Analysis of Heart Rate Variability in Normal and Diabetic ECG signals using Fragmentation Approach

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Abstract— In this work, an attempt is made to quantify the dynamics of the heart rate variability timeseries in normal and diabetic population using fragmentation metrics. ECG signals recorded during deep breathing and head tilt up experiments are utilized for this study. The QRS-wave of ECG is extracted using the Pan Tompkins Algorithm. Heart rate variability features such as heart rate, Percentage of Inflection Points (PIP) and Inverse of the Average Length of the acceleration/deceleration Segment (IALS) are extracted to quantify the variation in signal dynamics. The results indicate that the ECG signals and heart rate variability signals obtained in deep breathing and tilt exhibit varied characteristics in both normal and diabetics. Further, in the diabetic condition the fragmentation measures exhibit a higher value in both deep breathing and tilt which indicates increased alternations in the signal. Most of the extracted fragmentation features are statistically significant (p<0.005) in differentiating normal and diabetic population. It appears that this method of analysis has potential towards the development of systems for the noninvasive assessment of diabetes.

Clinical Relevance— This establishes a technique to quantify the variation in cardiovascular dynamics in normal and diabetic population.

I. INTRODUCTION

Diabetes is a chronic condition which affects the capabilities of the body to process sugars. It is estimated that the prevalence of this disease in India is expected to octuple by 2035 [1]. This alarming increase in the diabetic condition necessitates the development of health policies, infrastructure and treatment plans to control and mitigate morbidities.

Risk factors such as weight, inactivity, heredity, age, pregnancy and fat distribution are associated with diabetes [2]. The consequences of diabetes include complications such as chronic kidney disease, retinopathy, peripheral neuropathy and dementia [3]. Several studies have indicated that, about 20 – 70 % of patients with diabetes are affected by autonomic neuropathy [4]. Hence, reliable assessment of changes in the functioning of autonomic nervous system might aid in better diagnosis and treatment of such conditions.

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Heart rate variability (HRV) analysis has been widely used as a reliable measure to access cardiac health and autonomic nervous system function. [5] HRV is considered as the ability of heart to adapt and quickly respond to unpredictable stimuli, under varying circumstances. Low HRV is considered as a marker for cardiovascular risk [6]. It is found that the waist–hip ratio, anterior forearm skinfold thickness and sagittal abdominal diameter, are correlated with HRV parameters [6]. In recent years, several time domain features such as the square root of the mean squared difference of successive RR intervals (RMSSD), standard deviations of RR intervals (SDNN) and the percentage of adjacent NN intervals differing by more than 50 milliseconds (pNN50) [7]; and frequency domain parameters namely Low Frequency (LF) and High Frequency (HF) power have been used to characterize HRV. The HF power is associated with parasympathetic activity while the LF power is associated with both parasympathetic and sympathetic activity [8].

Nonlinear measures of HRV have also been introduced to characterize the complexity of the signal. Features such as Poincare plots, detrended fluctuation analysis, and sample entropy have been utilized. It has been found that these measures perform better compared to conventional features in differentiating normal and cardiovascular disease conditions [8]. Recently, fragmentation features have been introduced to assess the fluctuations of short time series [9]. These measures assess the amount of slow and rapid fluctuations in the signal. These features quantify the adaptive control of heart beat which is a result of the interaction between neuroautonomic and electrophysiological components of the system. Further, it has been reported that these features perform better compared to sample entropy and detrended fluctuation analysis in the classification of normal and cardiovascular diseases [9].

II. METHODOLOGY

A. Experimental Protocol

This study considers the signals from the "Cerebral Vasoregulation in Diabetes" Physionet database [10, 11].

This dataset consists of 37 diabetic participants and 49 controls (aged 55 to 75 years). The objective of this study is to evaluate the influence of type 2 diabetes on cerebral vasoregulation and functional outcomes. To study this, tests such as Valsalva maneuver, head-up tilt, and sit-to-stand experiments are performed. Measurements namely, cerebral blood flow using transcranial Doppler and MRI, heart rate,

blood pressure, respiratory parameters, balance walking, and retinopathy features, have been recorded.

