergaming can be an important element to improve the assessment of users' behavior during gameplay and boost the efficacy of Exergame-based interventions. In particular, physiological-adaptation approaches through "close-loop" systems, the so called biocybernetic loops, can be used for adapting videogame dynamics/events in response to the player's physiological responses [16]. These novel strategies have the potential to enhance user experience as well as fitness and therapy benefits [17]. However, one major limitation in field studies that use psychophysiological signals is their sensitivity to artifacts [5], with most signals being strongly affected by both voluntary and involuntary movements [18]. Hence, the potential of these signals in an Exergaming context and their real-world usage is still an open challenge.

We were interested in exploring the user's physiological and behavioral responses to positive and negative game events, and to game difficulty in an Exergame. This paper reports a controlled study with a group of active older-adults in which physiological signals are analyzed to evaluate the Exergame experience. With this study we aim at contributing to the identification of strategies for an effective use of physiological signals in Exergame interventions by addressing the following research question: How are exercise intensity, arousal and cardiorespiratory responses related in a controlled Exergame experience? We hypothesize that specific physiological responses can be systematically triggered by the manipulation of specific game parameters. Hence, our study provides insights on how psychophysiological methods can be used in Exergames to sustain exercising motivation, to provide physiologically driven exercise adaptation, and to personalize gameplay to the individual needs of users [8].

II. Related Work

The dual flow model is a framework that integrates psychophysiological responses in Exergaming in two different dimensions of the exercise: *attractiveness* and *effectiveness* [19]. *Attractiveness* can be modelled by the well-known flow model from Csikszentmihalyi by means of balancing user's skills with perceived challenge [20]. The second dimension, *effectiveness*, relates to the physiological responses to exercise in order to adjust the intensity of the exercise with the actual user fitness [19]. Several studies reported on the use of physiological measurements during Exergaming. Some authors have focused on quantifying behavior using a set of domain specific features [21], allowing the comparison of physiological changes induced by Exergaming in different populations [22]. For instance, Graves et al. [23] found that energy expenditure (EE) and heart rate (HR) during commercial Exergame (Wii Fit) activities were higher than during conventional handheld videogames; but lower than during treadmill exercise in adolescents, young and older adults. Other studies with commercial Exergames exploring EE and HR responses as biomarkers showed that the use of skill-based protocols (training until attaining a goal) increased both physical exertion and game proficiency [24]. McGuire et al. [25] showed that physiological responses (HR, EE and ventilation) are greater during multiplayer Exergame experiences than during single play modes. Other studies revealed that heart responses to Exergames can be larger than those elicited by conventional physical exercises. An experiment comparing brisk walk on a treadmill with Exergame practice in healthy adults showed significantly higher HR values and higher enjoyment levels during Exergame [26]. EDA has also been widely used as a measure of arousal in game user research [2] and for monitoring sympathetic modulation during exercise [27]. One study analyzed EDA responses for fatigue detection during Exergaming and identified that the basal skin conductance decreased with fatigue [28].

Exergaming in users with special needs has also been addressed. For instance, a study was carried out with participants with spinal cord injury to investigate whether Exergaming satisfied guideline-based intensity standards for exercise [29]. The authors concluded that intensity responses to Exergaming were sufficient to promote cardiorespiratory fitness in this population, as assessed by HR and oxygen uptake (VO_2). Some researchers have considered the use of physiological measurements for developing physiologically modulated Exergames. Generally, these Exergames are partially controlled by the cardiac signals using the concept of a target HR, a specific age-based pulse rate range to be maintained during the exercise to ensure optimal cardiovascular function [30]. Some of the adaptation rules are based in HR thresholds defined by a specific target HR which can be approximated from the age and sex of the subject [31]. Several adaptive cycling Exergames have been developed where factors such as safety (falls and tumbles), game mechanics mapping and the effectiveness of pedaling to increase exertion levels are considered [32]. For instance Ketcheson and colleagues [33] created HR power-ups, a game mechanism used to encourage users to meet the ACSM recommendations for aerobic exercise prescription [34]. Using in-game rewards when the target HR was reached, they created 3 different cycling videogames and carried out a test with 20 healthy young participants including a control condition (without HR power-ups). Results revealed that HR power-ups successfully increased the level of user's exertion during the experience spending more than 88 % of the interaction time at or above the target HR, consistent with ACSM recommendations [30]. Furthermore in [35] authors used neurophysiological measurements from EEG signals to influence user's Exergame performance during the interaction by disturbing the environment and input controller. In a different EEG study, the authors explored players' ability to successfully manage interference and allocation of attentional resources during regular exercise, videogames and Exergaming [3].

