Remote Monitoring of Biomedical Signal

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Abstract

The remote monitoring of the biomedical signal is an important tool for assessing the quality of life, control and prevention of diseases. In this research, we developed and validated a remote monitoring system for prevention and health promotion. The system architecture is composed of 3 main modules: a) interface for recording food intake and monitoring physical activity and heart rate frequency by a mobile application; b) interface for insert anthropometric assessment data of patient; c) web interface where all data is remotely shown through reports with information that can assist in preventive health actions. The study involved 70 children aged between 8 and 12 years. They were monitored for 4 months by the app installed in the children's own smartphones. Significant differences were observed in the frequency domain and nonlinear heart rate variability variables between each anthropometric group. Moreover, within the same group, there were also differences between night-morning and afternoon/evening time. Being the biggest variation in the frequency domain parameters during afternoon/evening time for the obese group.

1. Introduction

Problems in accessing health services currently represent one of the most important social and economic challenges faced by many countries around the world [1]. The main cause of this great problem has related mainly to the increase in the number of cases of chronic diseases associated with the lifestyle of modern society [2]. Risk behaviors in childhood, such as sedentary lifestyle and poor diet can cause cardiovascular diseases, diabetes, obesity, among others [3].

Considered one of the great public health problems of the 21st century [4], childhood obesity has affected currently an important share of the worldwide population [5]. It is estimated that approximately 2.8 million people die each year as a result of being overweight or obese [6]. The obesity can lead to adverse metabolic effects on blood pressure and cholesterol, which ultimately increases the risks of ischemic stroke and coronary heart disease [7]. According to WHO, it has been estimated that the heart disease rate might increase to 23.3% worldwide by the year 2030 [8]

The obesity is related to abdominal fat, autonomic imbalance and risk of cardiovascular disease [9]. The increase in the amount of total fat and the fat concentration in the trunk present a reduction in the autonomic modulation of the heart rate variability (HRV), evaluated by signal processing methods applied to the electrocardiogram patient monitoring [10]. Understanding the complex factors contributing to the growing childhood obesity epidemic is vital, not only for the improved health of the world's future generations, but for the healthcare system [11].

Integrating health remote monitoring to current smartphones has great potential to favor health teams in evidence-based prevention actions [12]. In this context, this research presents a remote monitoring system that use the smartphone to monitor cardiovascular risk factors on children diagnosed as being overweight and obese.

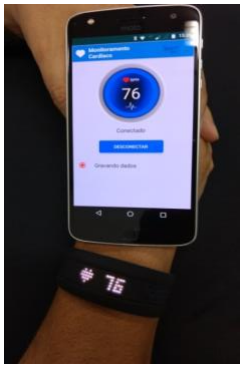
2. Material and Methods

FLEEM is an acronym that stands for Free-Living Energy Expenditure Monitoring System. The first version of the system was developed in a partnership between Mogi das Cruzes University and São Paulo University in 2013 [13], [14]. An improved version of the system was developed for biomedical data monitoring for prevention healthcare [15]. The current architecture of the system is composed of an application mobile for data acquisition of patients, a module designed to and physiological evaluations from the users performed by a multidisciplinary team in healthcare, and an integrated web-platform for data storage and analysis (figure 1).

Figure 1. FLEEM System. Remote monitoring of biomedical signal

The application mobile FLEEM has functions that allow users (patients) to record daily food intake and physical activities. It also enables the monitoring of daily activities and Heart Rate (HR) using sensors. The activity movements of the users are recorded by a smartphone equipped with an embedded accelerometer for daily intensity measurement of physical activity. The heart rate is measured using a monitoring fitbit bracelet called Miolink. The bracelet has an optical sensor that captures heartbeats and transmits HR data in synchronous time to the mobile device by Bluetooth connection. The mobile application FLEEM registers HR data and heartbeats period. This information is stored in the mobile device database for later transfer to the database of the web platform when the internet connection is established. For data transmission between the smartphone and the fitbit, it was implemented an algorithm of Bluetooth Light Energy 4.0 communication protocol. The heart rate monitoring screen of the mobile application FLEEM and the Miolink sensor are shown in figure 2.