The tests for this study were conducted in three phases. During the first visit, informed consent along with patient questionnaire regarding the autonomic symptoms and MRI safety was collected. Further, transcranial Doppler blood flow, autonomic tests (Deep breathing at 0.1 Hz, Valsalva maneuver and 5 minutes of tilt-up at 80°, 12 minute walk test), laboratory tests and Ophthalmologic examination was performed.

In the second visit, the evaluation of cerebral vasomotor reserve was conducted. In the final visit the Brain MR images were recorded to characterize the white matter distribution.

In this work, a portion of the autonomic tests performed on visit 1 is utilized. Specifically, the ECG signals (sampling rate: 500 Hz) recorded during deep breathing and 5 min of tilt-up at 80° are considered. The dataset also contained annotations to describe these signal segments. Subjects with proper annotation and good signal quality are considered for the study. Some of the subjects' data on day one was also missing in the dataset. Based on this, a total of 19 diabetic patients and 29 controls are considered.

The detailed description of the dataset can be found in [10,11].

B. Signal Processing

The following block diagram in fig. 1 illustrates the signal processing framework.
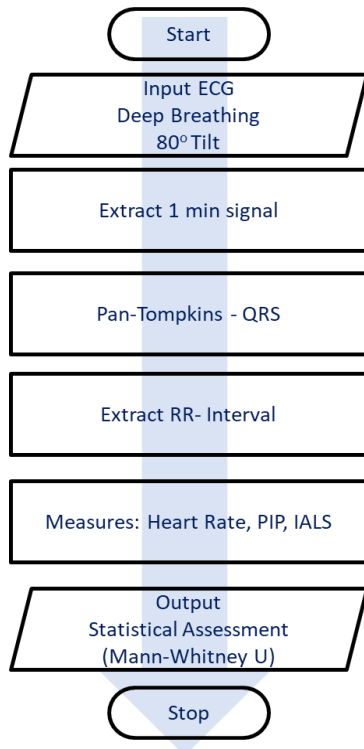

Figure 1. Flowchart of the signal processing framework

The input signal is segmented to extract 1 min of deep breathing interval and the central 1 min portion of the 5 min

tilt test interval. The extracted ECG signal is filtered and the QRS waveform is detected using the Pan-Tompkins algorithm [12]. The RR interval sequence is extracted and first difference is computed to obtain the HRV time series.

Features such as heart rate, Percentage of Inflection Points (PIP) and Inverse of the Average Length of the acceleration/deceleration Segment (IALS) are extracted to quantify the HRV.

PIP is defined as the ratio between the number of zero crossings in the first difference HRV time series and the length of the series It is expressed in percentage. IALS quantifies the number of continuous accelerating (ACC) and decelerating (DECL) segments in the time series and is given in eq. 2 [6].

$$ACC = 1 \text{ if } (R_{i+1} - R_i) > 0$$
$$DECL = 1 \text{ if } (R_{i+1} - R_i) < 0 \tag{1}$$

$$IALS = \frac{1}{Average(\# \text{ of cont.} ACC / DECL \text{ series})} \tag{2}$$

A higher PIP and IALS indicates presence of a more fragmented HRV [6].

C. Statistical Tests

The obtained features are compared between groups (control and Diabetics) using Mann Whitney U test. The features such as age, height, weight, and BMI data are also included for the analysis. The Bonferroni correction for multiple comparisons is performed. This results in an adjusted p-value <0.005.

III. RESULTS AND DISCUSSION

In fig. 2 (a, b), the raw representative ECG signals in normal and diabetic conditions during deep breathing and 80° tilt is shown. It is seen that in the deep breathing case a cyclic pattern is observed. This might be due to the modulation of ECG with the respiration rate. The changes in the amplitude of the ECG signal is prominent in the control subject. In the tilt case, the peak amplitude (R-wave) has more fluctuation in the control population compared to the diabetic subject.

In fig. 2 (c), the HRV series during deep breathing and tilt in control subject is shown. In deep breathing, the RR interval varies between 0.79 s and 1.08 s while in tilt the mean RR interval is 0.76 s. This indicates that the heart rate increases with tilt.

