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PUPILHEART HEART RATE VARIABILITY MONITORING FLUCTIONS ON MOBILE DEVICES

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ABSTRACT

Heart disease has now become a very common and impactful disease, which can actually be easily avoided if treatment is intervened at an early stage. Thus, daily monitoring of heart health has become increasingly important. Existing mobile heart monitoring systems are mainly based on seismocardiography (SCG) or photo plethysmography (PPG). However, these methods suffer from inconvenience and additional equipment requirements, preventing people from monitoring their hearts in any place at any time. Inspired by our observation of the correlation between pupil size and heart rate varaiability (HRV), we consider using the pupillary response when a user unlocks his/her phone using facial recognition to infer the user's HRV during this time, thus enabling heart monitoring. To this end, we propose a computer vision-based mobile HRV monitoring framework-PupilHeart, designed with a mobile terminal and a server side. On the mobile terminal, PupilHeart collects pupil size change information from users when unlocking their phones through the front-facing camera. Then, the raw pupil size data is pre-processed on the server side. Specifically, PupilHeart uses a one-dimensional convolutional neural network (1D-CNN) to identify time series features associated with HRV. In addition, PupilHeart trains a recurrent neural network (RNN) with three hidden layers to model pupil and HRV. Employing this model, PupilHeart infers users' HRV to obtain their heart condition each time they unlock their phones. We prototype PupilHeart and conduct both experiments and field studies to fully evaluate effectiveness of PupilHeart by recruiting 60 volunteers. The overall results show that PupilHeart can accurately predict the user's HRV.

INTRODUCTION

H EART is the most important organ of the human body, pumping blood to tissues and organs throughout the body and maintaining normal metabolism [1]. Heart disease can bring significant impacts on the safety of human life. According to the World Health Organization (WHO), about 17.5 million people die of heart disease each year, accounting for 30% of mortality [2]. Therefore, monitoring heart health in one's everyday life is of great importance to human beings. A typical indicator used to evaluate heart health is heart rate variability (HRV) [3], [4], also known as heart rate volatility, which is simply a measure of the variation in time between each heartbeat [5]. On the other hand, it also contains the implicit information on the regulation of cardiovascular system by neuro-humoral factors, and thus can be used to diagnose or prevent cardiovascular and other diseases. Moreover, according to [6], measurements of HRV and the quantification of its spectral components are powerful predictors of cardiovascular morbidity and mortality. Therefore, it may help assess the return to work of patients with ischemic heart disease.

Clinical analysis of HRV can reflect activity and balance of the cardiac autonomic nervous system (ANS) and related pathological states, etc [7]. In general, low HRV is considered a sign of current or future health problems because it shows your body is less resilient and struggles to handle changing situations. It's also more common in people who have higher resting heart rates. Thats because when your heart is beating faster, theres less time between beats, reducing the opportunity for variability. This is often the case with conditions like diabetes, high blood pressure, heart arrhythmia, asthma, anxiety and depression.

In other words, heart health monitoring can be achieved by monitoring HRV. Currently, there are two main categories of heart rate monitoring systems: medical and consumer heart rate monitors [8]. Medical heart rate monitors used in hospitals are usually wired and use multiple sensors, such as commonly used electrocardiogram machines in hospitals [9]. Meanwhile, portable medical devices also have been developed, which are called Holter monitors [10]. On the other hand, consumer heart rate monitors are designed for everyday use and are wireless. Specifically, there are two types of consumer heart rate monitors: electrical-based and optical-based [11]. The electrical monitors consist of two parts: a monitor/transmitter worn on a chest strap, and a receiver.

When a heartbeat is detected, a radio signal is transmitted, which is used by the receiver to display/determine the current heart rate [4], [12]. Instead, the optical-based heart monitoring system measure IEEE Internet of Things and Deep Learning,Volume:10,Issue:20,Issue Date:15.October.2023 2 the heart rate by shining light from an LED light across the skin and evaluating how it scatters off blood vessels, such as the popular smart watches [13], [14]. However, all these existing methods either require professional guidance or additional equipment, which is inconvenient for daily heart rate monitoring and increases cost of devices. In this context, we raise a question: can we monitor users' HRVs through some daily activities and without additional equipment and professional guidance? Recent studies have shown that both pupils and heartbeat are controlled by same nerves, i.e. sympathetic and parasympathetic nerves [15], [16]. Thus changes in the pupil are correlated with variations in the heartbeat. For example, when a person is frightened, the sympathetic nerve strengthens while the parasympathetic nerve weakens, resulting in a faster heartbeat and a smaller pupil diameter.

