International Journal of Scientific Research and Innovation ISSN 2455-0140
Volume 9, Issue 10, October 2023 IJSRI 1002

AI-BASED STROKE DISEASE PREDICTION SYSTEM USING ECG AND PPG BIO-SIGNALS

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Abstract— **The project is about early detection of Cardiac Autonomic Neuropathy using ECG signal. The presence of Cardiac Autonomic Neuropathy (CAN) is associated with increased cardiovascular mortality and is the cause of cardiac dysfunction and multiple clinical symptoms, including resting tachycardia, exercise intolerance, postural hypotension.Initially, the heart rates of various stages of the CAN, including that of a normal resting heart, are calculated. Then the same are studied by using comparative analysis. Once the characteristics are studied, the Poincare plots for the same are determined by plotting the matrix form R-R interval values in MATLAB. Furthermore, the width and length, also known as the SD (Standard Deviation) parameters of the obtained plot are calculated. The wider or narrower the elliptical curve of the plot, the more obvious turns out to be the symptoms of the CAN disease. Hence, CAN can be detected at an early stage by introducing comparative studies on the heart rates and SD parameters of various stages with that of the normal resting heart.**

***Keywords*— Cardiac Autonomic Neuropathy, Standard Deviation**

I. INTRODUCTION

CARDIOVASCULAR AUTONOMIC NEUROPATHYDISEASE

As the demand increases to monitor stress throughout the day, more research is conducted to find a way to continuously detect stress. To monitor stress throughout the day of ambulatory patients, a telehealth system which makes use of wearables is designed. This non-obstructive device will be able to record, process and detect stress from the ECG and respiratory signals. The detection of stress goes automatically based on machine learning. After processing all the data, the information should be accessible remotely for the patient in an environment where the privacy of each patient is safeguarded.

The project is divided into three parts, where two students worked on each part. The first part is the pre-processing part of incoming raw data from the wearable. On this data, a quality assessment should be done and, if necessary, the signal must be filtered from noises and artifacts. The second part is the stress detection part with machine learning, where stress will be detected by extracting certain features from the processed ECG and respiratory signal, which is done in the first part [1].

The third part is the overall system design, where the signal processing system and stress detection system are integrated into a graphical user interface (GUI), where relevant information for the user can be displayed, such as the heart rate and, more significantly, whether the user is stressed [2].

This thesis focuses on the first part of the project. The problem definition of the pre-processing is mainly divided into two subjects: filtering of the raw data and a quality assessment of the data. This thesis presents how the signal will be processed while entering, how the quality assessment of the signal is done, and how this signal is being filtered. The processed signal shall be used for further calculations and determinations by the stress detection group. The system design group will use the information from the pre-processing for visual display to the user.

State of the Art Analysis

Many research is done on processing ECG signals, analyzing the Heart Rate Variability (HRV) and the effect of stress on it [3][4][5]. By looking at sympathetic and parasympathetic activities of the body, stress can be determined. To quantify these activities, spectral analysis is conducted on HRV. Therefore, it is of the utmost importance that the ECG signal that is analysed for the determination of HRV. Techniques are developed to detect and remove artifacts from the ECG signal to obtain a reliable signal [6],[7]. A quality assessment is done on the filtered signal, to maintain the accuracy of the overall system to detect stress. Throughout the years, many methods are developed to assess and indicate the signal quality. Some methods are described in [8],[9],[10] and [11]. While there is much knowledge about processing ECG signals, there is still no consensus on how to interpret the respiratory signals

II.METHODS

Study population

A case control study was conducted in a single

research centre as a part of joint Lithuanian – Swiss project"Genetic Diabetes in Lithuania". The principal aim of the project was to screen for autoimmune antibodies and in order to select patients for the searching monogenic Diabetes and to compare the antibody positive withthe antibody negative population of the diabetes registry(<25 years of age). The total project cohort consisted of1209 subjects covering all pediatric patients (<18 years,
n = 860), and part of adult patients younger than 25 years(n = 349) diagnosed with T1DM in Lithuania. All patients had a physician diagnosis of T1DM between March 1990 and March 2015. In patients at the age less than 15 years insulin-dependent diabetes was diagnosed according to DIAMOND criteria [20]: diagnosis confirmed by physician, age at the onset less than 15 years, the date of the onset coincide with the day of the first insulin injection, the person is inhabitant of Lithuania.

