International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-4 Issue-10, March 2015

Assessment of Heart Rate Variability using Independent Component Analysis

S. Thulasi Prasad, S. Varadarajan

Abstract - According World Health Organisation reports, it is understood that cardiovascular diseases are increasing at an alarming rate and becoming main cause for more deaths. The early detection of cardiac related deceases is essential to save a patient from death. The ECG signal plays a key role in the early detection and diagnosis. In recent years there have been wide-ranging studies on Heart rate variability in ECG signals and Digital Signal Processing is becoming as an essential and effective pedagogical approach to solve a problem of detecting selected arrhythmia conditions from a patient's electrocardiograph (ECG) signals. Normally the Heart rate variability is studied based on RR interval and used analyse the sympathetic-parasympathetic autonomic stability, the risk of unpredicted cardiac death. Even there are several methods to analsye the ECG signal, the Blind Source Separation (BSS) approach is very useful and successful in extracting a cleaned ECG signal from a ECG which is mutilated badly by noise. The BSS approach, it is intended to estimate a set of underlying source signals of physiological activity from the sole observation of unknown mixtures of the sources. In this paper, first we addressed Independent Component Analysis (ICA) to remove noise and artifacts from ECGs. In the second step the noise free ECG signal is reconstructed from desired Independent Components. Finally QRS complexes, R peaks, RR intervals, and HR were found using suitable algorithms and performed a statistical analysis to finding HR Variability (HRV). This method is tested on ECG signals from in MIT-BIH Arrhythmia database.

Index Terms— Arrhythmia, AV node, ECG, HRV, ICA, MATLAB, QRS, RR interval, SA node.

I. INTRODUCTION

The Electro Cardio Gram (ECG) represents the electrical activity of human heart. The deviations in the normal electrical patterns indicate various cardiac disorders. In 1901, Willem Einthoven used a string galvanometer to measure ECG and assigned letters P, Q, R, S and T to the various deflections. In recent years several automated methods were invented for analysing the ECG signals using real-time processing techniques inturn to diagnose the cardiac diseases accurately. According to Einthoven the complete ECG wave is a trace as shown in the Fig. 1. The main parts of ECG waveform are the P wave, PR interval, QRS complex, ST segment, T wave and QT interval which represents polarization of atria and ventricles in a sequential manner. The type of wave and the action which causes them are summarized in Table-I

TABLE I. Types of waves and Action

Wave	Action
P-wave	Depolarization of the atria
Q-wave	Activation of the anterioseptal region of the ventricular myocardium
R-wave	Depolarization of the ventricular myocardium
S-wave	Activation of the posteriobasal portion of the ventricles
T-wave	Rapid ventricular repolarization

The flat horizontal segments of PR segment and the segment between TP segments constitute the baseline of the electrocardiogram. In a normal healthy heart, the baseline is equivalent to the isoelectric line (0 mV). The information pertaining the Heart Rate Variability, Auricular and Ventricular Hypertrophy, Myocardial Infarction [1]-[2] (heart attack), Arrhythmias, Pericarditis and coronary artery disease are concentrated in intervals and magnitudes of the P wave, QRS complex, T wave, PR segment, QT interval, ST interval, and ST segment of ECG signal. However, in a diseased heart the HR signal deviates from its normal range due to flow of injury currents during the conduction periods of the TP and PR intervals.

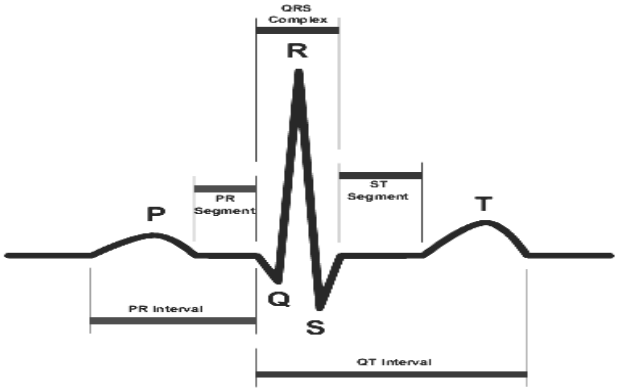

Fig. 1 Complete trace of one beat of ECG wave

II. PHYSIOLOGY OF HEART

The heart is a 4 chamber cone-shaped muscular pump located in the cavity of the thorax between the lungs and beneath the sternum [2]. Physiology of heart is shown in the Fig. 2. The heart pumps blood throughout the whole body to supply nutrients and oxygen to tissue, and carries away carbon dioxide and metabolic waste for excretion through the lungs and the kidneys, respectively.

Manuscript published on 30 March 2015.
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The upper left and right atria or auricles are separated from lower left and right ventricles by fibrous, non-conductive tissue and isolates electrically [1]-[2].