Based on this principle, we explore the quantitative correlation between pupil size and HRV. In addition, with the development of modern technology, the smartphone ownership is growing, and the number of smartphones based on facial recognition unlocking is also increasing. According to [17], [18], more than 800 million users around the world have smartphones with the function of face recognition and users unlock their phones 50 times on average per day. Therefore, we consider using the front-facing camera of mobile phones to record the change of user's pupils while he/she unlocks the phone with facial recognition while obeying the privacy policy, so as to achieve HRV monitoring of the user. If it works, pupil-based mobile HRV monitoring can bring some unique advantages over existing methods: • Convenience. Monitoring HRV on mobile devices is much more portable than professional equipment and does not require special instruments or professional guidance. • Accuracy. HRV monitoring based on mobile device unlocking involves different time periods and different physiological and mental states of users, which provides more samples and thus guarantees the accuracy of HRV monitoring. In our study, we first investigate the initial qualitative relationship between the heartbeat and the pupil size captured by the front camera of mobile phones. Based on this, we do a further job of infering HRV from pupillary response more comprehensively and accurately. Achieving this goal entails several key technical challenges. First, the physiological process of pupillary response is intricate: it is possible to extract some features from this process, but it is difficult to identify features that are relevant to HRV. Moreover, having found the features

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www.ijasem.org
Vol 18, Issue.2 April 2024

of pupillary response, it is hard to correspond directly to HRV.

LITERATUR REVIEW

The incidence of congenital heart disease

This study was designed to determine the reasons for the variability of the incidence of congenital heart disease (CHD), estimate its true value and provide data about the incidence of specific major forms of CHD. The incidence of CHD in different studies varies from about 4/1,000 to 50/1,000 live births. The relative frequency of different major forms of CHD also differs greatly from study to study. In addition, another 20/1,000 live births have bicuspid aortic valves, isolated anomalous lobar pulmonary veins or a silent patent ductus arteriosus. The incidences reported in 62 studies published after 1955 were examined. Attention was paid to the ways in which the studies were conducted, with special reference to the increased use of echocardiography in the neonatal nursery. The total incidence of CHD was related to the relative frequency of ventricular septal defects (VSDs), the most common type of CHD. The incidences of individual major forms of CHD were determined from 44 studies. The incidence of CHD depends primarily on the number of small VSDs included in the series, and this number in turn depends upon how early the diagnosis is made. If major forms of CHD are stratified into trivial, moderate and severe categories, the variation in incidence depends mainly on the number of trivial lesions included. The incidence of moderate and severe forms of CHD is about 6/1,000 live births (19/1,000 live births if the potentially serious bicuspid aortic valve is included), and of all forms increases to 75/1,000 live births if tiny muscular VSDs present at birth and other trivial lesions are included. Given the causes of variation, there is no evidence for differences in incidence in different countries or times.

History of global burden of disease assessment at theWorld Health Organization

The World Health Organization collaborated in the first Global Burden of Disease Study (GBD), published in the 1993 World Development Report. This paper summarizes the substantial methodological improvements and expanding scope of GBD work carried out by WHO over the next 25 years.

This review is based on a review of WHO and UN interagency work relating to Global Burden of Disease over the last 20 years, supplemented by a literature review of

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

published papers and commentaries on global burden of disease activities and the production of global health statistics.