In adult persons insulin-dependent diabetes was diagnosed according to criteria [21]: diagnosis confirmed by physician, age at the onset 15–39 years, the date of the onset coincide with the day of the first insulin injection, the person is inhabitant of Lithuania, ketones present in urine on the time of diagnosis of diabetes. Patients were identified from Lithuanian national diabetes data base
and invited to participate in the study on their visit to the family doctor and/or endocrinologist, a paediatric endocrinologist, meetings of diabetes societies, as well as by post, e-mails and phone calls.

III.SIMULATION RESULTS

NORMAL RESTINGHEART

The Poincare plot for the normal resting heart stage is shown below. The SD1 andSD2 parameters are 33.87 and 154 respectively.

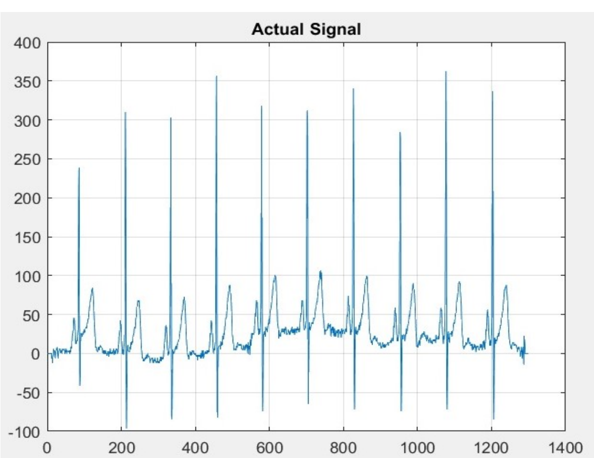


Fig.1Poincare plot of Normal Resting Heart

These parameters show the stability of the dynamic system's heart rate variability. So for a normal resting heart the plot show a stable and close range of points depicts a stable heart. So for a healthy heart the range of SD1 and SD2 lies between 36-48 and 125-160respectively.

EARLYCAN

The Poincare plot for the early CAN stage is shown below. The SD1 and SD2 parameters are 14.42 and 122.8 respectively. In the case of early CAN there is slight variation in the plot as the heart is subjected to minor irregularities.

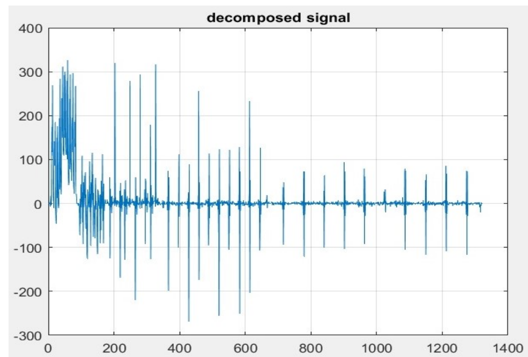


Fig.2 Poincare plot of Normal Resting Heart with SD

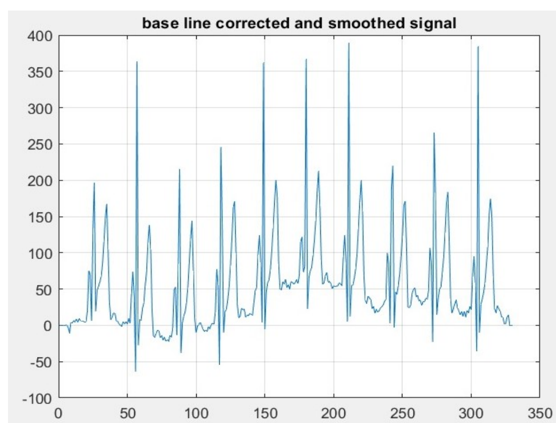


Fig.3 Poincare Plot of Early CAN

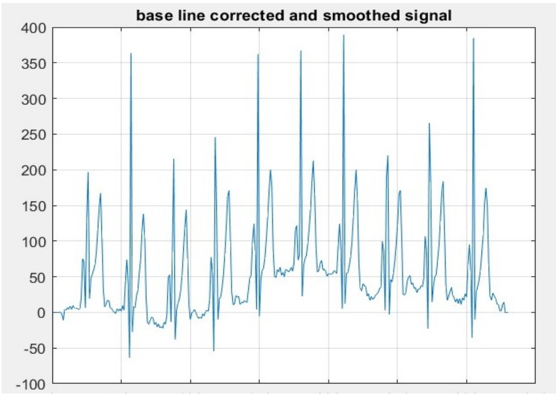


Fig.4 Poincare Plot of Early CAN with SD

DEFINITECAN

The Poincare plot for the definite CAN stage is shown below. The SD1 and SD2 parameters are 28.26 and 360.89 respectively. In case of Definite CAN there is increased irregularities in the heart beat.

