CLASSIFICATION OF ARRHYTHMIAS ON THE BASIS OF HEART RATE VARIABILITY

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ABSTRACT: Heart rate variability (HRV) is concerned with the analysis of intervals between heartbeats. It indicates balance between parasympathetic and sympathetic nervous system. There is significant relationship between autonomic nervous system (ANS) and cardiovascular mortality and ANS is strongly related with HRV. In this paper HRV is analyzed by time domain measure, frequency domain measure and Poincare plot analysis. Initially R peak detection is performed by R wave detection algorithm using wavelet transform. Also we can detect all five peaks P, Q, R, S, T using the same. After detecting R peaks RR interval is calculated from which further parameters are calculated like SDNN, SDANN, RMSSD, pNN50, Heart rate (Time Domain parameters) total power, low frequency component, High frequency component and their ratio (frequency domain parameters). Unlike these methods Poincare plot analysis is non-linear visual technique for assessment of HRV. Poincare plot comments about short term and long term variability. Ratio of these two parameters is also an important factor for arrhythmia classification. Also position and orientation of RR interval in Poincare plot is helpful in visual identification of arrhythmias. ECG signals used are Normal Sinus Rhythm, Atrial Fibrillation, Supraventricular Arrhythmia, Long term ST change, Malignant Ventricular Ectopy, Arrhythmia. Signals are obtained from MIT-BIH (Massachusetts Institute of technology Beth Israel Hospital) database.

KEYWORDS: Heart Rate Variability, QRS detection, Poincare Plot,Wavelet transform, Autonomic Nervous System.

I. INTRODUCTION

The electrocardiogram (ECG) signal is a recording of the heart's electrical activity and provides valuable clinical information about the hearts performance. Electrical activity during cardiac cycle is characterized by five separate peaks P, Q, R, S and T. The QRS detection is useful for the detection of

cardiac arrhythmias. Detection of peak of QRS complex or R wave is start for the HRV assessment that is different parameter calculation. For R-wave detection discrete wavelet transform is used. Wavelet transform overcome the limitations imposed by fixed duration windowing techniques in detecting time varying transients [3]. Wavelet transform is adaptive technique that captures spectral-temporal variations in QRS morphology.

To evaluate variation in heart rate Time Domain Measure is the simplest method. It

may be derived from direct measurement of RR (NN) interval (SDNN and SDANN) and from NN interval differences (RMSSD, SDSD, pNN50) [1]. Power spectral density (PSD) analysis provides the basic information of how power (variance) distributes as a function of frequency. Methods for the calculation of PSD may be generally classified as non-parametric and parametric method. There is correlation between time and frequency domain measure. RMSSD

and pNN50 correlate themselves and with HF power; SDNN and SDANN correlate significantly with total power and ULF component [1].

Poincare plot analysis is an emerging quantitative-visual technique which takes a sequence of intervals and plots each interval against the following interval. Shape of the plot is categorized into functional classes that indicate the degree of heart failure [2]. It is becoming a popular technique due to its simple visual interpretation and its proven clinical ability as a predictor of disease and cardiac dysfunction.

II. R-WAVE DETECTION

Recognition of ECG wave starts with the R identification; with the help of Wavelet transform. The wavelet transform, which has been used in biomedical signal processing also, has its role in ECG characterization and QRS detection. To overcome the limitations imposed by fixed duration windowing techniques in detecting time-varying transients, a general, adaptive technique that captures the spectral/temporal variations in QRS morphology is needed. Here one such technique based upon the discrete wavelet transform is dyadic wavelet transform (DyWT) is proposed. The dyadic wavelet transform inherently has a multi resolution capability. For small scale values, it exhibits high temporal and low spectral resolution whereas for large scale values, it exhibits low temporal and high spectral resolution that is it provides good time resolution at high frequency and better frequency resolution at low frequency. A multi-resolution approach to signal analysis using the Wavelet Transform has been previously applied in many fields. QRS detector based on the dyadic wavelet transform is robust both to noise and to nonstationarities in the QRS complex [3] [6] [7]. In the wavelet QRS detection the first four scales of the wavelet transformation are considered. The first scale contains high frequency noise and QRS complex The QRS complex is so prominent that it is clearly visible on all four scales; however it is most prominent in the second and third scales. The fourth scale contains lower frequency information including T-wave information and baseline drift. If we plot the coefficients we will observe that the frequency bands are separated and a1, a2, a3 and a4 are cleaner signal as shown in the Fig. 1.

