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1	Identification of Premature Ventricular Contraction (PVC) of
2	Electrocardiogram using Statistical Tools and Non-Linear
3	Analysis
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8 Abstract

- Non-linear analysis is a useful technique in a medical field specially in cardiac cases. Statistics
 tools Non-linear parameters have shown potentiality to the identification of diseases,
- ¹¹ especially in the analysis of biomedical signals like electrocardiogram (ECG). In this work,
- ¹² premature ventricular contraction (i.e abnormality) in ECG signals has been analysed using
- ¹³ various non-linear techniques. First, the ECG signal is processed through a series of steps to
- ¹⁴ extract the QRS complex. From this extracted feature, bit-to-bit interval (BBI) and
- ¹⁵ instantaneous heart rate (IHR) have been calculated.
- 16

Index terms— electrocardiogram (ECG), premature ventricular contraction (PVC), instantaneous heart rate
 (IHR), standard deviation(SD), central tendency measure (CT

¹⁹ 1 I. Introduction

he heart is the muscular organ that pumps the blood through the circulatory system by rhythmic contraction
and dilation. In vertebrate there may be up to four chambers with two atria and two ventricles. Measuring
the electrical activity of heart to show whether or not it is working normally and records the heart rhythm and
activity on a moving strip of paper or a line on a screen, in a word that is called ECG. Electrocardiogram (ECG)
is a wave that represents an electrical event in the heart, such as atrial depolarization, atrial repolarization,
ventricular depolarization, ventricular repolarization, or transmission, and so on [1-4].

²⁶ 2 T a) Heart and ECG

The electric current generated by depolarization and repolarization of the atria and ventricles is detected by 27 electrodes, it is amplified, displayed on an oscilloscope, recorded on ECG paper, or stored in memory. The 28 electric current generated by atrial depolarization is recorded as the P wave, and that generated by ventricular 29 depolarization is recorded as the Q, R, and S waves: the QRS complex. Atrial repolarization is recorded as 30 the atrial T wave (Ta), and ventricular repolarization, as the ventricular T wave, or simply, the T wave. The 31 sections of the ECG between the waves and complexes are called segments and intervals: the PR segment, the 32 ST segment, the TP segment, the PR interval, the QT interval, and the R-R interval. When electrical activity 33 of the heart is not being detected, the ECG is a straight, flat line -the isoelectric line or baseline. 34

³⁵ 3 II. Proposed Method

This work presents heart rate variability (HRV) analysis using some non-linear methods. The ECG signal to be analyzed is first processed [5] to extract the QRS complex. From that bit-to-bit interval (BBI) is calculated. From the BBI the instantaneous heart rate (IHR) is found. On this dataset of BBI and IHR, various non-linear parameters like Poincare plot analysis (PPA), central tendency measure (CTM), phase space portrait, detrended fluctuation analysis are determined. The result is very effective to distinguish the ECG signals between the healthy parameters of the of the of the of the order.

41 healthy person and that of the ailing person.

⁴² 4 a) Phase space portrait

Phase space or phase diagram is such a space in which every point describes two or more states of a system 43 variable. The number of states [6] that can be displayed in phase space is called dimension or reconstruction 44 dimension. It is usually symbolized by the letter d or E. From the given digitized data x(1), x(2), ?, x(n) of 45 the IHR or BBI, a matrix A is obtained with its two columns given by x(1), x(2), ?, x(n-?) and x(1+?), x(2+46 ?),.., x(n). Here ? is the time delay. The Phase space plot is constructed by plotting the data set with the time 47 delay version of itself. The attribute of the reconstructed phase space plot depend on the choice of the value 48 for ?. ? is measured through applying a autocorrelation function. Autocorrelation is a mathematical tool used 49 frequently in signal processing for analyzing functions or series of values, such as time domain signals. Informally, 50 it is a measure of how well a signal matches a with time-shifted version of itself, as a function of the amount of 51 time shift. More precisely, it is the crosscorrelation of a signal with itself. Autocorrelation is useful for finding 52 repeating patterns in a signal, such as determining the presence of a periodic signal which has been buried under 53 noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. ? is 54 typically chosen as the time it takes the autocorrelation function of the data to decay to 1/e or the first minimum 55 in the graph of the average mutual information. Here we used the two dimensional phase space portrait, i.e., d 56 57 = 2.

Here in this project, phase space analysis has been used on IHR time series and the results are analyzed to see if any significant difference is found between normal and abnormal data series.

Following are the portraits obtained using phase space portrait on IHR. They are presented along with theIHR plot against each sample.

⁶² 5 b) Poincare plot Analysis

The most commonly used non-linear method of analyzing heart rate variability is the Poincare plot. The Poincare plot analysis (PPA) [7] is a quantitative visual technique, whereby the shape of the plot is categorized into functional classes and provides detailed beat-tobeat information on the behaviour of the heart. Poincare plots are applied for a two-dimensional graphical and quantitative representation where ??? is plotted against ???+1.Most commonly, three indices are calculated from Poincare plots: the standard deviation of the shortterm RR-interval variability (SD1), the standard deviation of the long-term RR-interval variability (SD2) and the axes ratio (SD1/SD2) [8].

The standard deviation of the point's is perpendicular to the line-of identity denoted by SD1 describes shortterm variability which is mainly caused by RSA. It can be shown that SD1 is related to the timedomain measure SDSD by, The standard Poincare plot can be considered to be of the first order. For the healthy heart, PPA shows a cigar-shaped cloud of points oriented along the line of identity.