Figure 2. Screenshot of mobile application FLEEN and Miolink sensor



2.1. User Testing

In the study, 70 volunteers of both genders participated, aged 8 to 12 years, all of them enrolled in public schools in the city of Monteiro Lobato, State of São Paulo. They used the mobile application FLEEM for a period of 4 months. The HR of volunteers were monitored in the periods: mornings, afternoons and evenings for 10 minutes. Volunteers underwent an initial assessment, including anthropometric and physiologic measurements. The BMI (body/mass index), parameter adopted by the World Health Organization (WHO) to calculate the ideal weight of each person was used to classify 26 volunteers in groups of eutrophics (n = 6), overweight (n = 11), obese (n = 9).

2.1. Heart Rate Variability Analysis

Based on the measured heart rate data, HRV analysis was performed on the Fleem web platform. Linear (time and frequency domain) and nonlinear (kurtosis, Poincare (SD1 / SD2) and sample entropy) signal processing techniques were applied for the analyzed HRV [10], [16]–[19]. The computational algorithm of HRV analysis was developed in accordance with the recommendations of the European Society of Cardiology and the American Electrophysiology Patient Society [20].

Heart Rate Variability is a measure which indicates the variation in your heartbeats within a specific timeframe [18]. The normal clinical features of the electrocardiogram include the complex QRS which reflects the depolarization of the ventricles. Within the QRS complex, the peak R has the most prominent amplitude and is commonly tracked on medical equipment for HR monitoring. With Miolink sensor, the heartbeats are analyzed with PPG (photoplethysmography). In the PPG signal, it's the steepest increase in the signal prior to the peak that marks a heartbeat. Instead of R-R intervals, we measure interbeat intervals or IBIs.

The Miolink sensor acquires the individuals' HR per second and transmits it to the FLEEM System app. The interval between beats (in seconds) is the raw measurement used to quantify HRV and was obtained inversely (HR/60), since HR is shown in BPM. Once the distance (in seconds) between two beats is calculated in a certain instant, the next HR sent by the sensor allows estimation of the distance (in seconds) between the current beat and the next beat (or R peak). It is done recursively, and a surrogated vector is reconstructed allowing the identification of the time position of the R-peaks and the intervals between beats. It is followed by calculating the R to R intervals (RR) through the time difference between a sequence of two beats (time position of the current beat minus the time position of the previous beat). The pre-processing ends by resampling the RR vector at 4 Hz with a cubic spline to obtain equally spaced data to be used for standard HRV spectral analysis [21]

3. Results

Tables 1-3 show the HRV analysis between periods: night-time, day-time and evening-time. Significant

differences (p <0.05 - *) were observed in the frequency domain and nonlinear HRV variables between each anthropometric group and in relation to the considered period. As shown in table 1, the characteristic metrics of the time domain; maxNN, SDNN, RMSSD and NN50 have p <0.05 for the Anova One-Way test. The Bom-Ferroni test showed significant differences between the groups of overweight and obese children compared to the group of eutrophic children

Table 1. HRV analysis in the time-domain

Variable	p Anova One-Way	p Pos-Hoc Bom Ferroni
meanHR	0.6410	> 0.05
meanNN	0.4570	> 0.05
minNN	0.2290	> 0.05
maxNN SDNN	0.0414* 0.0300*	0.04* (Overweight vs Obese) 0.03* (Eutrop. vs Overweight); 0.02* (Overweight vs Obese)
RMSSD	0.0150*	0.041* (Eutrophic vs Obese); 0.019* (Overweight vs Obese)
NN50	0.0150*	0.045* (Eutrophic vs Obese); 0.019* (Overweight vs Obese)
pNN50	0.1240	> 0.05

On the other hand, almost all the frequency domain variable characteristics of each group (see table 2) show significant differences between the different periods, except for the variable "ULF".