Stress Analysis Based on Simultaneous Heart Rate Variability and EEG Monitoring

Stress is a significant risk factor for various diseases such as hypertension, heart attack, stroke, and even sudden death. Stress can also lead to psychological and behavioral disorders. Heart rate variability (HRV) can reflect changes in stress levels while other physiological factors, like blood pressure, are within acceptable ranges. Electroencephalogram (EEG) is a vital technique for studying brain activities and provides useful data regarding changes in mental status. This study incorporates EEG and a detailed HRV analysis to have a better understanding and analysis of stress. Investigating the correlation between EEG and HRV under stress conditions is valuable since they provide complementary information regarding stress. Methods: Simultaneous electrocardiogram (ECG) and EEG recordings were obtained from fifteen subjects. HRV /EEG features were analyzed and compared in rest, stress, and meditation conditions. A one-way ANOVA and correlation coefficient were used for statistical analysis to explore the correlation between HRV features and features extracted from EEG. Results: The HRV features LF (low frequency), HF (high frequency), LF/HF, and rMSSD (root mean square of the successive differences) correlated with EEG features, including alpha power band in the left hemisphere and alpha band power asymmetry. Conclusion: This study demonstrated five significant relationships between EEG and HRV features associated with stress. The ability to use stress-related EEG features in combination with correlated HRV features could help improve detecting stress and monitoring the progress of stress treatments/therapies. The outcomes of this study could enhance the efficiency of stress management technologies such as meditation studies and bio-feedback training.

A CNN based multifaceted signal processing framework for heart rate proctoring using Millimeter wave radar ballistocardiography

The recent pandemic has refocused the medical world's attention on the diagnostic techniques associated with cardiovascular disease. Heart rate provides a real-time snapshot of cardiovascular health. A more precise heart rate reading enables a better

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

understanding of cardiac muscle activity. Although many existing diagnostic techniques are approaching the limits of perfection, there remains potential for further development. In this paper, we propose MIBINET, a novel multifaceted approach for real-time proctoring of heart rate from **M**illimeter wave (mm-wave) radar ballistocardiography signals via inter-beat-interval (**IBI**) using a convolutional neural **NET**work (CNN). The central theme of our approach is to synergize the feature extraction capabilities of CNN with novel signal processing techniques, resulting in enhanced estimation accuracy while simultaneously reducing computational complexity. This proposed network can be used in hospitals, homes, and passenger vehicles due to its lightweight and contactless properties. It employs classical signal processing prior to fitting the data into the network. Although MIBINET is primarily designed to work on mm-wave signals, it is found equally effective on signals of various modalities such as PCG, ECG, and PPG.

Our approach outperforms state-of-the-art techniques by more than 5% in inter-beat-interval (IBI) estimation accuracy. The architecture achieves a 98.73% correlation coefficient and a 20.69 ms Root-Mean-Square Error (RMSE) over 11 different test subjects. The paper contributes by being the first to apply CNN-based feature extraction in concert with unique signal processing strategies to mm-wave radar data for heart rate monitoring. Our methodology also introduces a synthetic IBI augmentation technique, custom loss function, and novel post-processing methods, all contributing to the robust performance of the model in various settings and modalities.

Cardiorespiratory function, resting metabolic rate and heart rate variability in coal miners exposed to hypobaric hypoxia in highland workplace

Owing to intermittent/acute exposure to hypobaric hypoxia, highland miners may often suffer, the physiological characteristics between highland and lowland miners, however, are rarely reported. The objective of this study was to compare the physiological characteristics of coal miners working at disparate altitudes.Twenty-three male coal mining workers acclimating to high altitude for 30 ± 6 days in Tibet (highland group; approx. 4500 m above sea level; 628.39 millibar), and 22 male coal mining workers in Hebei (lowland group; less than 100 m above sea level; 1021.82 millibar) were recruited. Tests were conducted to compare