The HRV series in the diabetic subject during deep breathing and tilt test is shown in fig 2 (d). The RR interval during deep breathing varies from 0.70 s to 0.97 s. In case of tilt, it varies between 0.65 s and 0.71 s. In comparison with control, the deep breathing signal has lower values of RR interval. Similarly in the case of tilt, slow variation in the RR interval sequence is observed. A heart rate of 65.56 bpm (deep breathing) and 79.26 bpm (tilt) are observed in control. In case of diabetic subject, the heart rates are found to be 73.76 bpm (deep breathing) and 87.61 bpm (tilt).
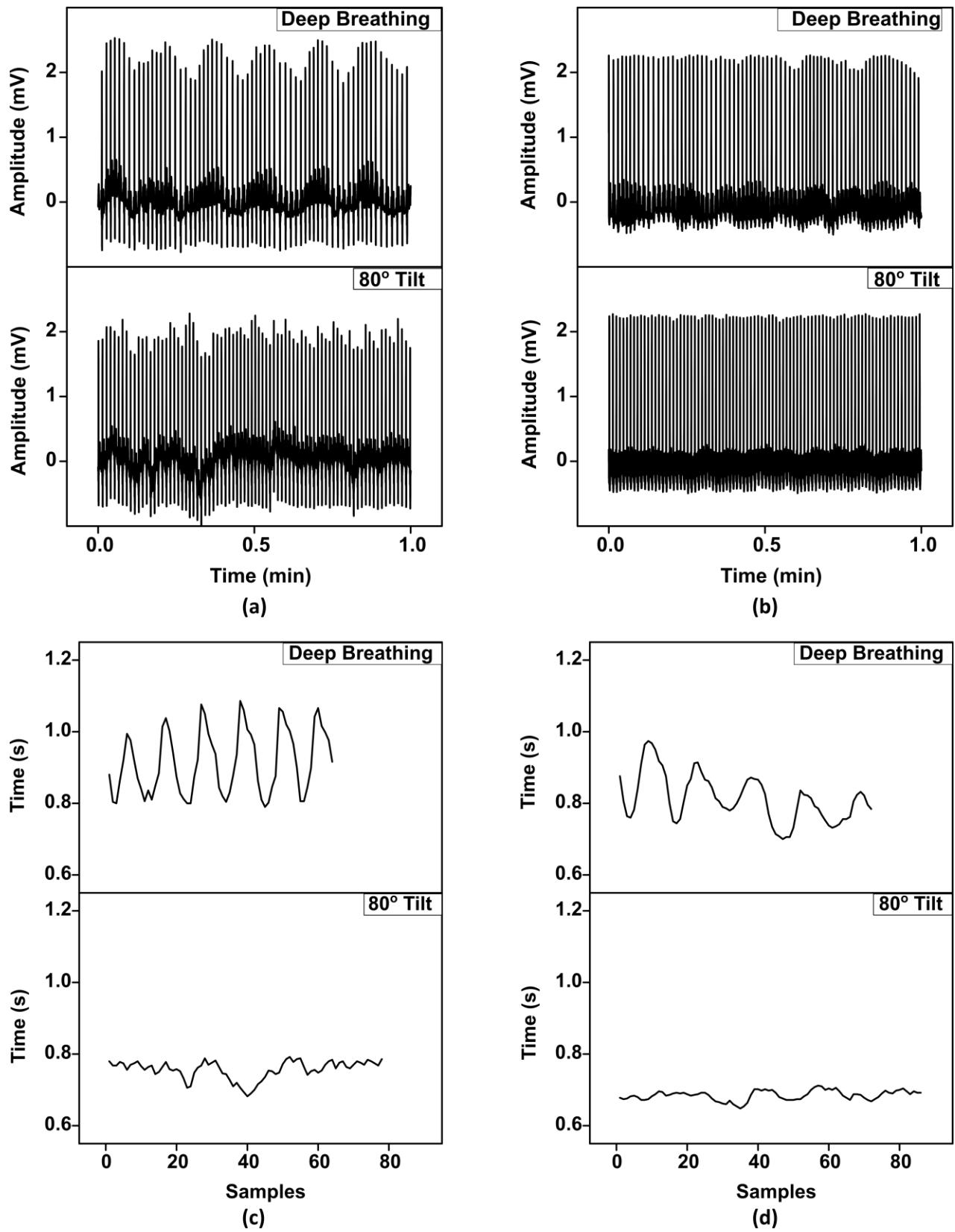
Figure 2. Representative Raw ECG signal during deep breathing and 80° tilt and their corresponding heart variability signal for (a, c) healthy control and (b, d) diabetic subject
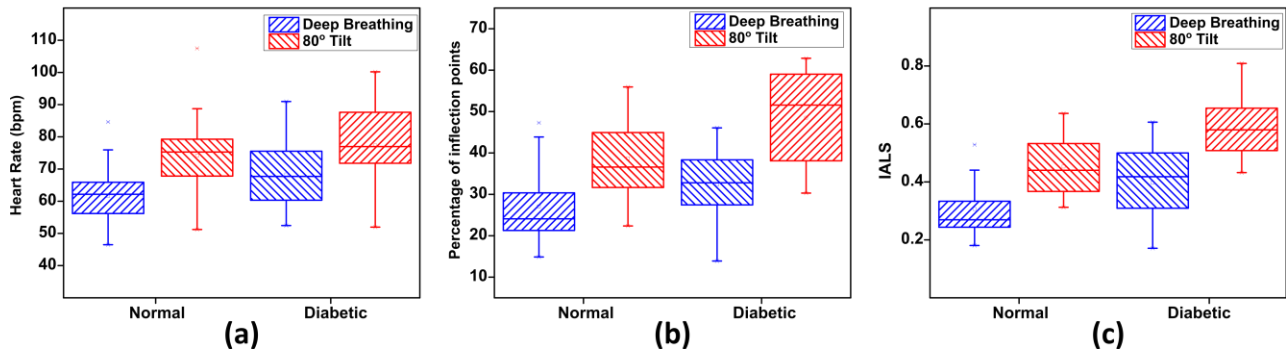
Figure 3. Features namely (a) Heart Rate, (b) Percentage of Inflection points and, (c) Inverse of the average length of the acceleration/deceleration segment in Normal and Diabetic Conditions

