Biomedical Signal Processing and Control 42 (2018) 145–157

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Heart rate variability analysis using neural network models for automatic detection of lifestyle activities

Sarah Christina Matta[a], Ziad Sankari[b], Sandy Rihana[a,*]

[a] Faculty of Biomedical Engineering, The Holy Spirit University of Kaslik, USEK, Kaslik Campus, Jounieh, Mount Lebanon, Lebanon
[b] CardioDiagnostics SAL, R&D Medical Company, Dbayeh, Lebanon

ARTICLE INFO

Article history:
Received 20 April 2017
Received in revised form 6 January 2018
Accepted 27 January 2018

Keywords:
Heart rate variability
Artificial neural network
Activity recognition
Classification
ROC
Confusion matrix

ABSTRACT

The quality of life and individual well-being are crucial factors in disease prevention. Particularly, healthy lifestyle lessens the risk and occurrence of main diseases, such as cardiovascular diseases and metabolic disorders. Since a patient has an active role in being a co-producer of his/her health, innovative devices and technologies have been devoted to helping folks in self-evaluation and expected to play a key role to maintain their well-being. In this work, we present a very promising assessment tool for health, Heart Rate Variability (HRV). HRV is the difference in time between one heartbeat and the next. HRV measurement is simple and non-invasive, it is derived from recording of electrocardiogram (ECG) on free-moving subjects. The main aim of this work is to investigate the dynamics in the autonomic regulation of the heart rate by using frequency and temporal analysis to correlate between the HRV and these physiological patterns.

In addition to the applied frequency and temporal analyses, pattern recognition is also accomplished using Neural Networks which are further implemented and explored in this work. In the first place, the detection of the sleep/awake states is achieved. Next, a multiclassification of different types of activities such as sleeping, walking, exercising and eating is performed.

© 2018 Elsevier Ltd. All rights reserved.

1. Introduction

“Health should be defined as a state of complete physical, mental and social well-being, and not merely as the absence of disease and infirmity”, according to the World Health Organization. This is even marked by the role of lifestyle in illness risk. For instance, the risk of developing non-communicable diseases (NCD) which are leading causes of morbidity and mortality can be reduced by acting on lifestyle activities such as diet, physical activity and sleep. Thus, lifestyle interventions become a core factor in disease prevention. Furthermore, the development of innovative technologies for individual self-assessment is a very promising path towards the implementation of modern and effective solutions in disease prevention [1].

In this work, we focus on Heart Rate Variability (HRV). HRV primarily depends on the extrinsic regulation of the heart rate and so is believed to reveal the heart’s ability to detect and rapidly adjust to promptly varying stimuli. HRV mirrors the autonomic stability between the sympathetic and parasympathetic nervous systems [2]. In fact, the Autonomic Nervous System (ANS) is a part of the nervous system that non-voluntarily controls all organs and systems in the body [3]. The ANS is composed of two subsystems of distinct neural pathways: the Sympathetic Nervous System (SNS) and the Parasympathetic Nervous System (PNS) [4].

Although some internal organs are innervated by only one type of subsystems, either parasympathetic or sympathetic pathways, the heart is characterized by being dually innervated by both subsystems [5]. In fact, the main initiator of the electrical impulses is the Sinoatrial node (SA node) which is referred to as the pacemaker of the heart. The beat generated from the SA node is called the sinus beat [6]. In contrast, disturbances due to the abnormal impulse generation or abnormal impulse conduction result in non-sinus beats [7].

The SA node generates impulses about 100–120 times at rest. Nevertheless, in healthy subjects resting heart rate is not commonly that high. This is due to the continuous control of the ANS over the output of SA node activity [3]. The SA node receives the neural impulses from the ANS [5]. Therefore, SA node is regulated by the ANS (both SNS and PNS), and consequently the heart’s electrical activity is the result of the PNS and SNS regulation. Assessments of autonomic function reflects the ability of this system to stimulate the SA node [7].

* Corresponding author at: Department of Biomedical Engineering, Faculty of Engineering, Holy Spirit University of Kaslik, Kaslik Campus, Jounieh, Lebanon.
E-mail address: sandyrihana@usek.edu.lb (S. Rihana).

https://doi.org/10.1016/j.bspc.2018.01.016
1746-8094/© 2018 Elsevier Ltd. All rights reserved.

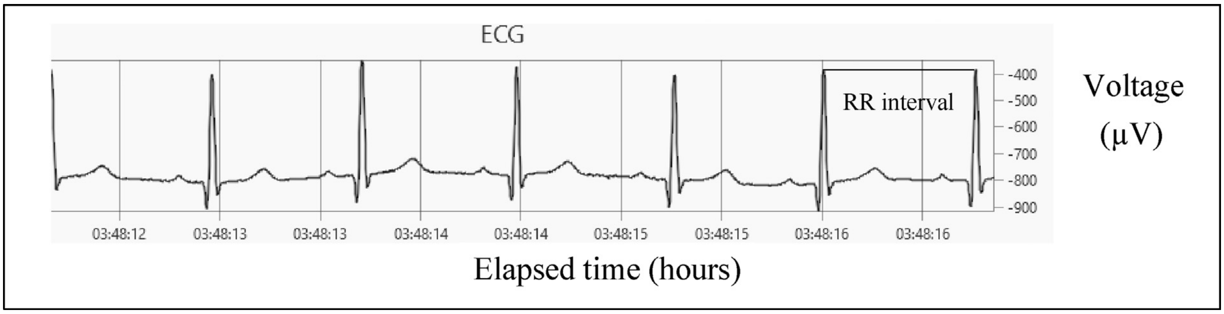

Fig. 1. ECG signal that illustrates beat to beat variability in RR interval.