Table 2. HRV analysis in the frecuency-domain

Variable	p Anova One-Way	p Pos-Hoc Bom Ferroni
log(ULF)	0.2790	> 0.05
log(VLF)	0.0210*	0.027* (Eutro. vs Overweight)
log(LF)	0.0430*	0.037* (Eutrophic vs Obese); 0.041* (Overw. vs Obese)
log(HF) ratio LF-HF	0.0090*	0.04* (Overweight vs Obese) 0.03* (Eutrophic vs Obese); 0.009* (Overw. vs Obese)

Poincaré characteristic variables, in turn, showed significant differences in the SD1 and SD1-SD2 ratios and, in both post-Bom-Ferroni tests, showed significant differences between overweight and obese (table 3).

Table 3. Poincaré plot indexes of HRV

Variable	p Anova One-Way	p Pos-Hoc Bom Ferroni
SD1	0.0490*	0.041* (Overweight vs Obese)
SD2	0.4400	> 0.05
ratio SD1 - SD2	0.0350*	0.031* (Overweight vs Obese)

4. Discussion

In the contemporary setting in which traditional health services and processes are undergoing major transformations to meet present and future needs, we have developed a new remote monitoring system for preventive health care. With the Fleem system, it was possible to remotely monitor the HRV of 26 children which have been previously classified according to their anthropometric characteristics measurements (eutrophic, overweight and obese).

The results show that some parameters of the HRV are characteristic of each anthropometric group. This means that alterations in the body composition in an individual contribute to the regulation of heartbeats by overloading the activity of the sympathetic/parasympathetic system, be it during the day, afternoon or night [22]. Some studies have shown that indicators of abdominal obesity correlate better with high coronary risk than BMI [23], [24].

5. Conclusion

This research shows that the described online, low-cost and affordable tool is reliable for remote monitoring. The implementation of the monitoring system over 4 months provided a wealth of information, including parameters in the time domain, frequency domain and the nonlinear parameters of the HRV of children diagnosed as being overweight and obese. The results obtained through monitoring are a rich source of knowledge that can assist in clinical and technological research, as well as generate important information for planning public health policy actions.

Acknowledgments

Funding for this project was obtained from the Sao Paulo Research Foundation (Brazil) FAPESP (grant #2015/50064-0 and #2017/0988-1), University of Mogi das Cruzes (UMC) and Coordination of Improvement of Higher Level Personnel (CAPES). The authors are grateful to all contributors to this study.

