Heart Rate Variability in Exergaming
Feasibility and Benefits of Physiological Adaptation for Cardiorespiratory Training in Older Adults by Means of Smartwatches

J. E. Muñoz[1,2], E. R. Gouveia[1,3], M. S. Cameirão[1,2] and S. Bermúdez i Badia[1,2]
[1]*Madeira Interactive Technologies Institute, Universidade da Madeira, Funchal, Portugal*
[2]*Faculdade de Ciências Exatas e da Engenharia, Universidade da Madeira, Funchal, Portugal*
[3]*Faculdade de Ciências Sociais, Universidade da Madeira, Funchal, Portugal*

Keywords: Heart Rate Variability, Smartwatch, Exergaming, Biocybernetic Loops, Older Adults, Cardiorespiratory Fitness, Physiological Computing.

Abstract: Exergames are videogames that use physical movement to mediate player's interactions with digital contents. Multiple adaptation mechanisms have been used to enhance the effectiveness of employing Exergames to promote physical exercise. One of the most interesting strategies utilizes physiological signals to infer the status of player's cardiorespiratory responses and create real-time game adaptations. This strategy is called biocybernetic-adaptation and despite its promising potential, quantitative studies identifying measurable benefits are scarce. We developed a between-subjects study measuring the autonomic-cardiac regulation differences between conventional cardiorespiratory training methods and a physiologically modulated Exergame in a group of fifteen older adults. We used heart rate (HR) data measured through smartwatches and a floor-projection setup to encourage players to exert in targeted HR zones. We presented the analysis of the time users spent in the target zone and the Heart-Rate-Variability (HRV) in time and frequency domains during training sessions of 20 minutes length. Two time-domain (SDNN and RMSSD) and one frequency-domain (VLF) HRV parameters showed significant differences, revealing lower HRV values in the physiologically adaptive condition when compared with conventional training. Our data suggests that smartwatch technology can be accurate enough to assess HRV changes, and that a HR based physiologically adaptive Exergame induces less HRV.

1 INTRODUCTION

Exercise videogames (Exergames) have demonstrated their feasibility for being used to promote physical activity in the older population (Larsen et al., 2013). The inclusion of multiple techniques for adapting Exergames to the user's fitness profile has shown that this ludic way of working out can be structurally used as training programs (Hoffmann et al., 2014; Velazquez et al., 2017). Recent advances in human computer interaction, and specifically in the field of physiological computing, have permitted the use of biosignals to monitor and even influence the inner responses of Exergame's players (Stach et al., 2009). By means of this biocybernetic mechanism, cardiorespiratory signals such as heart rate (HR) or the respiration rate can be used to drive an intelligent adaptation of the system's difficulty, thus allowing a better adjustment to the recommended exertion levels (Ketcheson et al., 2015). Despite encouraging results of preliminary studies, the efficacy of such approach has rarely been compared with conventional training methods, therefore occluding the comparative and measurable benefits of this technology (Larsen et al., 2013).

Heart rate variability (HRV) has been widely recognized as a reliable tool to assess cardiac autonomic modulations. HRV covers a big set of measurements that describe the variations between instantaneous heart beats (Ernst, 2014). The use of HRV metrics to assess the effects of cardiorespiratory exercise has allowed a quantification of the associated cardiac benefits in the older population (Stein et al., 1999). HRV analysis can be a cornerstone in demonstrating the efficacy of physical exercise through Exergames. Particularly, in the assessment and quantification of effectiveness of novel

MuÃśoz J., Gouveia E., CameirÃčo M. and Badia S.
Heart Rate Variability in Exergaming - Feasibility and Benefits of Physiological Adaptation for Cardiorespiratory Training in Older Adults by Means of Smartwatches.
DOI: 10.5220/0006601401450150
In *Proceedings of the 5th International Congress on Sport Sciences Research and Technology Support (icSPORTS 2017)*, pages 145-150
ISBN: 978-989-758-269-1

adaptation mechanisms (Russoniello et al., 2013; Zavarize et al., 2016).

Even though the gold standard instrument for measuring HRV is the electrocardiograph (ECG), the use of novel wearable sensors such as smartwatches, wrist and chest bands, and headphones have been popularized as being surrogate of HRV. The main advantages of those sensors are the non-invasiveness, portability and low-cost (Parak and Korhonen, 2014). Several studies have compared the measurement reliability of the heart beats by means of wearable sensors versus ECG monitors during stationary and non-stationary conditions (Jo et al., 2016; Stahl et al., 2016). Results demonstrated that HRV measurements from wearable sensors can be used as an alternative for ECG in ambulatory situations.

