Distinguishing Diabetic Patients from Non-Diabetic Patients by Heart Rate Variability Using Kubios & Labview by Noninvasive Method

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Abstract— The basic purpose behind the whole project is to find out the level of diabetes in a patient with the help of their Heart Rate Variability. The disease like Diabetes mellitus is a big threat to the human beings of this generation. They are so much prone to the junks that they have forgotten how to live a healthy life. Generally due to diabetes mellitus the heart rate variability is reduced. This marks that the cardiac autonomic regulation is not going on in a proper manner. So this can result to cardiac diseases and can turn down to immature death in future.

Key words: Heart Rate Variability, Diabetes Mellitus, Time Domain, Frequency Domain, Convolution, Correlation

I. INTRODUCTION

Regularity in heart rate is predominantly taken as an indication of a vigorous heart but the verity or actuality of the given statement is different and doesn't match the pre-conceived notions. Any alteration or swing in the cardiac rhythm is often considered to be a sign of a healthy cardiac autonomic nervous system. Evaluation of Cardiac autonomic performance can be done non-invasively through measurements of HRV.

Heart rate variability (HRV) analysis has substantiated to be a fitting quantitative index for the autonomous cardiovascular activity. Therefore, it is used as foreboding marker in many different pathologies, Diabetes Mellitus (DM) poses a chronic side effect and affects both peripheral and autonomous neural system. The frequency domain parameters of HRV signal, enumerated during supine, sitting to standing and the deep-breathing state, have ensued in an understanding of the effect of the Autonomic Nervous System on the HRV signal. This particular motion or application consist of probing and monitoring the variations of the heart rate, which are regulated almost undisputedly by the two branches of the nervous system namely, sympathetic nervous system and Para-sympathetic nervous system. In the frequency domain the HRV spectrum has been found to have two bands of interest namely i) Sympathetic (S) band (0.025- 0.125) Hz and (ii) Para-Sympathetic (PS) band (0.125-0.400) Hz power spectrum of HRV signal, estimated using the Fast Fourier Transform algorithms, show an appreciable variation in the two states of recording. The tests usually take around six minutes to perform and a half an hour to analyze the result in order to identify the type of neuropathy. The present expert system is designed with the aim of being used by nurses and other paramedical personnel as the end-users. The result sheet derived as the output from the signal processing algorithms can be utilized for detection of DM and heart deices prior to clinical events, coupled with implementation of preventive management strategies, to delay the progression of these diseases.

II. METHODOLOGY

Analysis of HRV consists of a series of measurements of successive RR interval variations of sinus origin which provide information about autonomic tone. Different physiological factors may influence HRV such as Gender, Age, Circadian rhythm, Respiration and Body position. Measurements of HRV are non-invasive and highly reproducible. They may generally be performed on shorter periods ranging from 0.5 to 6 minutes particularly in the field of dynamic electrocardiography.ECG data were collected from a group of 50 patients with diabetes and 50 healthy volunteers. The subjects under study were in the age group of 21-40 years and sugar level of diabetes patients checked up by One touch sugar testing machine. First the subjects were asked to sit comfortably and were asked questions regarding to the necessary information. After that we requested to breathe naturally for 2 mins in order to be stable. The electrocardiographic (ECG) recording system has been designed and developed for real time data acquisition and for this purpose we used NIDAQ USB6008 as DAQ machine. The ECG signal obtained from 4 lead electrodes, is amplified and sampled at 256Hz by the A/D converter. LABView software is used to exchange the data from analog to digital form, to perform the calculations, and to produce the ECG waveform onto the monitor. The digitized ECG signal is processed by MATLAB software and Kubios HRV software. We compared the value of MATLAB software with the analyzed value of Kubios HRV software and trying to get relation from the compared values.