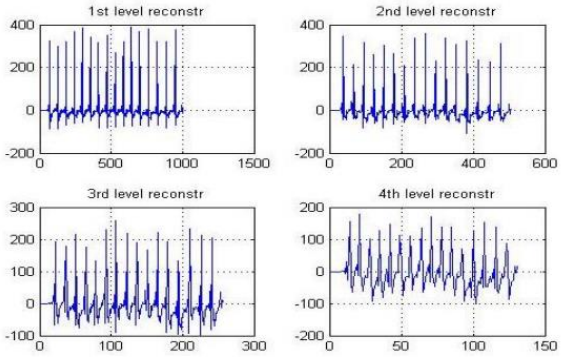

Fig. 1: RECONSTRUCTION LEVEL IN WAVELET DETECTION IN NSR (17052)

Detecting R peak in the down sampled Signal: First find the values which are greater than threshold of the actual signal. Invariably these are R peaks. The sample values in Original Signal will be different than the decomposed signal. If we observe the signal very closely, R-Peak is not a single Impulse peak; therefore there are chances of multiple points in the same peak satisfying the criteria. So first we will remove the R locations that are too close.

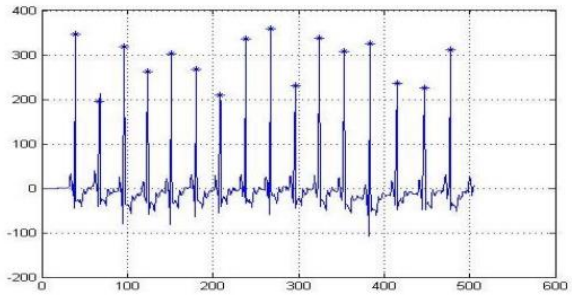

Fig. 2: DETECTION OF R-PEAK IN DOWN SAMPLED SIGNAL NSR (16273)

Detecting R peak in the Original Signal: Search for the position of all the location in signal which is greater than threshold. They are R locations. But we must know that R Location in decomposed signal is at least 1/4th of the actual R location of the same point. Hence we will first map the detected positions to original signal as shown in the Fig. 3

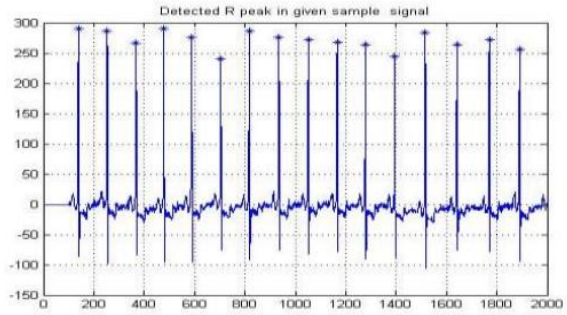

Fig. 3: DETECTION OF R-PEAK IN ACTUAL SIGNAL NSR (16273)

III. METHODS OF HRV ANALYSIS

A. Time Domain Analysis:

Time domain analysis covers statistical and geometric methods of heart rate variability. Statistical indices are calculated on a beat-to-beat basis and are based on Euclidian root mean square (RMS) metrics. To evaluate variation in heart rate Time Domain Measure is the simplest method. In a continuous electrocardiographic (ECG) record, each QRS complex is detected, and the normal-to-normal (NN) intervals (that is all intervals between adjacent QRS complexes resulting from sinus node depolarization), or the instantaneous heart rate is determined. From a series of instantaneous heart rates or cycle intervals, particularly those recorded over longer periods, more complex statistical timedomain measures can be calculated [1]. These may be divided into two classes, (a) those derived from direct measurements of the NN intervals or instantaneous heart rate, and (b) those derived from the differences between NN intervals. These variables may be derived from analysis of the total electrocardiographic recording or may be calculated using smaller segments of the recording period. The latter method allows comparison of HRV to be made during varying activities, e.g. rest, sleep, etc.

The simplest variable to calculate is the standard deviation of the NN interval (SDNN), i.e. the square root of variance. Since variance is mathematically equal to total power of spectral

analysis, SDNN reflects all the cyclic components responsible for variability in the period of recording. Other commonly used statistical variables calculated from segments of the total monitoring period include SDANN, the standard deviation of the average NN interval calculated over short periods, usually 5 min, which is an estimate of the changes in heart rate due to cycles longer than 5 minute. The most commonly used measures derived from interval differences include RMSSD, the square root of the mean squared differences of successive NN intervals, NN50, the number of interval differences of successive NN intervals greater than 50 ms, and pNN50 the proportion derived by dividing NN50 by the total number of NN intervals. All these measurements of short-term variation estimate high frequency variations in heart rate and thus are highly correlated [1].