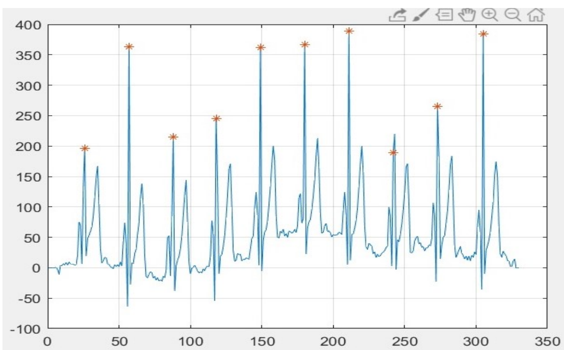


Fig.5 Poincare plot of Definite CAN

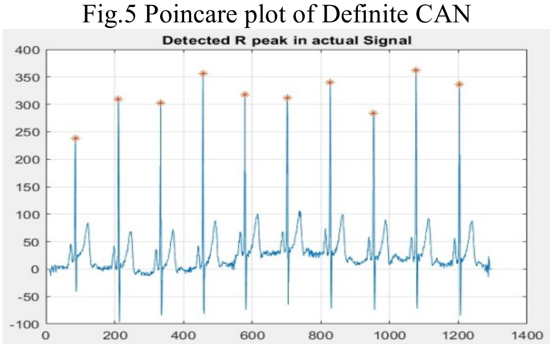
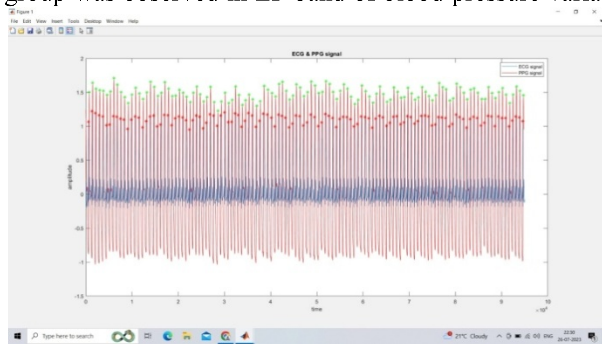
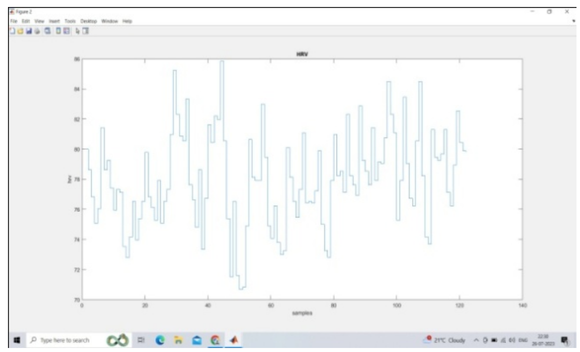


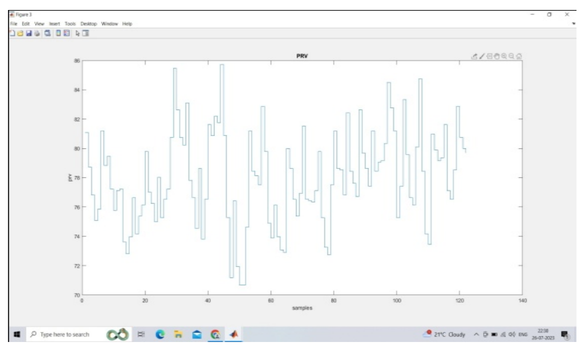
Fig.6Poincare plot of Definite CAN with SD

OUTPUT

In young patients with T1DM significant reduction of spectral power in HF band of the HRV was found, whereas no significant difference between DM group and control group was observed in LF band of blood pressure variability.