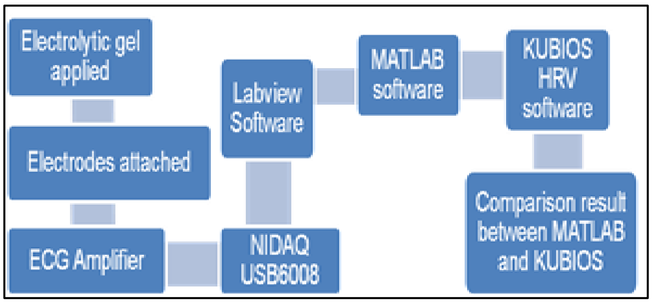

Fig. 1: Block Diagram of Data collection and analysis process.

III. ALGORITHM

BEGIN
Step 1: Set T:=data(:,1)
Step 2: Plot T
Step 3: Read: L as L:=length(T)

Step 4: Display L
Step 5: Set M:=max(T)+3
Step 6: Display M
Step 7: INPUT v:=[ ], i:=1
Step 8: If i>L Then go to Step 17
Step 9: WHILE (i<=L) DO
Step 10: If (T(i)+3)>=2
Step 11: Then
Display (T(i)+3)
Step 12: Display i
Step 13: Set v:=[v,i]
Step 14: Set i:=i+90
Step 15: Else
Set i:=i+1
Step 16: END – WHILE
Step 17: Display v
Step 18: Read: n as n:=length(v)
Step 19: Display n
Step 20: INPUT A:=[ ], F:=[ ]
Step 21: Repeat for q 1 to (n-1)
Step 22: Set PPINV=((v(q+1)-v(q))/256)
*Step 23: Set Hr:=(256/(v(q+1)-v(q)))*60*
Step 24: Set F=[F,Hr];
Step 25: Display HrStep 26: Display PPINV
Step 27: Set A:=[A, PPINV]
Step 28: END – For
Step 29: Display A
Step 30: Read: X as X:=mean(A)
Step 31: Display X
Step 32: Read: J as J:=std(A)
Step 33: Display J
Step 34: Read: D as D:=mean(F)
Step 35: Display D
Step 36: Read: H as H:=std(F)
Step 37: Display H
END

IV. RESULT & ANALYSIS

A. *Non Diabetic Subject*

From the distribution bar graph [Fig.2] it is observed that the subject's distribution of the RR graph and the HR graph is dense throughout the range for a mean heart rate 71.21.

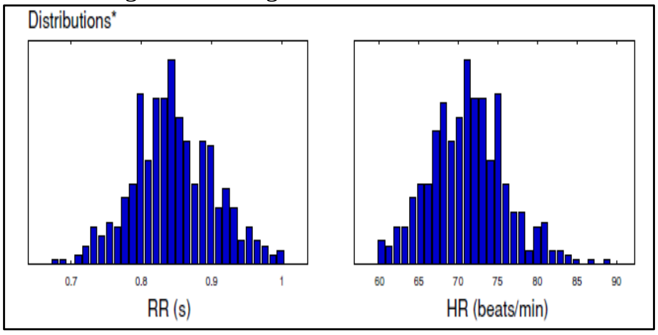

Fig. 2: Distribution Curve of Non Diabetic Subject

As the amplitude of the graph is higher in the 70 to 75 range of the HR graph so the mean heart rate is obtained as 71.21

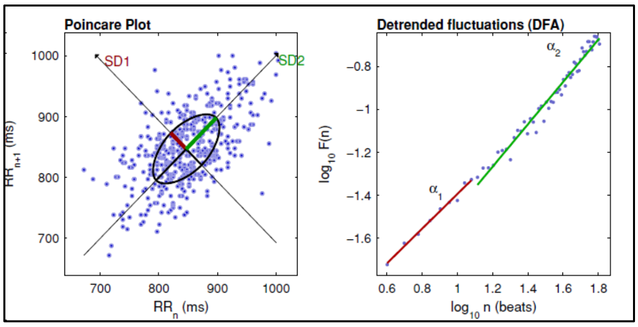

Fig. 3: Poincare & DFA of Non Diabetic Subject

The Poincare plot [Fig.3] is used to plot the RR interval of a subject. The Poincare plot of the above subject is shown in this diagram. At the intersection of the SD1 and the SD2 line is an ellipse. It is observed that the diameter of the ellipse is wider than that of a diabetic subject. A large number of points are enclosed within the diameter of the ellipse making the area enclosed within the ellipse dense. Other points are scattered outside the ellipse in a random manner.