In fig. 3 (a) the heart rate of all the participants in normal and diabetic population is depicted. In deep breathing, it is seen that the diabetic population has a higher median heart rate (C:62.15 bpm, D:67.72 bpm). The differences in heart rate in the tilt case is miniscule (C:75.27 bpm, D:76.98 bpm). Further, the intersubject variability is also high in the case of tilt condition. Additionally, the tilt heart rate is higher than the deep breathing case.

In fig. 3 (b), the distribution of PIP features in normal and diabetic population is shown. Higher values of PIP feature is observed in the case of diabetic population in both deep breathing and tilt experiments. Further, the tilt case has more than 40% increase in values compared to deep breathing case. Fig. 3 (c) shows the variation in IALS feature in normal and diabetic population. It is seen that the median values of the feature in diabetic condition are higher than the normal (C:0.31 D:0.45). This indicates that the signal has increased alternations. Further, the tilt condition has increased fragmentation compared to deep breathing.

Amongst the two fragmentation features, the IALS feature shows greater separation between the two conditions. The IALS feature has a lower interquartile range and this indicates lower intersubject variability. This feature results in a p-value<0.005 and is found to be significant.

This study illustrates that during deep breathing the fragmentation values are lower. This might be due to the respiratory mediated arrythmia which results in a smooth waveform [9]. The results of this study also suggest that in case of diabetes the fragmentation is higher. This is in line with previous studies conducted to characterize cardiovascular diseases where a higher value is associated with diseased condition [9].

IV. CONCLUSION

In this study an attempt has been made to analyses the variability in heart rate in normal and diabetic population in two different experimental conditions. For this, the ECG signals are recorded during deep breathing and head tilt test are considered. These signals are segmented and the RR intrevals are identified using the Pan-Tompkins algorithm. The resultant heart rate variability time series is analysed using fragmentation measures such as PIP and IALS. The

results indicate unique ECG and HRV signal patterns. The fragmentation of the series increases with the diabetic condition. Further, the tilt also induces an increase in fragmentation. This might be due to the adaptation of the heart rate during the experiment. Fragmentation features (PIP Tilt, IALS Deep Breathing and Tilt) are significant in differentiating normal and diabetic conditions with p<0.005. It appears that this method of analysis can be extended to characterize cardiac related complications in diabetic population

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