The aim of this study was to investigate the autonomic HR regulation during a physiologically adaptive training session deployed through an Exergame. To that end, we relied on the HRV analysis from a smartwatch to explore the behavior of time and frequency domain markers and compared it against a conventional exercise routine in a group of fifteen seniors. Our analysis is mainly focused in the feasibility of using HRV from smartwatches to detect significant differences between both activities instead of analyzing the accuracy level of the HRV measurements.

2 MATERIALS AND METHODS

2.1 Subjects

Fifteen community-dwelling active older adults from a local gymnasium were recruited (11 females and 4 males ages 66 ± 7 years, height 1.60 ± 0.08 meters, weight 73.7 ± 14.8 Kg). Two users reported being medicated for high levels of blood pressure and two reported past heart-issues. All participants typically exerted twice per week at the senior gymnasium in sessions of 45 minutes length approximately. Cardiovascular parameters measured from the sample include HR during resting (HR_{rest} = 72.9 ± 12.9 BPMs), maximum HR (HR_{max} = 161.7 ± 4.7 BPMs) and maximum oxygen uptake (VO_{2max} = 34.5 ± 0.4 $ml*Kg^{-1}*min^{-1}$).

2.2 Experimental Setup

To assess the impact of the physiologically adaptive exercise training over the HRV markers, we carried out a comparative study following a between-subjects design. For that, we used a *Conventional training* condition as control and compared it with our *HR-adaptive training* approach. The workout for the *HR-adaptive training* condition length 20 minutes. Thus, we took only the first 20 minutes of the *Conventional* training to carry out the comparative analysis.

Conventional Training: This exercise was conducted by the physical activity instructors at the local senior gymnasium. The workout consisted in different routines including cardiorespiratory circuits, strength and balance exercises using sticks and weights as well as flexibility and stability training. Only the first 20 minutes of the exercise sessions were considered for the analysis.

HR-adaptive Training: To create a physiologically adaptive system based on real-time HR measurements, we developed a customizable Exergame. Our Exergame is an adaptation of the classic 2D pong, which challenges players to hit a ball using a virtual paddle. Our implementation uses a floor-projection setup that encourages players to perform lateral movements to reach the ball and destroy small blocks to earn points. The tracking of movements is achieved through the Kinect V2 sensor and represented in the Exergame with a virtual paddle. The setup is illustrated in figure 1.

Figure 1: Exercise videogame developed to test the physiological adaptation based on real-time measurements of HR. Adapted from (Muñoz et al., 2016).

The system uses the concept of target HR (Heyward and Gibson, 2014) to adapt the difficulty level of the Exergame via modifying the ball velocity as follows:

- *IF* the 30-seconds-average HR is lower than the target HR, *then* increase the difficulty (increase the ball velocity).
- *IF* the 30-seconds-average HR is higher than the target HR, *then* decrease the difficulty (decrease the ball velocity).

***Physiological Measurements**:* HR data was recorded using the Moto360 smartwatch, which uses an optical PPG (photopletysmography) sensor to internally compute the HR levels in beats-per-minute and stream the values to a mobile phone. By using a physiological computing framework (J.E. Muñoz et al., 2017), HR levels are streamed at 1 Hz to the Exergame and then used to compute the target HR and adapt the system in real-time. The time in the target HR zone (in minutes) was computed for each condition following the American College of Sports and Medicine (ACSM) recommendations for older adults meaning exert at 40% to 70 % of the HR reserve (Rahl, 2010).

HRV Analysis: HR data from the smartwatch were used to extract several HRV parameters using the PhysioLab software, a Matlab-based multimodal signal processing toolbox (Muñoz et al., 2017). HR data were converted to R-R intervals (in miliseconds) to carry out the HRV analysis. In the time domain, two parameters called the SDNN (standard deviation of NN intervals) and the RMSSD (root-mean-square standard deviation) were considered for the analysis. The HRV spectrum was computed using a Welch's power-spectral-density estimation with a Hanning window. Then, each frequency component was weighted using an area-under-the-curve approach as follows: high frequency (HF: 0.15-0.4 Hz), low frequency (LF: 0.04-0.15 Hz) and very low frequency (VLF: 0.003- 0.04 Hz). These HRV descriptors have been shown to be very effective in describing heart resilience and cardiac autonomic regulation, showing an overall increase in the indexes in response to exercise training (Stein et al., 1999).