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www.ijasem.org
Vol 18, Issue.2 April 2024

ventilatory parameters, circulation parameters, resting metabolic rate (RMR), and heart rate variability (HRV) indices between the two groups in resting state.Ventilation volume per minute (VE) of the highland group was markedly raised compared to that of the lowland group (11.70 ± 1.57 vs. 8.94 ± 1.97 L/min, $p = 0.000$). In the meanwhile, O2 intake per heart beat (VO2/HR) was strikingly decreased (3.54 ± 0.54 vs. 4.36 ± 0.69 ml/beat, $p = 0.000$). Resting metabolic rate relevant to body surface area (RMR/BSA) was found no significant difference between the two groups. Evident reduction in standard deviation of NN intervals (SDNN) and remarkable increase in ratio of low- and high- frequency bands (LF/HF) were manifest in highland miners compared to that of lowland ones (110.82 ± 33.34 vs. 141.44 ± 40.38, $p = 0.008$ and 858.86 ± 699.24 vs. 371.33 ± 171.46, $p = 0.003$; respectively).These results implicate that long-term intermittent exposure to high altitude can lead miners to an intensified respiration, a compromised circulation and a profound sympathetic-parasympathetic imbalance, whereas the RMR in highland miners does not distinctly decline.

Identifying HRV patterns in ECG signals as early markers of dementia

The appearance of Artificial Intelligence (IA) has improved our ability to process large amount of data. These tools are particularly interesting in medical contexts, in order to evaluate the variables from patients' screening analysis and disentangle the information that they contain. We propose in this work a novel method for evaluating the role of electrocardiogram (ECG) signals in the human cognitive decline. This framework offers a complete solution for all the steps in the classification pipeline, from the preprocessing of the raw signals to the final classification stage. Numerous metrics are computed from the original data in terms of different domains (time, frequency, etc.), and dimensionality is reduced through a Principal Component Analysis (PCA). The resulting characteristics are used as inputs of different classifiers (linear/non-linear Support Vector Machines, Random Forest, etc.) to determine the amount of information that they contain. Our system yielded an area under the Receiver Operating Characteristic (ROC) curve of 0.80 identifying Mild Cognitive Impairment (MCI) patients, showing that ECG contain crucial information for

ISSN2454-9940
www.ijasem.org
Vol 18, Issue.2 April 2024

predicting the appearance of this pathology. These results are specially relevant given the fact that ECG acquisition is much more affordable and less invasive than brain imaging used in most of these intelligent systems, allowing our method to be used in environments of any socioeconomic range.

We are living currently in a world with a high amount of data. Unlike other previous periods in history, the problem now is that there are much more data than means of processing it. In fact, having data itself is not beneficial if we cannot process them, which implies that it is crucial to separate information from noise. This is particularly interesting in medicine, where routine analysis provide us a number of variables that summarize the health of the patient. Most important, these descriptors can be potentially used to predict the future outcome of the patient's health based on the present information. The application of Artificial Intelligence (AI) to the analysis of this data has revolutionized the identification of several pathologies. In fact, previous studies have proposed models for an early detection of neurological disorders such as Alzheimer's (Arco, Ortiz, Castillo-Barnes, Górriz, and Ramírez, 2023, Arco, Ortiz, Gallego-Molina, et al., 2023, Arco et al., 2021, Wang et al., 2023; Arco et al., 2019) or Parkinson's (Arco, Ortiz, Castillo-Barnes, et al., 2022, Arco, Ortiz, Ramírez, et al., 2023, Coelho et al., 2023, Sigcha et al., 2023), and for a distinction between different pulmonary affections (Alizadehsani et al., 2021, Arco, Ortiz, Ramírez, et al., 2022). Although these works rely on medical imaging, it is possible to analyze other physiological signals to determine the diagnosis of a patient, such as electroencephalography (EEG) signals, which are extraordinarily relevant for the study of dyslexia (Gallego-Molina et al., 2022, Rodríguez-Rodríguez et al., 2023, Štajner et al., 2019, Wang and Bi, 2022) or epilepsy (Abou-Abbas et al., 2023, Beniczky et al., 2021, Bosl et al., 2021, Ilias et al., 2023).