The literature suggests that physiological signals such as HR and EDA can contribute to the understanding of the effects of both exercise and game user experience. However, there is still a lack of understanding on how physiologically modulated

Exergames can induce the desired effects in users. For this reason, here we present an experiment conducted to study how physiological responses (measured by ECG and EDA signals) and activity levels (measured through kinematic analysis) relate to Exergame dynamics. More concretely, we explore the influence of game difficulty and game events in the psychophysiological states of elderly users in a within-subjects experiment with an Exergaming condition and a Control condition. To do that, we carried out an experiment using a custom made Exergame, allowing the synchronous recording of users' behavior and responses with the game parameters, aiming to perform a causality analysis. In this research we also address the problem of movement induced artifacts in EDA and ECG signals. We finalize the paper discussing the implications of this work in game user research for Exergaming.

III. METHODS

A. Videogame

1) Design: the used videogame, called Exerpong, is an adaptation of the classic 2D Pong in which the player controls a virtual paddle to bounce a ball. Two different interaction modes are available: Exergaming and Control (with a conventional joystick). Exerpong was developed using the Unity 3D game engine (Unity Technologies, San Francisco, USA). The RehabNet Control Panel (Reh@Panel) software [36] is used to interface a depth sensor with Unity 3D. Through calibration, the user's waist position is mapped to control a virtual paddle. Three different difficulty levels were implemented (easy, medium and hard) based on the modification of the velocity of the ball, size of the ball, and the size of the paddle. No scores were provided to avoid influencing long-term perception of success or failure. Game events were unequivocally labelled as missed balls or ball interceptions. Audiovisual stimuli (red and green visual feedback and positive and failure sounds) were used during gameplay to provide feedback on performance.

2) Experimental Setup: a white PVC surface (2.5 m x 3.0 m) was used to project the Exerpong game on the floor in front of the participants (Figure 1). The projection had a resolution of 1280x720 pixels and the perspective was corrected to the surface using a mapping application.

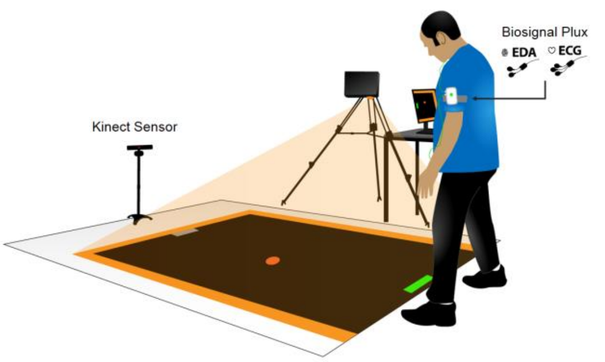

Figure 1. Diagram depicting the Exerpong setup consisting of a Kinect sensor, a projected environment and a wearable physiological kit. The user stands in front of the projection and controls a virtual paddle.

We used the fighting stick EX2 for Xbox360 to enable the control of the virtual paddle with a joystick in the Control condition. Users sat in a chair in front of the floor perpendicular to the paddle-movement axis, and controlled the joystick using their right hand. A Kinect v1 sensor (Microsoft, Microsoft, Washington, USA) enabled the control of the virtual paddle through body motion in the Exergaming condition. EDA and ECG signals were recorded through a Bluetooth connection using the BioSignal Plux toolkit (Plux Wireless Biosignals, Lisboa, Portugal), a wearable body-sensing platform. EDA signal was recorded using two Ag/AgCl electrodes attached to the middle phalanges of the middle and index fingers of the participant's left hand. ECG signals were recorded using a surface mount triode dry electrode with standard 2 cm spacing of silver chloride electrodes placed on the V_2 pre-cordial derivation. Conductive gel to facilitate signal recording was used in some participants when necessary.