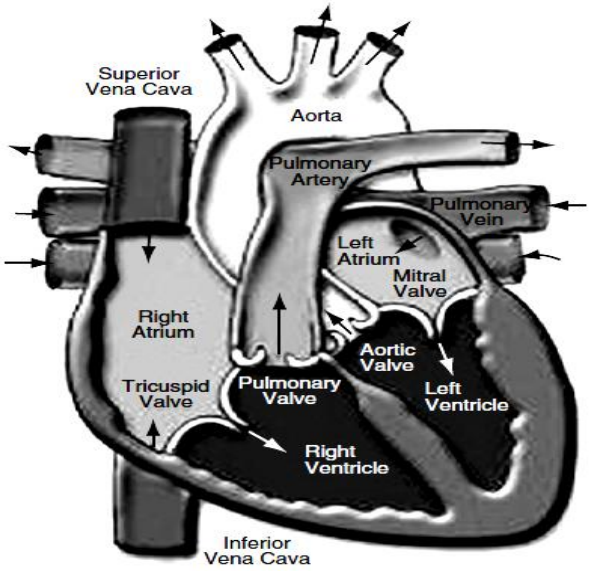

Fig. 2 Physiological features of human heart

The heart receives impure blood into the right atrium from the body through large veins called the superior and inferior vena cava. Simultaneously the poor blood is received into left arteries from the lungs through pulmonary veins. This forms the relaxation phase of the heart. At the end of the relaxation phase the blood is received into right and left ventricle from right and left atria. In the next phase, known as contraction phase, the right and left ventricles together contracts to pump the impure blood into the lungs and pure blood into Aorta respectively. The chambers of the heart alternately contract and relax in a rhythmic cycle. During the period of contraction (systole), the heart pumps blood out through the arteries; during the period of relaxation (diastole), the heart fills with blood. One complete sequence of filling and pumping blood is called a cardiac cycle, or heartbeat. The sinoatrial node (SA node), which is part of the heart's intrinsic conduction system, controls the rhythm of contraction of the heart.

The heart will continue to beat as long as its cells are alive. This nature of the automatic heartbeat is referred to as automaticity. Automaticity is due to the spontaneous electrical activity of the SA node. The SA node generates the electrical impulses and spreads through the heart via a nodal tissue pathway (conduction system). The conduction system coordinates and synchronizes the events of the cardiac cycle (contraction, relaxation, opening and closing of valves) to operate the heart as a pump. In a healthy adult heart at rest, the SA node generates 60 to 100 electrical impulses per a minute which accounts for heart beat rate. From the SA node, the signal travels through the right and left atria and results in Atrial depolarization. This causes the atria to contract, which helps move blood into the heart's lower chambers, the ventricles [2]. The electrical signal moving through the atria is recorded as the P wave on the ECG. This wave is normally less than 120 ms wide and corresponds with the start of Atrial muscular contraction. The P-R interval, which is measured from the onset of the P-wave to the onset of the QRS-complex, is normally within 120-200 ms (Note that if the Q-wave is present, the PR interval should terminate on the onset of Q-wave although it would still be labeled as PR interval). Atrial contraction typically lasts longer than the PR interval. Similarly, ventricular depolarisation results in the spreading of the electrical impulse throughout the ventricular myocardium. Depolarisation is triggered when the pacemaker impulse from the SA node comes through the Atrioventricular node [1]-[2] and spreads through the ventricular conduction system to the myocardium.

III. METHODOLOGY

In our proposed method the ICA (Independent Component Analysis) [3] is used for a better separation. ICA is a quite powerful technique and is able (in principle) to separate independent sources linearly mixed in several sensors. In our proposed method ICA has been used to separate out artifacts embedded in the data (since they are usually independent of each other).

A. Problem Formulation

ICA represents one solution of the Blind Source Separation problem (BSS) [4]-[5], which is the extraction of a set of signals based merely on their mixtures. In particular let us mention ECG, which is a mixture of signals from nodes presented in the heart. Basic ICA model assumes linear combination of source signals (called components)

$$\mathbf{X = AS} \qquad \textbf{(1)}$$

Where X, S are the two vectors representing the observed signals and source signals respectively and A is an unknown matrix called the mixing matrix and. Mixture matrix A is then of size n x n (in general A does not need to be square, but many algorithms assume this 'property'), X and S get the size n x m, where n is number of sources and m is length of record in samples. Incidentally, the justification for the description of this signal processing technique as blind is that we have no information on the mixing matrix, or even on the sources themselves. The objective is to recover the original signals, S, from only the observed vector X. Denoting the output vector by **V**, the aim of ICA algorithms is to find a matrix **U** to undo the mixing effect. That is, the output will be given by

$$\mathbf{V=UX} \qquad \textbf{(2)}$$

Where, **V** is an estimate of the sources. The sources can be exactly recovered if **U** is the inverse of A up to a permutation and scale change.