The duration of a cardiac cycle can be measured by the RR interval from the ECG because the R peaks are the easiest to detect in the ECG signal as illustrated in Fig. 1 [8]. The control of the HR is modulated by both SNS and PNS branches of ANS. The PNS regulates the heart functions rapidly. In contrast, the SNS regulates the heart functions slower [8]. The ANS is therefore responsible for changing the duration of RR interval from one beat to another. This phenomenon is called Heart Rate Variability (HRV) [9].

HRV is an efficient measure of overall health and is considered to be an important marker of physiological and pathological conditions. Hence, this makes HRV analysis a window to the ANS state that can be used for biofeedback purposes [2]. This is usually performed using software such as eMotion HRV Scanner software which offers analysis and reports of HRV measurement from ECG signal up to 5 days. In addition, to facilitate the evaluation and recognition of the causes for fluctuations in HRV, there is an option of eMotion HRV with 3-axis accelerometer with sampling frequency of 10 Hz for each axis. This option makes it possible to see the person's physical activity during measurement which helps making the conclusions based on the measured and analyzed data [10].

One more type of existing industrial HRV applications is Firstbeat Lifestyle Assessment software [8]. Firstbeat Technologies has developed this software for analyzing the health of employees in real life. In order to achieve this, first, the ECG is acquired using Firstbeat Bodyguard device 2 that utilizes two electrodes. During acquisition, the subject is asked to keep a diary of their actions over 3 days. Then, HRV measurement is analyzed by Firstbeat Lifestyle software. Report which includes stress, recovery and physical activity is delivered to the subject [8].

Moreover, HRV technology has shown a growing interest in displaying real time information for biofeedback by gathering the HRV information and processing them using a smartphone. For instance, SweetWater Health™ has developed SweetBeat HRV application, in which the data is acquired using a Bluetooth low energy chest strap heart rate monitors [11]. SweetBeat offered the ability to track heart rate variability (HRV) and heart rate recovery (HRR) to assess readiness for exercise, stress levels, determine food allergies, and even detect underlying chronic health issues [12].

All these applications suggest that a possible correlation may be made between HRV and different activities such as sleeping, sitting, walking, exercising and eating.

Sleep is one of the most important recovery mechanisms, allowing recovery from daily stress and strains. During recovery, the body is in a relaxed state and parasympathetic activity is dominating [13]. The autonomic cardiovascular modulation is different during day and night periods [14]. HRV is perceived to quantify this modulation. Bonnemeier et al., [15] have investigated 166 healthy volunteers (81 women and 85 men; age 42 ± 15 years, range 20–70) without evidence of cardiac disease. They have shown that estimates of overall HRV (geometric triangular index, standard deviation of Normal to Normal intervals) and long-term components of HRV (Standard deviation of the averages of normal to normal intervals for all 5-min segments) were low at nighttime and increased in the morning hours [15]. Similarly, Ramaekers et al., [16] already reported a significant difference between day and night HRV, reflecting a higher vagal modulation during the night. Some HRV parameters are derived from frequency, temporal and nonlinear methods. Steven Vandeput [14] has shown that there is a significant difference between day-night values of these parameters. For example, HR was significantly lower during the night [14].

Rajendra presented the time, frequency and nonlinear measures of HRV at two different physical postures (sitting and lying). The statistical analysis yielded a significant difference between these parameters in the two postures. He showed that the HRV becomes greater when the subject changes his posture from sitting position to the lying position. In the sitting position, the HR increases because more effort is involved. In contrast, in the lying position, the decrease in the blood pressure resulted in a lower HR [17].

There is a wide interest in studying the effect of exercise training on HRV, and the link between over-training and the ANS. During walking and exercising, the HR increases due to both a parasympathetic withdrawal and an augmented sympathetic activity [18]. Jeong et al., [19] have developed classification algorithm using stepwise statistical analysis and canonical discriminant functions to recognize the level of exercise: rest, exercise, recovery. Rest corresponds to the period that preceded the exercise. In contrast, recovery relates to the period that followed the exercise. They compared HRV time domain parameters, HRV frequency domain parameters and combined HRV time and frequency parameters. Among the temporal HRV parameters used: mean of RR intervals, standard deviation of RR, number of RR interval that differ more than 50 ms and baseline width of RR interval histogram. Among the frequency domain HRV parameters: absolute power of very low frequency and low frequency bands, ratio between low frequency and high frequency bands for fast Fourier transform spectrum estimation method, peak frequency of very low frequency band for auto regression spectrum estimation method. Classification evaluation was done using sensitivity, specificity, accuracy, and leave-one–out cross validation. They showed that combining time domain and frequency domain HRV parameters improves classification accuracy. The comparisons among the discriminant analysis demonstrated that using both parameters give the highest overall accuracy of 95.6%. However, this study was limited by the small size of data (only 5 volunteers) [19].

Energy intake and eating behavior has austere effect on the health state [20]. It is an indicator of well-being, energy level and overall health [21]. The ANS activity is affected by the key stimulus of food intake. Sebastian Päßler et al. [20] have validated the use of HRV analysis during food intake by evaluating the time and frequency HRV parameters before, during and after eating. The result

Download English Version:

https://daneshyari.com/en/article/6950900

Download Persian Version:

https://daneshyari.com/article/6950900

Daneshyari.com