B. Physiological Signal Processing

1) EDA signal processing and feature extraction: to eliminate high-frequency noise, an 8^{th} order low-pass filter with a cut-off frequency of 15 Hz was applied. To filter spurious spikes produced by physical movements we used a 5^{th} order median filter. EDA data from different users were normalized as a percentage of their minimum and maximum values to allow for comparison. Phasic EDA responses or Galvanic Skin Responses (GSR) - noticeable episodes of sudden increases of skin conductance caused by arousal [37] - were assumed to begin between 1 and 4 seconds following stimulus onset [38]. GSRs were extracted synchronous with the Exerpong game events to study their relationship (Figure 2). An event specific GSR index was computed as follows:

$$GSR_{index}(x) = \frac{GSR_x}{GSRs} * 100\% \qquad (1)$$

Where *x* can be either *BI (ball interceptions)* or *MB* (*missed balls)* events and the index computes the % of *x* specific GSRs out of the total of GSRs detected. This percentage quantifies the responsiveness of each user to each type of game events.

2) ECG signal processing and feature extraction: baseline wandering, an amplitude shifting phenomena, due to gross movements but also to tiny movements such as respiration [39], was filtered and analyzed using the PhysioLab toolbox, a multivariate physiological softwware tool [40].

3) Some EMG noise in the ECG signal was unavoidable and could not be filtered. To extract HR information, the ECG waveform was analyzed and detection of the R-peaks was carried out. Different detection parameters were used in PhysioLab for resting, Exergaming and Control conditions.

4) Results of R-peak detection were manually reviewed and corrected when necessary.

5) In the temporal domain, HR and HR variability (HRV) parameters were extracted. HRV analysis assesses the

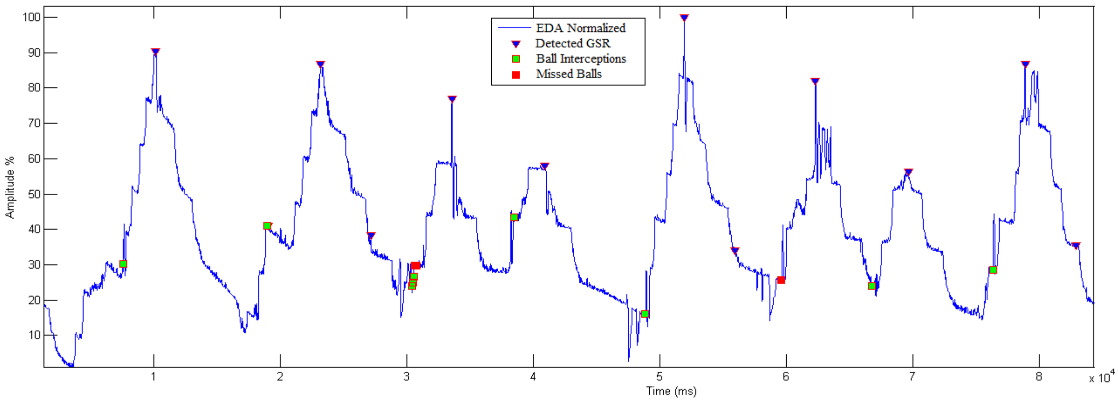

Figure 2. Example EDA signal processing of one participant. GSRs are detected and matched with ball interceptions and missed balls.

regulation of cardiac activity by analyzing beat-to-beat dynamics (RR intervals) [41].

6) The SDNN (standard deviation of normal RR intervals) and RMSSD (square root of the mean squared differences of successive RR intervals) parameters - which have been reported as good biomarkers of parasympathetic regulation [42] - were computed. In addition, several cardio-respiratory fitness parameters derived from ECG were computed. First, the maximum HR (HR_{max}) - which provides information about the highest HR an individual can safely achieve - was computed using Tanaka's formula [31]. Second, the maximum oxygen uptake (VO_{2max}) - which reflects the functional capacity of the cardio respiratory system [30] - was estimated using the HR during resting (HR_{rest}) and HR_{max}. Finally Energy Expenditure (EE) ($KJ*min^{-1}$) - which refers to the amount of energy that a person uses to be physically active - was computed from HR data using the prediction equation developed by Keytel et al. [43]. EE was subsequently converted to Metabolic Equivalents (METs) dividing it by the equivalent amount of oxygen used by the body during resting (1 MET = 3.5 ml O_2 * Kg-1 * min-1)[30].