2.3 Statistical Analysis

Data normality was assessed through the Kolmogorov-Smirnov test. When non-normal, data were analysed with non-parametric tests. A repeated measures ANOVA analysis was carried out to compare the HRV markers in both conditions. All statistical tests were analysed using SPSS (21.0, BPM Corp, Armonk, NY) with a significance level of 5%.

3 RESULTS

3.1 Time in the Target HR

Participants spent significant more number of minutes $F(1.0, 14) = 48.8$, $p < 0.05$ in the target HR zone for the HR-Adaptive condition (M=12.3, SD=7.7) once compared with the Conventional (M=4.4, SD=4.5).

3.2 HRV Analysis in the Time Domain

The time domain branch of the HRV analysis was assessed through the comparison of the SDNN and RMSSD for both the *Conventional* and the *HR-adaptive* workouts (see figure 2).

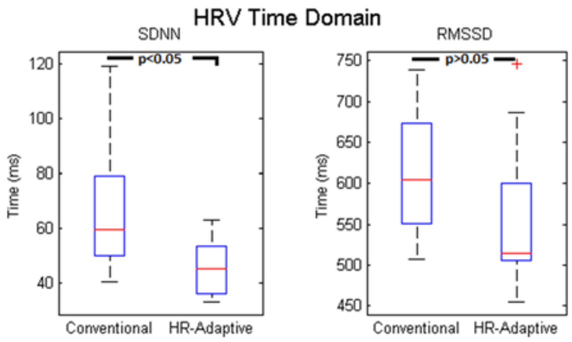

Figure 2: Boxplots for the SDNN and RMSSD parameters representing the time domain measurements of HRV for both *Conventional* and *HR-adaptive* conditions.

Participants showed lower values of SDNN and RMSSD parameters for the HR-adaptive condition (SDNN: M= 44.8, SD=9.6, RMSSD: M=559.2, SD=81.7) once compared with the Conventional (SDNN: M=67.6, SD=22.5, RMSSD: M=612.5, SD=73.1). The statistical analysis revealed that the difference was significant for the SDNN ($F(1.0, 14.0) = 21.8$, $p<0.05$, $r = 0.61$) and the RMSSD ($F(1.0, 14.0) = 6.8$, $p<0.05$, $r = 0.33$) values.

3.3 HRV Analysis in the Frequency Domain

The frequency domain branch of the HRV analysis was assessed using the high, low and very low components of the spectrum (see figure 3). A Friedman test revealed that the HR adaptation did not significantly affect the HF ($\chi^2(1)=3.2$), $p > 0.05$, nor any of the LF ($\chi^2(1)=3.2$) components of the HRV spectrum. Furthermore, the repeated measures ANOVA showed significant differences for the VLF component ($F(1.0, 14.0) = 26.5$, $p<0.05$, $r = 0.65$)

.

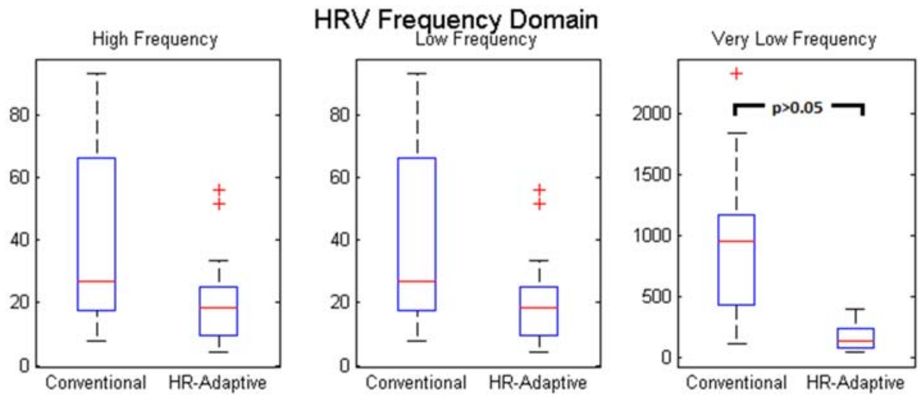

Figure 3: HRV analysis in the frequency branch represented by the high, low and very low components of the spectrum for both Conventional and HR-adaptive conditions.