Since many of the measures correlate closely with others, the following four are recommended for time–domain HRV assessment: SDNN (estimate of overall HRV); SDANN (estimate of long-term components of HRV), and RMSSD (estimate of short-term components of HRV). The RMSSD method is preferred to pNN50 and NN50 because it has be2tter statistical properties [1]. The methods expressing overall HRV and its long- and short-term components cannot replace each other.

B. Frequency Domain Analysis:

Frequency-domain measures pertain to HR variability at certain frequency ranges associated with specific physiological processes. Before frequency-domain analysis is performed, all abnormal heartbeats and artifacts must be detected and the following parameters evaluated: Total Power (TP), High Frequency (HF), Low Frequency (LF) and Very Low Frequency (VLF).and removed, then cardio tachogram (sequence of RR intervals) must be re-sampled to make it as if it is a regularly sampled signal. The sampling rate has to be properly chosen. A low sampling rate may produce a jitter in the estimation of the R wave fiducial point which alters the spectrum considerably. The optimal ranges are 250–500 Hz or perhaps even higher, while a lower sampling rate may not behave satisfactorily. Baseline and trend removal may affect the lower components in the spectrum. It is advisable to check the frequency response of the filter or the behavior of the regression algorithm and to verify that the spectral components of interest are not significantly affected.

Power spectral density (PSD) analysis provides the basic information of how power (i.e. variance) distributes as a function of frequency. Methods for the calculation of PSD may be generally classified as non-parametric and parametric. In most instances, both methods provide comparable results. The advantages of the non-parametric methods are: (a) the simplicity of the algorithm employed (Fast Fourier Transform— FFT— in most of the cases) and (b) the high processing speed [1].

Measurement of VLF, LF and HF power components is usually made in absolute values of power (ms2), but LF and HF may also be measured in normalized units (n.u.) which represent the relative value of each power component in proportion to the total power minus the VLF component. This representation emphasizes the controlled and balanced behavior of the two branches of the ANS. Moreover, normalization tends to minimize the effect on the values of LF and HF components of the changes in total power. Nevertheless, n.u. should always be quoted

with absolute values of LF and HF power in order to describe in total the distribution of power in spectral components.

Three main spectral components are distinguished in a spectrum calculated from short term recordings of 2 to 5 min: very low frequency (VLF), low frequency (LF), and high frequency (HF) components. The distribution of the power and the central frequency of LF and HF are not fixed but may vary in relation to changes in autonomic modulations of the heart period.

C. Poincare Plot Analysis:
The Poincare plot is a valuable HRV analysis technique due to its ability to display nonlinear aspects of the interval sequence. The length and width of the Poincare plot have been suggested as indicative of the levels of long- and shortterm variability. It is reasonably clear that the standard deviation of the delta-RR intervals, as measured by SDSD, RMSSD, or SD1, is a measure of short-term HRV. The standard deviation of the RR intervals, as measured by SDRR, is employed as a measure of long-term HRV [2]. Standard Deviation of the RR Interval: It is often employed as a measure of overall HRV. It is defined as the square root of the variance of the RR intervals

$$SDRR = \sqrt{E\left[{RR_n}^2\right] - (\overline{RR})^2} \qquad (1)$$

Where the mean RR interval is denoted by RR = E[RRn]

Standard Deviation of the Successive Differences: It is an important measure of short-term HRV. It is defined as the square root of the variance of the sequence $\Delta RR_n to\, \Delta RR_{n+1}$

$$SDRR = \sqrt{E\left[{\Delta RR_n}^2\right] - (\overline{\Delta RR_n})^2} \qquad (2)$$

Note that second term under the square root is equal to E[RRn] - E[RRn+1] = 0 for stationary intervals. This means that the root-mean square (rms) of the successive differences is statistically equivalent to the standard deviation of the successive differences

$$SDSD = rmsSD = \sqrt{E[(RR_n - RR_{n+1})^2]} \qquad (3)$$

Statistically, the plot displays the correlation between consecutive intervals in a graphical manner. The RR interval in a Poincare plot typically appears as an elongated cloud of points oriented along the line-of-identity. The dispersion of point's perpendicular to the line-of-identity reflects the level of short-term variability. The dispersion of points along the line-of-identity indicates the level of long-term variability. To characterize the shape of the plot mathematically, most researchers have adopted the technique of fitting an ellipse to the plot. A set of axis oriented with the line-of-identity is defined. The axis of the Poincare plot is related to the new set of axis by rotation of 45 degrees.