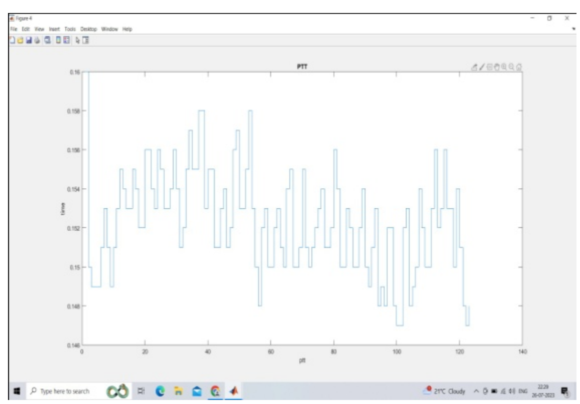


Fig.7 Output

They suggested that abnormalities in cardiac parasympathetic regulation precede impairment of blood vessels sympathetic control in young diabetics [35]. The measures of time domain analysis of our study were significantly lower among T1DM youth with CAN when compared with control group ($p < 0.05$). Also R-R max / R-R min ratio and CV were the lowest during deep breathing among T1DM youth with CAN (showing decrease in parasympathetic activity). We analysed sensitivity and specificity of the coefficient of variation (parameter of time-domain analysis) for diagnosing CAN and have found that the most valuable CV was during deep breathing (values <1.45 reflected sensitivity 97.3%, specificity 96.2%). The results of spectral analysis of our study confirmed the significant decrease in HF, LF and total power (showing decrease in parasympathetic and sympathetic activity) among patients with CAN. Also we have found that LFPA and HFPA were significantly lower among cases than compared with control group, but these indices are not so valuable from mathematical point of view. Power Spectral Analysis and HRV have been employed in trials for the detection of autonomic neuropathy in patients with Charcot's disease. Similarly to Charcot's arthropathy, patients with recurrent vascularneuropathic ulcers appear to share analogous cardiac autonomic dysfunction [9]. Hikita et al. [36] demonstratedthat HRV is reduced in diabetic patients with silentischemia when compared with non-diabetic patients with silent or painful ischemia in 24-h ambulatory electrocardiographic recordings. Katz et al. showed that a simple test that measured.

IV.CONCLUSION

This thesis proposes two systems which can be used for the pre-processing of ECG signals and respiratory signals which can be used for further computations to detect stress. These signals are obtained from three different recordings in which the subjects were asked to perform different tasks. The ECG system consists of two main art, which are the filtering and the signal quality part.

The signal quality part consists of a three-step quality check, which is performed at the beginning and after pre-processing of the signal. The signal quality part is based on the following parts: the quantification of the relative power of the ECG within the band of interest, weight computation based on the ACF and a heart rate evaluation. The respiratory signal system out of three main parts. These parts are the filter part and the signal quality part.The signal quality part consists out of two checks. The first one is the quantification of the relative power of the respiratory signal within the band of interest, this is similar to the ECG power check. The second part is the breath check, which checks whether a breath is taken faster than 2 seconds or slower than 10 seconds.The respiratory rate calculation part is the third part of the respiratory signal part and calculates the respiratory rate per respiratory signal segmentof 70.0975% between the quality labels from the dataset and the ECG system. However 29.9025 % of the of When comparing the results of the algorithm with the the labels from dataset CinC2017, there was a coherence ECG segments did not have a coherence. From this percentage, 17.5666% are data which are labeled as a badquality ECG segment by the dataset while the ECG system passes it as a good quality signal. The remaining 12.3359% is labeled as good by the dataset, while these segments are labeled as a bad quality segment by the ECG system. 29.9025% is a high amount of segments which are incorrectly labeled by the ECG system. The data with the 17.5666% truly apposes as a problem, because further analysis is done with this data. Thus it can be concluded that the ECG system is working but not as accurate as intended.

The respiratory signal results were not as expected. This is concluded by analyzing the Stress dataset, which is one of the three datasets that are used in this thesis. This dataset consist of different phases, in which two phases consist of subjects whom talking. The expectation is that these phases contain more bad quality signals than the phases in which the subject is quiet because talking effects the respiration of a subject. The expectation is true for ST phase which has the highest percentage of bad signals while the AT has the lowest. However a overall consensus of a good quality respiratory signal is not yet achieved in literature, so analyzing a signal with a bad quality indicator is a hard task, because it is not well known whether this signal is truly good or bad. This makes much needed improvements on the respiratory signal system hard.

An important contribution of this work is the giving the ability to locate the segments which contaminated by using ACF and graph theory. Furthermore, the algorithm proposed in this project is easy to implement and suitable for on-line environment since it is able to compute in real-time. Moreover, the average computationtime is 0.0379 0.0128 seconds, which is fast enough for a real-time recording every 10 seconds.

The system can be improved by computing only ECG and deriving the Respiratory rate from it. This will bean advantage because the limitation of the number of sensors on a wearable system.

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