4 DISCUSSION

In this study, we wanted to quantify the difference between exertions with a physiological adaptive strategy versus a conventional approach for cardiorespiratory training in a group of fifteen active older adults. Firstly, the analysis of the time spent in the target HR zone demonstrated the effectiveness of the adaptive strategy to engage users to exert in the desired levels. In the HR-adaptive condition, users were almost three times more minutes in the target HR zone once compared with conventional training approaches.

Secondly, time and frequency domain parameters of the HRV analysis revealed significant differences between the two approaches. Our results suggest that less HR variability might be desirable to provide safe and controlled scenarios for cardiorespiratory training in the aged population. The inspection of the time domain analysis revealed that both the RMSSD and the SDNN markers showed lower values for the HR-adaptive training compared to the conventional approach. Generally, increases of these variables have been associated with good levels of cardiac resilience and workload regulation (Kleiger et al., 2005). However, it is worth noticing that higher values of HRV do not necessarily translate into better physical or cognitive performances for all activities (Luque-Casado et al., 2013). For this reason, we emphasize that a more controlled cardiorespiratory training around the target HR zone might significantly reduce the risks associated with over-exercising in the older population. Consequently, HR behaviour outside this zone is not desirable. Conversely, low HRV values are expected from more controlled cardiorespiratory training pointing at avoiding accidents with sudden and/or abrupt changes in HR.

The frequency domain only reflected significant differences in the VLF component, maybe the major determinant of physical activity reflecting sympathetic activity (Ernst, 2014). It has been hypothesized that modifications in respiratory patterns could affect the modulations of the VLF component in the older population (Perini et al., 2000). Therefore, we believe that the low values of VLF due to the HR-adaptive condition may reflect the sustained body responses needed to maximize the time they exerted in the target HR zone. Moreover, from figure 3 one can observe that the data dispersion is much reduced in the HR-adaptive condition reinforcing our hypothesis: the less variability during the workout outside the target HR zone, the better.

Finally, one of the limitations in this study concerns the accuracy levels for the HRV analysis from the smartwatch data. Normally, wearable devices use optical sensors which are tagged as having low precision for measuring HR values. Nevertheless, investigations in HRV data from PPG sensors (also called pulse rate variability - PRV) suggest that there is not an important difference between both measurements during non-stationary conditions; therefore, PRV could be used as a surrogate of HRV (Gil et al., 2010) (Mike Prospero, 2016). This is also supported by our data that shows that smartwatch technology provides enough sensitivity to discriminate among conditions and perform an HRV analysis.

5 CONCLUSIONS

In this study, we demonstrated how smartwatch technology is a feasible tool to perform HRV analysis, and could be used to objectively assess the impact of physiologically adaptive training over the autonomic cardiac regulation in healthy older adults. Importantly, results demonstrate the effectiveness of using physiologically adaptive Exergames to maximize the time elders spent in the recommended exertion levels. Our findings also suggest a careful interpretation of HRV markers (time and frequency domain) during physical exercise, since it is not clear how or whether more variability can enhance training effectiveness. In contrast, we hypothesized that considering the recommended levels for cardiorespiratory training established for the older population, HR values should not display large changes but be confined in a controlled manner around the desirable target HR. Although this work is a first step in this direction, more studies are required to disentangle the role of HRV to support the cardiorespiratory training in older people.

ACKNOWLEDGEMENTS

Authors would like to thank the staff personnel of “Ginásio de Santo António - Funchal” for the collaboration during the experiment as well as the volunteers for the commitment with the procedure. Teresa Paulino for developing the Exergame, contributing in the development of the physiological computing system and the final integration of the system. This work was supported by the Portuguese Foundation for Science and Technology through the Augmented Human Assistance project (CMUP-ERI/HCI/0046/2013), Projeto Estratégico UID/EEA/50009/2013, and ARDITI (Agência Regional para o Desenvolvimento da Investigação, Tecnologia e Inovação).

REFERENCES

Ernst, G., 2014. Heart rate variability. Springer.

Gil, E., Orini, M., Bailón, R., Vergara, J.M., Mainardi, L., Laguna, P., 2010. Photoplethysmography pulse rate variability as a surrogate measurement of heart rate variability during non-stationary conditions. Physiol. Meas. 31, 1271. doi:10.1088/0967-3334/31/9/015.

Heyward, V.H., Gibson, A., 2014. Advanced Fitness Assessment and Exercise Prescription 7th Edition. Human Kinetics.