Heart rate variability (HRV) refers to the fluctuation in the time interval between successive heartbeats or the variation in the heart rate itself. This metric has been increasingly adopted in both clinical and research applications (Billman, 2015). Notably, a comprehensive review explored the connection between HRV in wellness and illness, highlighting that variations in HRV can provide insight into the operations of the sympathetic and parasympathetic systems (Kristal-Boneh, Raifel, Froom, & Ribak, 1995). Another piece of research proved the correlation between HRV and coronary artery disease, uncovering that HRV exhibits irregularities

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www.ijasem.org
Vol 18, Issue.2 April 2024

in several instances of ischemic heart disease (Huikuri, 1995). Additionally, a separate study explored the link between HRV and inflammation indicators in cardiovascular diseases, concluding that HRV has a relation with circulating cytokines in cardiovascular functionality in humans (Haensel, Mills, Nelesen, Ziegler, & Dimsdale, 2008). Other studies have focused on how HRV affects critical illness and care (Buchman, Stein, & Goldstein, 2002), as well as lupus disease activity (Thanou et al., 2016), and kidney failure (Ranpuria, Hall, Chan, & Unruh, 2007).

EXISTING SYSTEM

In recent years, researchers have paid more attention to monitor people's HRV in mobile scenarios. We roughly categorize those methods into two groups. Methods in the first group exploit photoplethysmography (PPG) to measure HRV [19]–[25]. Specifically, the mechanism mentioned in [19] works by placing a finger on the phone camera while turning on its flash and calculating the amount of light absorbed by the finger tissues by taking photos from the phone camera to calculate heart rate. Moreover, Bolkovsky et al. [20] use both Android phones and iPhones to capture RR intervals and then derive HRV through a complex algorithm. In addition, the effect of sampling rate between Android phones and iPhone on the accuracy of HRV measurements is also explored. Mobile phone PPG is also advocated by Plews et al. [21], showing that PPG correlated almost perfectly with ECG, with acceptable technical error in estimation and minimal differences in standard deviations. The rolling shutter camera mechanism has been utilized to extract CIS-photoplethysmography (CPPG) data points from CMOS image sensor (CIS) pixel rows, enabling the extraction of high frame rate CPPG signals from a common built-in low frame rate smartphone's CIS [25]. As for the specific applications, PPG is utilized as a tool to estimate HRV in patients with spinal cord injury (SCI) [24].

Disadvantages

- In the existing work, the system did not implement Connecting Pupil with HRV model which leads less effective.
- This system is less performance due to lack of Graph Neural Network and other ml classifiers.

Proposed System

1) We conduct an in-depth study of the relationship between HRV and pupil size in mobile scenarios. To the best of our knowledge, this is the first work to explore the quantitative relationship between people's papillary response and HRV on mobile devices.

2) High-dimensional time-series features associated with user's HRV are identified by using a 1-D CNN to excavate the general physiological processes of papillary responses.

3) We use RNN to train the high-dimensional time-series features extracted by 1-D CNN so as to model the relationship between pupil and HRV.

4) We validate the effectiveness of PupilHeart through an extensive trial by recruiting a total of 60 volunteers.1 The results show that the accuracy of PupilHeart achieves up to 91.37% on average.

Advantages

- Convenience. Monitoring HRV on mobile devices is much more portable than professional equipment and does not require special instruments or professional guidance.
- Accuracy. HRV monitoring based on mobile device unlocking involves different time periods and different physiological and mental states of users, which provides more samples and thus guarantees the accuracy of HRV monitoring.

CONCLUSION

In this paper, we have proposed PupilHeart as a computervision-based mobile HRV monitoring system, including a mobile terminal and a server side. On the mobile terminal, during face recognition, PupilHeart has collected pupil size information through the front facing camera on mobile phones. On the server side, after preprocessing the raw pupil size data, PupilHeart has extracted high-dimension features using 1DCNN, and based on this, has built a pupil-HRV model by RNN. On that basis, PupilHeart has achieved daily HRV monitoring. We have prototyped PupilHeart and conducted experimental and field studies to thoroughly evaluate the efficacy of it by recruiting 60 volunteers. The overall results have shown that PupilHeart can accurately predict a user's HRV when unlocking phones using face recognition. In general, PupilHeart provides us with a prototype for exploring pupil size and HRV, shedding lights on a viable yet innovative idea for realizing mobile HRV monitoring systems. In future works, we will expand the diversity of experiments in terms of devices, subjects, and environment conditions to further improve our PupilHeart system.

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