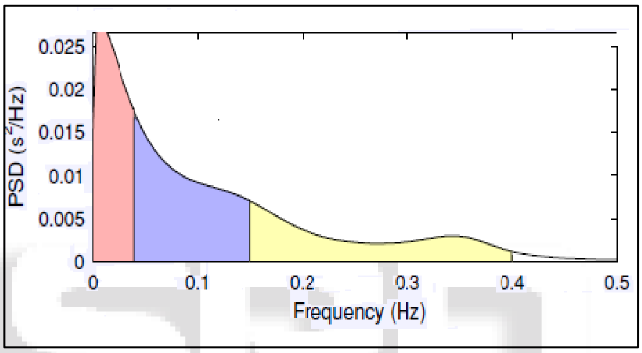

Fig. 4: Average Power Spectral Density of Non-Diabetic Subject

B. *Diabetic subject*

From the distribution bar graph[Fig.5] it is observed that the subject's distribution of the RR graph and the HR graph is sparse

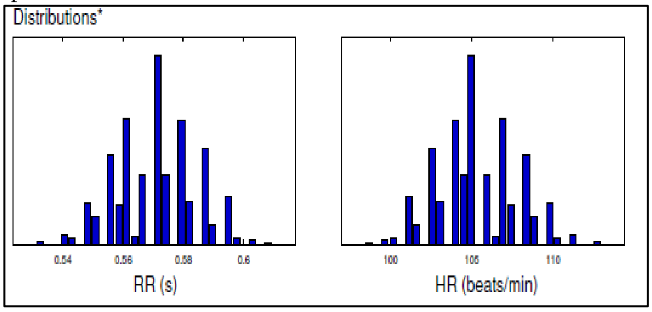

Fig. 5: Distribution Curve of Diabetic Subject

Through out the range for a mean heart rate 105.29. The sparse distribution characterizes the graphs for diabetic subjects. As the amplitude of the graph is higher around 105 region range of the HR graph so the mean heart rate is obtained as 105.29.The Poincare plot of[Fig.6] the above subject is shown in this diagram. At the intersection of the SD1 and the SD2 line lies an ellipse.

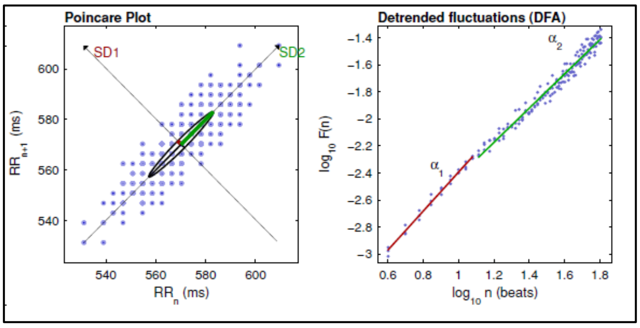

Fig. 6: Poincare & DFA of Non Diabetic Subject

It is observed that the diameter of the ellipse is very less compared to the diameter of a non diabetic subject. A few points, hardly one or two are enclosed within this small diameter and maximum number of points are scattered outside the ellipse in a random fashion.