7) Kinematic signal processing and feature extraction: given 3D user tracking information from the Kinect sensor, we computed the kinetic energy (KE) of each joint as the norm of their velocity vector. The body kinetic energy was approximated as the weighted sum of each joints' KE, as follows:

$$KE(f) = \frac{1}{2}\sum_{i=1}^{n} m_i v_i^2 \qquad (2)$$

where m_i indicates the mass of the i-th joint. We used a mathematical approximation assuming a uniform distribution of each tracked joint, that is m_i was the self-reported mass of each individual divided for the number of joints (17 using Kinect V1).

C. Questionnaires

The Subjective Units of Distress Scale (SUDS) was used as a subjective measure of the level of distress, fear, anxiety or discomfort on a scale of 0-10. The usability of Exerpong in the two interaction modes was assessed with the System Usability Scale (SUS) [44]. SUS provides a quantification of usability through information on users' interaction. The SUS has been used already in Exergaming [45].

D. Participants

Seventeen community-dwelling older adults (14 women, 3 men, ages 64.5 ± 6.4 years, height 1.57 ± 0.67 m, mass 69.1 ± 12.2 Kg.) were recruited at a local senior sports facility. Senior fitness tests scores in balance-8 Foot Up and Go (*M*=4.6 ± *SD*=0.6), cardiorespiratory - 2 minutes Step Test (*M*=97 ± *SD*=18) and musculoskeletal - 30 second Chair Stand Test (*M*=18 ± *SD*=2) were used to characterize the functional fitness level of users. All participants were right handed, had no recent upper/lower limb injuries, were able to stand up without any help and had no neurological disorders that prevented the understanding of the experiment. 58.8% of the participants had no past experience with computer games. All participants gave their informed consent prior to participation.

E. Protocol

Participants were invited to play Exerpong in its two configurations, Exergaming and Control, in the same session and day (Figure 3). Each game block (easy, medium, and hard) was programmed to increment the difficulty every 30 seconds. Each game block lasted for 3 minutes. Before the start of the experiment, participants were instructed on the use of the different interaction modes. Participants were required to keep silence during gameplay and be seated and calm for 5 minutes between conditions to allow physiological signals to return to a resting state. The order of conditions was randomized such that half of the participants started with the Control condition and half with the Exergaming one. Each condition lasted approximately 30 minutes (including setup, instructions, resting, gameplay and questionnaires). The SUDS scale was projected on the floor and answers automatically collected after each game block during the resting periods. The SUS was gathered through semi-structured interviews after each experimental condition.

F. Data Collection

Physiological and kinematic information was recorded synchronously with Exerpong data. Exerpong data and events were stored at a sampling frequency of 30 Hz for post-processing. Physiological data was acquired at a 1000 Hz

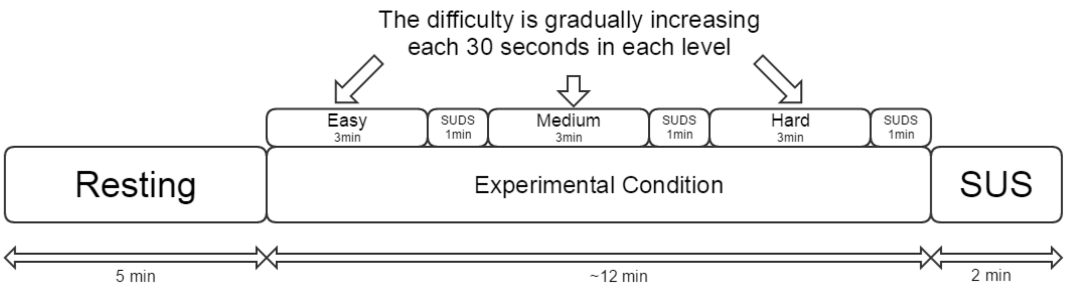

Figure 3. Experimental Procedure. The procedure is the same for both experimental conditions (Exergaming and Control). The SUDS: Subjective Units of Distress Scale, SUS: System Usability Scale

sampling rate and the kinematic data was captured using the Kinect v1 provided spatial coordinates (X-horizontal, Y-vertical and Z-depth) of 17 body points. Data were stored in CSV files and processed using Matlab v2012a. EDA data sets of four participants were discarded due to high noise, non-removable artifacts and data corruption.