In Poincare plot analysis here is the record of seven normal person's and seven abnormal person's ECG and analysis SD, ??EAN Detrended Fluctuation Analysis is an interesting method for scaling the long-term autocorrelation of nonstationary signals ??9] ??10] ??11][12]. It quantifies the complexity of signals using the fractal property. This method is a modified root mean square method for the random walk. Mean square distance of the signal from the local trend line is analyzed as a function of scale parameter. There is usually power-law

dependence and interesting parameter is the exponent.

Detrended fluctuation analysis (DFA) measures the correlation within the signal. The correlation is extracted for different time scales. First, the RR interval time series is integrated, (?) = ? (??? ??=1 ? ??) ? ? ? ? ? k=1,?.N ? ..(2.3)

Where ??? ? ? is the average RR interval. Next, the integrated series is divided into segments of equal 83 length n. Within each segment, a least squares line is fitted into the data. Let ?(?) denote these regression 84 lines. Next the integrated series (?) is detrended by subtracting the local trend within each segment and the 85 root-mean-square fluctuation of this integrated and detrended time series is calculated by, This computation is 86 repeated over different segment lengths to yield the index (?) as a function of segment length n. Typically?(?) 87 increases with segment length. A linear relationship on a double log graph indicates presence of fractal scaling 88 and the fluctuations can be characterized by scaling exponent? slope of the regression line relating log (?) to log 89 90 n.

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92 ?(?) = ? 1 ? ? [?(?) ? ? ? (?)] ? ?=1 2 (2.4)

In the DFA method, the fractal-like signal (1/f noise) results in exponent value ? =1.0, the white noise results in value 0.5, and the Brownian noise in value 1.5. White noise indicates a simulated uncorrelated random time series. The white noise is the value at one instant that does not correlate with any previous value, and the Brownian noise is the integration of the white noise. The 1/f noise can be interpreted as a "compromise" between the complete unpredictability of white noise and the much smoother "landscape" of Brownian noise.

Here DFA1 & DFA2 for the normal patients and abnormal patients are taken and plotted them. (2.5)

Where, From the phase space plot for IHR, there lies significant difference between normal and abnormal rhythms. For the normal rhythm, there is normal attractor which forms a slope of almost 45 degree with the axes and there is slight dispersion around that attractor. For the abnormal rhythm, it is seen that their phase

space portrait fill more space in the plane and there is random attractor present in the plot. Here from the 102 figure it is seen that the all data of the normal patients is close to center. But for the abnormal patients the 103 data scatter from the center as a result the area fill-up by the abnormal patients is more than the area fill-up 104 by the normal patients. Using the DFA method it can be distinguished healthy from unhealthy subjects. Also 105 can be determined which signal is more regular and less complex -useful for analyzing biomedical signals. It's 106 concluded that using non-linear dynamics methods like DFA method is a quantitatively and qualitatively study 107 of physiological signals. Here from the Figure 3.14 to 3.19 it is seen that central tendency is gradually increased 108 with respect to the standard deviation than the normal patients. At the same way for the abnormal patients 109 central tendency is not sharply increased with respect to standard deviation and the CTM values is always lower 110 than 0.5 for abnormal patients. The normal patients's CTM value is similarly increased with respect to SD 111 increase from 10% to 100 %. But for abnormal patients CTM values is increased gradually with respect to SD 112 increase from 10% to 100. The normal patients's CTM value's is much higher than both abnormal patients's so 113 it can be perfectly said that the normal patients's is much more healthy than other normal patients. ?(??) = 1, 114 if r a a a a i i i i ?????????? 5.021212]) () [((2.6) = 0, otherwise)]115

¹¹⁶ 7 Conclusion and Future Work

In this work PVC in ECG data set have been identified. The whole work is based on the fact that R-R intervals 117 for normal rhythm data set tend to invariant and for the abnormal rhythm data set tend to vary a lot. This 118 work describes the application of phase space portrait, Poincare Plot, DFA and CTM. Phase Space Portrait is a 119 visible technique. From Poincare Plot a significant difference between normal and abnormal rhythm have been 120 achieved. DFA determine the fluctuation of RR interval from the Slope. For normal rhythm value of CTM is 121 more than the abnormal rhythm. Here clear difference for the normal and abnormal rhythm and high level of 122 accuracy between them has been achieved. So it can be said that it is better to use CTM for classifying the 123 ECG as normal or abnormal. In this paper abnormality of ECG signal have been detected specially in PVC 124 cases. In future several frequency domain methods (i.e cross entropy analysis, Lyapunov Exponents, Support 125 Vector Machine (SVM), Discrete Cosine Transform (DCT)) will be added to detect the abnormalities of heart. 126 Future work may also include working with more number of abnormal records to generalize the detection of beat 127

abnormality type. 1 2 3



¹²⁸

Figure 1:

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Figure 2: Figure 3 Figure 3



Figure 3: Figure 3 . 6 :



Figure 4: Figure 3 . 7 :



Figure 5: F



Figure 6: Figure 3.



Figure 7: F



Figure 8: Figure 3 . 2016 F©Year 2016 F



Figure 9:

Figure 10:

7 CONCLUSION AND FUTURE WORK

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Identification of Premature Ventricular Contraction (PVC) of Electrocardiogram using Statistical Tools and Non-Linear Analysis

[Note: $F \odot 2016$ Global Journals Inc. (US)]

Figure 11: Table 2 .

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Figure 12: Table 2 .

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