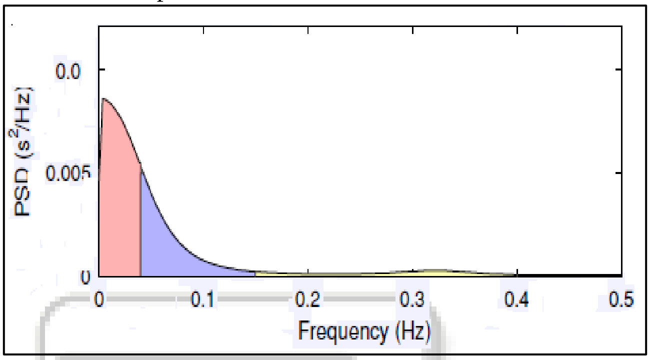

Fig. 7: Average Power Spectral Density of Diabetic Subject

V. DEVIATION OF DIABETIC PATIENTS FROM NON DIABETIC PATIENTS BY DIFFERENT PARAMETERS

The distinction of diabetic patients from non diabetic patients is made with the help of the following parameters:

- HF Peak (Hz)
- Standard Deviation of NN Interval (ms) (SDNN)
- Successive NN Interval Differing More Than 50% (Nn50 (count))
- Percentage Value off NN50 Count (pNN50(%))
- RR Triangular Index
- Root of the Mean of the Sum of Squares of Differences Between Adjacent NN Interval (RMSSD(ms))
- SDNN $=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(RR_i-\overline{RR})^2}$ --(1) RMSSD $=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n-1}(RR_{i+1}-RR_i)^2}$ -----(2)
- pNN50 = P$|RR_{i+1}-RR_i|$>50ms ----(3)

Where RR is the average R-R interval, RR_i denotes the time from i^{th} to $i+1^{st}$ R-peak, N denotes the total number of intervals. The R-R interval is determined from the ECG graph obtained from the Diabetic and Non Diabetic Patient.

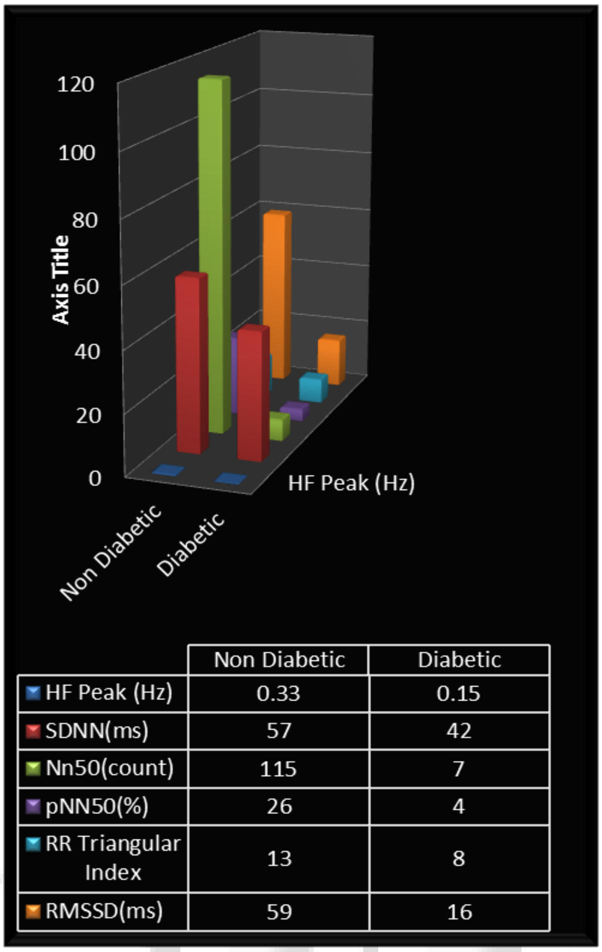

Fig.8: Graphical Representation of Different parameter of Diabetic and Non Diabetic Patient

VI. CONCLUSION

From Fig. 8 by different parameter the diabetic patient can be easily distinguish from Non. Diabetic patient. From fig.4 and Fig.7 the power spectral density can easily distinguish Diabetic patient from non Diabetic patient. There are various problems that are lying with the glucose monitor because this is an invasive technique. Due to this sometimes patents might get shock and dehydrated. Some patients take more time for blood coagulation. They will suffer blood loss. So from all this we can say that measuring Heart Rate Variability with the help of the electrical activity of heart is a non-invasive method. More experiments and works must be done on it to become more confident about the whole matter. So this can be concluded that this procedure will surely bring a better life of the humans.

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