G. *Statistical Analysis*

The two principal components of a Principal Components Analysis (PCA) were used to identify colinearities and redundancy in the parameters extracted from EDA and ECG signals. Two parameters were selected from EDA [$GSR_{Index}(BI)$ and $GSR_{Index}(MB)$] and three parameters from ECG (HR, SDNN and METs).
The normality of all distributions was assessed using a Kolmogorov-Smirnov test. When data were non-normal, non-parametric tests were used. A two-way repeated measures ANOVA was used to compare experimental conditions and difficulties. Differences between difficulty levels were assessed by evaluating contrasts. Main and interaction effects were also explored. For kinematic and game performance data, a non-parametric analysis using Friedman test was used to assess the effect across conditions. Furthermore, a Wilcoxon signed-rank test was used for pairwise comparisons for the main effect of difficulty. All statistical tests were performed using SPSS (21.0, IBM Corp, Armonk, NY) and the significance level was set to 5% ($p < 0.05$). The PCA analysis was carried out in Matlab.

IV. Results

A. *Is game performance better during Exergaming or Control?*

Game performance was defined considering the number of ball interceptions and missed balls. Participants showed higher performance in the Exergaming condition (ball interception, M=61.8, SD=5.69, missed balls, M=55.0, SD=6.4) as compared to the Control condition (ball interception, M=52.1, SD=5.1, missed balls M=59.8, SD=6.6). A Friedman test revealed that there was a significant difference in game performance depending on which condition was used, $\chi2\ (1) = 12.75$, $p < .05$. User's performance decreased considerably in the hard difficulty level by increasing the number of missed balls in the two conditions. A Wilcoxon test revealed significant performance differences for easy-to-medium and easy-to-hard difficulties, $T = 124$, $r = -2.25$, $T = 119$, $r = -2.01$, respectively.

B. *Is electrodermal activity modulated by game interface or events and difficulties?*

GSR_Indexes for ball interceptions and missed balls, for the two conditions and three difficulty levels, were computed. There was a significant main effect of condition for the $GSR_{Index}(BI)$, F (1.0, 12.0) = 8.84. Users were more responsive to ball interceptions during Exergaming than during conventional interaction for easy (Control: M=36.6, SD=22.0, Exergaming: M=44.6, SD=27.9) and medium (Control: M=34.5, SD=17.7, Exergaming: M=56.4, SD=18.4) difficulties. No significant differences for game difficulty were found for $GSR_{Index}(BI)$. Instead, $GSR_{Index}(MB)$ differed across the main effect of the type difficulty, F (2.0, 24.0) = 60.0, but not for the main effect of condition. Pairwise comparisons identified significant differences among all difficulty level comparisons: easy-medium ($p = 0.001$), medium-hard ($p \leq 0.05$) and easy-hard ($p \leq 0.05$).

C. *Are electrocardiography and exercise levels modulated by game interface, difficulty and game events?*

HR response to the game, computed as the average HR during the experimental condition minus HR_{rest}), for Control and Exergaming and difficulty levels are shown in figure 4. A higher HR during Exergaming condition, and a modulation with the difficulty level was identified. There was a significant main effect of the type of condition on participant's HR, F (1.0, 16.0) = 92.7.

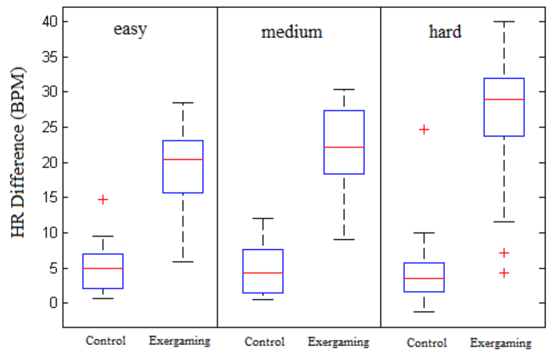

Figure 4. Boxplot of HR responses ($HR - HR_{rest}$) by difficulty and condition.

The interaction effect between the type of condition and the type of difficulty used, F (1.0, 16.0) = 5.69 was also significant indicating that the condition had different effects on user's HRs depending on the difficulty. Furthermore, a post hoc test using Bonferroni correction revealed that HR values for easy compared with medium difficulty levels were significantly different, F (1.0, 16.0) = 5.6. The remaining comparisons revealed no significant differences.

An analysis of HRV revealed a significant main effect of the type of condition used for the intervention on the user's SDNN values, F (1.0, 16.0) = 5.9. SDNN values for Exergaming (M=84.1, SD=56.1) were higher compared to Control (M=52.7, SD=44.9). There was no significant effect of the difficulty level over the SDNN values for the experiment.