Hoffmann, K., Wiemeyer, J., Hardy, S., Göbel, S., 2014. Personalized adaptive control of training load in Exergames from a sport-scientific perspective, in: Games for Training, Education, Health and Sports. Springer, pp. 129–140.

J.E. Muñoz, E. Rubio, M. Cameirao, S. Bermúdez, 2017. The Biocybernetic Loop Engine: an Integrated Tool for Creating Physiologically Adaptive Videogames, in: 4th International Conference in Physiological Computing Systems. Presented at the PhyCS 2017, Madrid, España.

Jo, E., Lewis, K., Directo, D., Kim, M.J., Dolezal, B.A., 2016. Validation of biofeedback wearables for photoplethysmographic heart rate tracking. J. Sports Sci. Med. 15, 540.

Ketcheson, M., Ye, Z., Graham, T.C.N., 2015. Designing for Exertion: How Heart-Rate Power-ups Increase Physical Activity in Exergames, in: Proceedings of the 2015 Annual Symposium on Computer-Human Interaction in Play, CHI PLAY ’15. ACM, New York, NY, USA, pp. 79–89. doi:10.1145/2793107.2793122.

Kleiger, R.E., Stein, P.K., Bigger, J.T., 2005. Heart rate variability: measurement and clinical utility. Ann. Noninvasive Electrocardiol. 10, 88–101.

Larsen, L.H., Schou, L., Lund, H.H., Langberg, H., 2013. The Physical Effect of Exergames in Healthy Elderly—A Systematic Review. Games Health J. 2, 205–212. doi:10.1089/g4h.2013.0036.

Luque-Casado, A., Zabala, M., Morales, E., Mateo-March, M., Sanabria, D., 2013. Cognitive performance and heart rate variability: the influence of fitness level. PLoS One 8, e56935.

Mike Prospero, 2016. Who Has The Most Accurate Heart Rate Monitor? Tomsguide.

Muñoz J.E., Bermudez S., Rubio E., Cameirao M., 2016. Modulation of Physiological Responses and Activity Levels During Exergame Experiences, in: 2016 18th International Conference on Virtual Worlds and Games for Serious Applications. IEEE, p. In press.

Muñoz, J.E., Gouveia, E.R., Cameirão, M.S., i Badia, S.B., 2017. PhysioLab-a multivariate physiological computing toolbox for ECG, EMG and EDA signals: a case of study of cardiorespiratory fitness assessment in the elderly population. Multimed. Tools Appl. 1–26.

Parak, J., Korhonen, I., 2014. Evaluation of wearable consumer heart rate monitors based on photopletysmography, in: Engineering in Medicine and Biology Society (EMBC), 2014 36th Annual International Conference of the IEEE. IEEE, pp. 3670–3673.

Perini, R., Milesi, S., Fisher, N.M., Pendergast, D.R., Veicsteinas, A., 2000. Heart rate variability during dynamic exercise in elderly males and females. Eur. J. Appl. Physiol. 82, 8–15.

Rahl, R.L., 2010. Physical activity and health guidelines. Recomm. Var. Ages Fit. Levels Cond. From 57.

Russoniello, C.V., Zhirnov, Y.N., Pougatchev, V.I., Gribkov, E.N., 2013. Heart rate variability and biological age: Implications for health and gaming. Cyberpsychology Behav. Soc. Netw. 16, 302–308.

Stach, T., Graham, T.C., Yim, J., Rhodes, R.E., 2009. Heart rate control of exercise video games, in: Proceedings of Graphics Interface 2009. Canadian Information Processing Society, pp. 125–132.

Stahl, S.E., An, H.-S., Dinkel, D.M., Noble, J.M., Lee, J.-M., 2016. How accurate are the wrist-based heart rate monitors during walking and running activities? Are they accurate enough? BMJ Open Sport Exerc. Med. 2, e000106.

Stein, P.K., Ehsani, A.A., Domitrovich, P.P., Kleiger, R.E., Rottman, J.N., 1999. Effect of exercise training on heart rate variability in healthy older adults. Am. Heart J. 138, 567–576.

Velazquez, A., Martínez-García, A.I., Favela, J., Ochoa, S.F., 2017. Adaptive exergames to support active aging: An action research study. Pervasive Mob. Comput. 34, 60–78.

Zavarize, S.F., Paschoal, M.A., Wechsler, S.M., 2016. Effects of physiotherapy associated to virtual games in pain perception and heart rate variability in cases of low back pain. Man. Ther. Posturology Rehabil. J. Rev. Man. Ther. 14.