References

1. Aceto G, Persico V, Pescapé A. The role of Information and Communication Technologies in healthcare: taxonomies, perspectives, and challenges. J Netw Comput Appl [Internet]. 2018;107(July 2017):125–54. Available from: http://dx.doi.org/10.1016/j.jnca.2018.02.008
2. Yach D, Hawkes C, Gould CL, Hofman KJ. The global burden of chronic diseases: Overcoming impediments to prevention and control. J Am Med Assoc [Internet]. 2004 Jun 2;291(21):2616–22. Available from: http://jama.jamanetwork.com/article.aspx?articleid=198852
3. WHO. Global recommendations on physical activity for health. Geneva; 2010.
4. [WHO] WHO. Obesity and overweight. [Internet]. Geneva: WHO. 2018 [cited 2018 Oct 23]. Available from: http://www.who.int/en/news-room/fact-sheets/detail/obesity-and-overweight
5. Who WHO. Consideration of the evidence on childhood obesity for the Commission on Ending Childhood Obesity: Report of the Ad hoc Working Group on Science and Evidence for Ending Childhood Obesity. World Heal Organ. 2016;219.
6. WHO. Global Health Risks: Mortality and Burden of Disease Attributable to Selected Major Risks. Geneva, Switzerland; 2009.
7. Díaz-Hellín P, Fontecha J, Hervás R, Bravo J. NFC as a Childhood Obesity Treatment Tool. J Med Syst [Internet]. 2015 Sep 8;39(9):96. Available from: http://link.springer.com/10.1007/s10916-015-0299-y
8. Deaton C, Froelicher ES, Wuc LH, Hod C, Shishani K, Jaarsma T. The Global Burden of Cardiovascular Disease in Women. Curr Treat Options Cardiovasc Med [Internet]. 2018 Oct 27;20(10):81. Available from: http://link.springer.com/10.1007/s11936-018-0676-1
9. World Health Organization. WHO | What is overweight and obesity? [Internet]. Who. 2012 [cited 2018 Oct 23]. Available from: http://www.who.int/dietphysicalactivity/childhood_what/en/index.html
10. Camm AJ, Malik M, Bigger JT, Breithardt G, Cerutti S, Cohen RJ, et al. Heart rate variability: standards of measurement, physiological interpretation and clinical use. Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. 1996;
11. Kozlovszky M, Karoczkai K, Jokai B, Ruda B, Kacsuk D, Meixner Z. Children obesity treatment support with telemedicine. 2014 37th Int Conv Inf Commun Technol Electron Microelectron MIPRO 2014 - Proc. 2014;(May):275–8.
12. Silva BMC, Rodrigues JJPC, de la Torre Díez I, López-Coronado M, Saleem K. Mobile-health: A review of current state in 2015. J Biomed Inform [Internet]. 2015 Aug;56:265–72. Available from: http://dx.doi.org/10.1016/j.jbi.2015.06.003
13. Lopez LJR, Goroso DG. Monitoring System of Assessment of Energy Expenditure to Human in Free-living Condition by Mean of Information and Communication Technologies. Proc Med-e-Tel, Luxemb. 2010;550–5.
14. Ramires Lopes LJ. Modelo para quantificar o gasto energético humano desenvolvido em plataforma android. University of Mogi das Cruzes; 2012.
15. Pereira da Silva D, A. S. Bissaco M, Rodrigues da Silva R, Gustavo Goroso D. Desenvolvimento de sistema e-health para prevenção e assistência à saúde. In: Anais do 9º Congresso Brasileiro de Telemedicina e Telessaúde - CBTms [Internet]. São Paulo, São Paulo: Even3; 2019. p. 1–21. Available from: https://www.even3.com.br/anais/cbtms9/145137
16. ChuDuc H, NguyenPhan K, NguyenViet D. A Review of Heart Rate Variability and its Applications. APCBEE Procedia [Internet]. 2013;7:80–5. Available from: http://www.sciencedirect.com/science/article/pii/S2212670813001188%5Cnhttp://www.sciencedirect.com/science/article/pii/S2212670813001188/pdf?md5=77816f79df35f7c66aca7e983d247b24&pid=1-s2.0-S2212670813001188-main.pdf
17. Electrophysiology TF of the ES. Heart Rate Variability. Circulation [Internet]. 1996 Mar;93(5):1043–65. Available from: https://www.ahajournals.org/doi/10.1161/01.CIR.93.5.1043
18. Shaffer F, Ginsberg JP. An Overview of Heart Rate Variability Metrics and Norms. Front Public Heal [Internet]. 2017 Sep 28;5(September):258. Available from: http://journal.frontiersin.org/article/10.3389/fpubh.2017.00258/full
19. Corrales MM, Torres B de la C, Esquivel AG, Salazar MAG, Naranjo Orellana J. Normal values of heart rate variability at rest in a young, healthy and active Mexican population. Health (Irvine Calif) [Internet]. 2012;04(07):377–85. Available from: http://www.scirp.org/journal/doi.aspx?DOI=10.4236/health.2012.47060
20. Force T, Society E, North T, Society A. Guidelines Heart rate variability. 1996;354–81.
21. Bartels R, Neumamm L, Peçanha T, Carvalho ARS. SinusCor: An advanced tool for heart rate variability analysis. Biomed Eng Online. 2017;16(1):1–15.
22. Graves L, Garnett SP, Cowell CT, Baur LA, Ness A, Sattar N, et al. Waist-to-height ratio and cardiometabolic risk factors in adolescence: Findings from a prospective birth cohort. Pediatr Obes. 2014;9(5):327–38.
23. Nyamdorj R, Qiao Q, Söderberg S, Pitkäniemi JM, Zimmet PZ, Shaw JE, et al. BMI compared with central obesity indicators as a predictor of diabetes incidence in mauritius. Obesity. 2009;17(2):342–8.
24. Nyamdorj R, Qiao Q, Lam TH, Tuomilehto J, Ho SY, Pitkäniemi J, et al. BMI compared with central obesity indicators in relation to diabetes and hypertension in Asians. Obesity. 2008;16(7):1622–35.

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