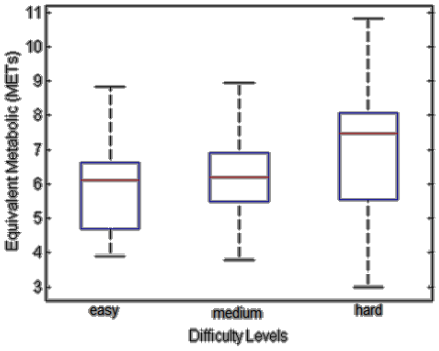

Figure 5. Metabolic Equivalents (MET) exerted during Exergaming for easy, medium and hard difficulties.

Data showed that the METs during Exergaming were significantly affected by the difficulty level, *F* (1.25, 1.0) = 5.09, *p*< .05, although pairwise comparisons indicated no significant differences between difficulty levels: easy (M=6.05, SD=1.34), medium (M=6.38, SD=1.36), and hard (M=6.98, SD=1.99). The computed METs reveal that the Exergaming condition induces moderate physical activity levels (5.0 <METs<6.99 [30]) regardless of its difficulty level (Figure 5).

D. *Is user's movement intensity affected by game difficulty during Exergaming?*

The influence of game difficulty over movement intensity, measured as the KE, during the Exergame condition is shown in figure 6.

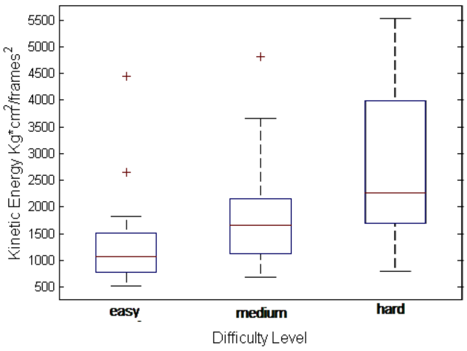

Figure 6. Boxplot of Kinetic energy for each difficulty level during Exergaming condition.

A Friedman test revealed that the difficulty level had a significant influence over KE, $\chi 2$ (2) = 12.87, p < .05. KE values were: M=1361, SD=959 in easy, M=1866, SD=1045 in medium and M=2766, SD=1381 in hard. A Wilcoxon test revealed significant pairwise differences in KE for easy-to-hard and medium-to-hard difficulties *T = 118, r = -2.5,T* = 128, *r* = -3.1, respectively.

E. *Questionnaires*

The usability of the videogame was rated as good (defined as SUS > 71.4 [46]) in both Control (M=78.2, SD = 14.7) and Exergaming (M=84.7, SD = 14,7). A Wilcoxon signed-rank test showed that the 5-point difference in favor of Exergaming was not significant. Subjects' ratings on distress as assessed by the SUDS was low for both Control (M=2.38, SD = 2.24) and Exergaming (M=2.33, SD = 2.34), and not significantly different. However, a Friedman test revealed that the difficulty level had a significant effect on the SUDS score: Control: $\chi^2(2) = 15.5$, p < .05 and Exergaming $\chi^2(2) = 19.8$, p < .05.

V. DISCUSSION

A. *Exergaming and skill-based protocols*

In our experiment, users started from a beginner difficulty level and progressed gradually to higher levels of difficulty. This approach allows the development of a sense of competency and mastery and it is aligned with past reported Exergaming experiments [47]. Our data reveals that the different difficulty settings had a different impact over game performance for Exergaming and Control conditions. More concretely, enhanced user performance was identified for the Exergaming condition. Moreover, the use of Exergames with simple game mechanics (such as the Exerpong) facilitates to carry out a causality analysis via matching physiological responses with specific and non-simultaneous game events.

B. *Rewards, punishments and skin conductance responses*

Our EDA analysis revealed higher arousal levels during Exergaming than control, showing a strong effect of positive feedback in GSRs [$GSR_{Index}(BI)$]. This finding is consistent with higher engagement levels and the reported increased performance. Some of the GSRs classified as *BI* (positive or rewarding) might come from misclassification of anticipatory responses due to the higher occurrence of events registered for the higher difficulty levels, and the higher level of attention required to perform the task. Movement artefacts could have also induced a false GSRs. However, movement artefacts would appear in both *BI* and *MB*, and therefore would have influenced also the computation of $GSR_{Index}(MB)$. Then, if this were the case, a balanced effect would be expected in Exergaming and Control condition, and this was not the case.