In the reference system of the new axis, the dispersion of the points around the x1 axis is measured by the standard deviation denoted by SD1. This quantity measures the width of the

Poincare cloud and, therefore, indicates the level of short-term HRV. The length of the cloud along the line-ofidentity measures the long-term HRV and is measured by SD2 which is the standard deviation around the x2 axis. These measures are related to the standard HRV measures in the following manner:

$$SD1^2 = Var(x_1) = Var\left(\frac{1}{\sqrt{2}}RR_n - \frac{1}{\sqrt{2}}RR_{n+1}\right) = \frac{1}{2}\mathrm{Var}(RR_n - RR_{n+1}) = \frac{1}{2}SDSD^2 \quad (4)$$

Thus, the SD1 measure of Poincare width is equivalent to the standard deviation of the successive intervals, except that it is scaled by 1/(square root of 2) This means that we can relate SD1 to the auto covariance function

$$SD1^2 = \emptyset_{RR}(0) - \emptyset_{RR}(1) \quad (5)$$

With a similar argument, it may be shown that length of the Poincare cloud is related to the auto covariance function

$$SD2^2 = \emptyset_{RR}(0) + \emptyset_{RR}(1) \quad (6)$$

By adding, equation (5) and (6), we get

$$SD1^2 + SD2^2 = 2SDRR^2 \quad (7)$$

Finally,

$$SD2^2 = 2SDRR^2 - \frac{1}{2}SDSD^2 \quad (8)$$

Equation (8) allows us to interpret SD2 in terms of existing indexes of HRV. It can be argued that SD2 reflects the long-term HRV. So we can summarize Poincare plot as
Pros: Simple visualization tool, Outlier (ectopic beat or artifact) identifier, possible insights into short-term and long-term variability. Cons: Derived statistics not independent of other time domain measures.

IV. RESULTS

ECG signals used are obtained from MIT-BIH database. ECG signals of Normal Sinus Rhythm (NSR) are used as normal subject database and Atrial Fibrillation, Supraventricular Arrhythmia, Malignant Ventricular Ectopy, Long Term ST change and Arrhythmia database is used for abnormality analysis.

First block of figure 4 shows Poincare plot of Normal Sinus Rhythm. It is clustered together and shows good quality of ECG signal. The RR intervals appear between 0.2 sec to 1 sec. mostly clustered signal appears between 0.3 to o.75 sec. Poincare plot of Atrial Fibrillation is mush irregular and we cannot define certain pattern of it. Sometimes it appears quit clustered and sometimes very dispersed. Third block of Fig. 4 represent Poincare plot of Malignant Ventricular Ectopy and it is scattered. The RR intervals appear between 0.2 sec to 1.6 sec .some clustered appears between 0.3 to 1 sec. Outside this range there is significant scattering. Poincare plot of Long Term ST database is not that mush scattered but it is not also like NSR. It is scattered but

in groups. The RR intervals appear from 0.5 sec to 1.8 sec but mostly clustered groups appear from 0.6 sec to 1.6 sec. Poincare plot of Supraventricular Arrhythmia is of comparable quality with Poincare plot of Normal Sinus Rhythm. The RR intervals appear from 0.4 sec to 1.2 sec. As arrhythmia is a very vast class Poincare plot of Arrhythmia is obtained with different patterns in which RR intervals are appear around the line of identity but not tightly clustered and in some it is much dispersed but in some definite pattern. Overall Poincare plot is strong parameter to classify different arrhythmias but if we combine it with other parameters then it becomes very effective.

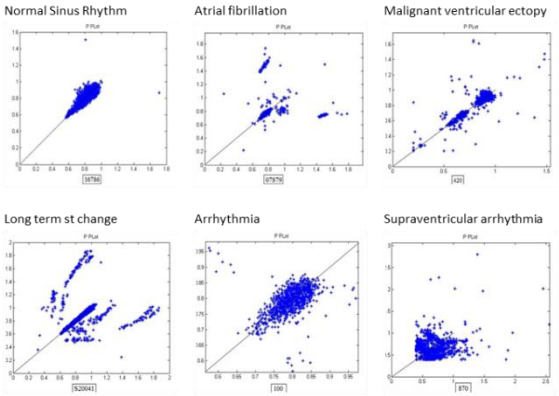

Fig. 4: POINCARE PLOT ALL ECG SIGNALS

Fig. 5 shows R-peak detection for different arrhythmia signals. ECG signals for each arrhythmia is different but Rpeak detection using Wavelet Transform is robust and can detect R peaks exactly.