From the game designer perspective, higher number of GSRs can be interpreted as a positive finding because the elicitation of arousal responses is known to have a positive effect in sustaining motivation [21]. Further, some GSRs during the Exergaming condition could have been produced by normal sweating during physical training: However, this would not be sufficient to explain the effect of difficulty in $GSR_{Index}(MB)$. In fact, it seems like exercise affects the tonic phase of EDA signals more than the phasic phase [37].

C. HR modulations and HRV analysis in Exergaming interventions

To attain good levels of cardiorespiratory fitness, adults are recommended to exercise at an intensity of 60% of HR_{max} [30]. This can be reached by extending exercise practice (which could lead boredom), but also providing personalized dynamic difficulty approaches to encourage people to reach healthy and safe fitness goals during Exergaming experiences. Our analysis of the ECG data confirms that exercise levels and game parameters modulate cardiorespiratory responses. First, HR increased in response to increased difficulty levels in the Exergaming condition. Second, the HRV analysis elucidated significant effects for condition and not for difficulty. Thus, our results indicate that parasympathetic activity is modulated mainly by the game interface rather than difficulty. Lower values of SDNN may indicate low stress regulation, and may be linked with poor exercise performance [48]. Hence, the higher SDNN values measured during Exergaming show that exercise-related activities can improve the parasympathetic modulation in older adults. This modulation due to Exergaming can produce benefits such as reducing the sense of stress [48], strengthening the immune system, reducing blood pressure, enhance exercise recovery and lift the mood [41]. Including HRV assessment in Exergaming programs could improve exercise prescription, as it has been shown that HRV measurements are beneficial in exercise training prescription in moderately active men and women [48].

D. Physical activity assessed through Kinect and electrocardiography

EE results show that the intensity of physical activity was modulated by difficulty levels of Exerpong in the Exergaming condition. The METs analysis revealed that moderate physical activity levels, adequate for an older population, can be achieved through simple Exergames starting at very easy difficulties. From the KE quantification, we reported that users were more active during the hard difficulty compared to easy and medium. Consequently, we show that physical activity levels can be intentionally modulated by changing game parameters to reach specific fitness goals. Piana and colleagues [21] found that high KE mean/variances were associated with happiness while sadness was associated with low KE mean values but high variances. In addition, we observed that users with high competitive skills challenged themselves to be able to have high scores during the higher difficulty condition despite the fact that the game was designed to push them to the frustration.

E. Self-reported distress

In game user research it is important to complement psychophysiological measurements with subjective methodologies such as questionnaires or structured surveys [2]. Subjective data from the usability questionnaire shows that both interfaces were relatively easy and comfortable to use by the elderly, providing a good level of confidence and supporting the feasibility of implementing this technology in senior sport facilities. Besides, the distress questionnaire revealed low stress levels during both conditions, although modulated by game difficulty. This finding is consistent with the stress levels found with the analysis of the physiological responses.

VI. Conclusions

This paper describes an attempt to systematically study how physiological responses can be modulated through in-game parameters in an Exergaming experience. This work intends to improve the personalization of Exergames through physiologically-responsive strategies that could boost the health benefits produced in scenarios such as the promotion of active aging, rehabilitation and fitness. In this study, exercise intensities were strongly modulated by game difficulty levels, suggesting the feasibility of the dynamic adaptation of game parameters by analyzing user’s physiological responses. Furthermore, EDA analysis revealed that positive feedback was better at producing arousal responses. Hence, game designers can capitalize on this feature to create more affective-responsive games. Game difficulty also modified HR responses and a HRV analysis demonstrated that the interface (handheld or motion) had the strongest influence in the modulation of beat-to-beat heart’s behavior. These findings contribute towards a body of evidence to use psychophysiological methods to improve Exergaming adaptability.

VII. Future Work

In the future, we will implement and evaluate multiple adaptive rules for the Exerpong game based on the detection of psychophysiological states and the biomarkers identified in this paper. These rules will be implemented by computational models that will estimate the state of the user (e.g. fatigue, mental workload, distress) through descriptors such as SDNN or GSRs indexes [4]. These close-loop strategies will be evaluated in terms of enjoyment and fitness criteria, comparing several adaptive rules instead of use the classical conventional-novel approach as described in [16].

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