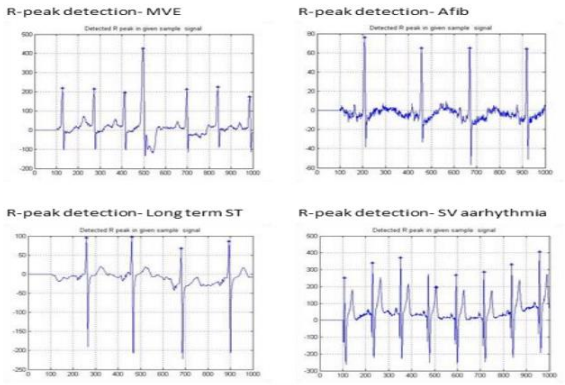

Fig. 5: R-PEAK DETECTION

This algorithm is useful for detection of not only R-peak but also all other peaks also. Once R-peak is detected we can detect all other peaks with reference to R-peak. For this purpose source transformation is used but it is not that much robust to noise. But we can get fair detection of all other peaks as shown in Fig. 6 (as it detect peak of arrhythmia signal also quite efficiently). Form this figure we can also say that T wave detection is not that much accurate.

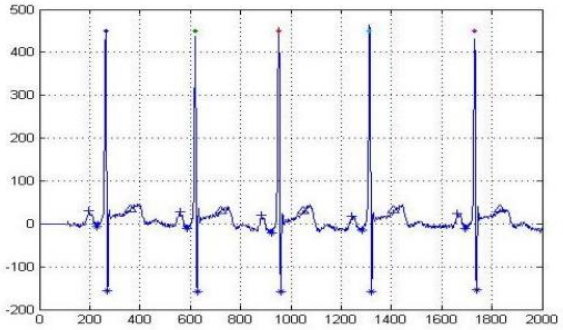

Fig. 6: DETECTION OF ALL PEAKS ARRHYTHMIA (115)

Table 1 gives analysis of Time Domain Measure for each arrhythmia along with normal signal and Table 2 describes about values of LF-HF ratio which gives balance level of parasympathetic and sympathetic nervous system and ratio of SD1 and SD2 for different arrhythmias which describes long term and short term variability.

Table 1: TIME DOMAIN ANALYSIS

ECG Signal	Time Domain Parameters			
	SDNN	SDANN	RMSSD	pNN50
NSR	137±41	118±37	17±12	9.5±6.5
Arrhythmia	480±619	268±255	9.08±6.62	19.8±15.3
ST Change	116±39	64±30	4.69±3.18	9±10.96
SV Arrhythmia	184±110	86±46	9.29±3.17	34.6±14.4
Afib	584±442	120±80	11.91±9.10	7.41±4.49
MVE	---------	437±497	14.39±7.30	42.1±21.4

Table 1: FREQUENCY DOMAIN AND POINCARE PLOT ANALYSIS

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V. CONCLUSION

Heart rate variability has considerable potential to assess the role of autonomic nervous system fluctuations in normal healthy individuals and in patients with various cardiovascular and non-cardiovascular disorders. Heart rate variability studies should enhance our understanding of physiological phenomena, the actions of medications and disease mechanism.

Large prospective longitudinal studies are needed to determine the sensitivity, specificity, and predictive value of HRV in the identification of individuals at risk for subsequent morbid and mortal events. Poincare plot is strong parameter to distinguish between different disorders than time domain measures. Good quality HRV signals produce a Poincare plot with all data points clustered together while corrupted HRV signals will results in a Poincare plot with scattered data points. Also from Table 1 we can distinguish other arrhythmias from Normal Sinus Rhythm easily except Long Term ST. Values of NSR and Long Term ST change are quite close. Malignant Ventricular Ectopy and Supraventricular Arrhythmias results are quite different than NSR but close to each other. Same is with Atrial Fibrillation and Arrhythmia. Higher the heart rate variability, the quicker and more flexibly the heart adapts to external and internal influences and better the organism react to the environment. Low HRV indicates a reduced capacity for adaption and may suggest serious health impairment. But still need more efforts to distinguish between different disorders from time domain measures only.

In time domain analysis, from Table I we can observe that atrial fibrillation and arrhythmia database (as arrhythmia is very wide range classification) are not well distinguished with time domain parameters. Frequency domain analysis also plays a vital role in analysis and identification of different arrhythmias. From Table II we can conclude that values of LF-HF ratio for NSR and ST change are close. Also some values of Atrial Fibrillation are overlapping. Malignant Ventricular Ectopy produces very much unexpected values. So we can say that along with the time domain the identification can be done more efficiently. Also we can say that if we combine all methods effectively then with coordination of medical expert it is possible to classify different arrhythmia on the basis of Heart Rate Variability.

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