The BSS/ICA methods try to estimate components that would be as independent as possible and their linear combination is original data. Estimation of components is done by iterative algorithm, which maximizes function of independence, or by a non-iterative algorithm, which is based on joint diagonalization of correlation matrices [4]-[5]. ICA has one large restriction that the original sources must be statistically independent. This is the only assumption we need to take into account in general. The reconstructed ECG can be derived by using the following equation

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$$X=U^{-1}V \quad (3)$$

Where, **V** is the matrix of derived independent components with the row representing the noise or artifacts set to zero. ICA is a technique to separate linearly mixed sources. For instance, let's try to mix and then separate two sources. Let us consider two signals A, and B from two independent sources as shown in Fig. 3(a) and Fig .3(b) respectively.

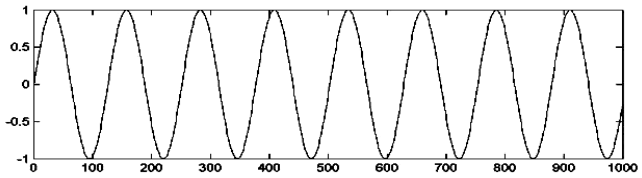

Fig. 3(a) Signal A from first independent source

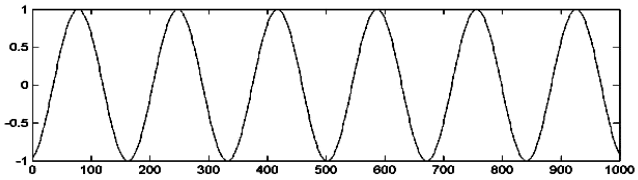

Fig. 3(b) Signal B from second independent source

We then mix linearly these two sources. The one mix is equal to **A** – 2* **B** and shown plotted in Fig. 3(a). The other mix is obtained from the linear combination of **A** and **B** as 1.73***A** + 3.41***B** and shown plotted in Fig. 3(b).

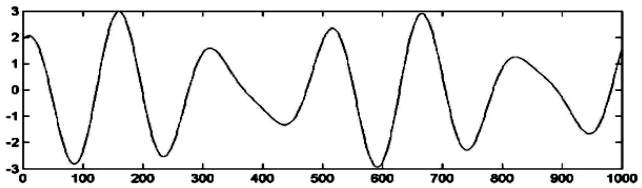

Fig. 3(a)

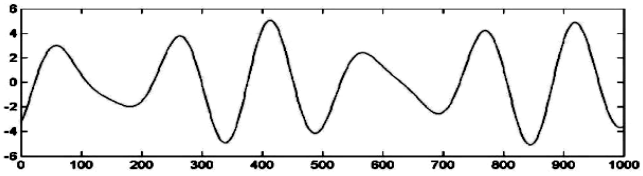

Fig. 3(b)

By using ICA algorithm (in this case, fastICA), We evaluated the ICs and plotted in Fig. 4. From these ICs the independent signals **A** and **B** can easily be identified [6].

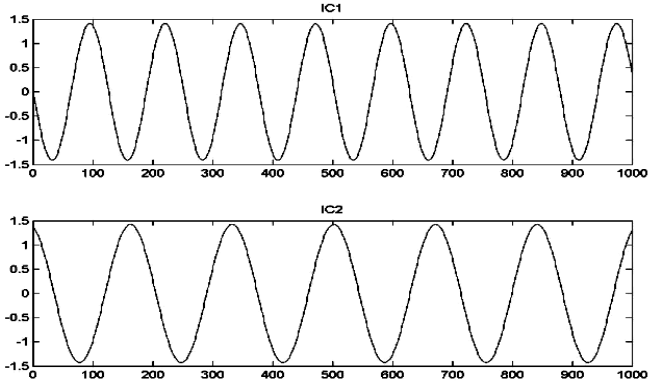

Fig. 4

B. Problem Approach

After getting ICs it is necessary to determine the order of the independent components in order to identify normal ECG [7], noise and abrupt alterations. As the ICs corresponding to noise and abrupt alterations have more distinctive properties than that of original signal both in time and frequency domains, we may employ the statistical properties of these waveforms to recognize the original ECG automatically instead of identifying visually. The noise is identified by using kurtosis and abrupt changes by using variance. The kurtosis is the fourth order cumulant. For a signal ***x(n)***, it is classically defined as in equation (4) by dropping ***n*** for convenience

$$Kurt(x) = E(x^4) - 3[E(x^2)]^2 \quad (4)$$

Here the kurtosis is zero for Gaussian densities. The normal ECG will have large Kurtosis value than continuous noise. In our approach, a threshold is chosen from analysis of sample waveforms, and a component whose modulus of kurtosis is below this threshold will be considered as continuous noise.

There are several ways to detect abrupt changes which are usually short transients. The variance or energy is more or less similar and negligibly small for all IC waves except for those IC waves containing abrupt changes. Thus the IC waves whose variance is large can be identified as abrupt variations or noise. The variance of signal ***x(n)*** is given by

$$x_{\text{var}} = \sum_{n=1}^{N-1} [x(n) - \overline{x(n)}]^2 \quad (5)$$

Here ***x(n)*** is the mean value of ***x(n).*** In our approach we calculated the modulus of Kurtosis value of each ICA component and compared with the threshold. If the modulus of Kurtosis exceeds the threshold, that IC is marked as continuous noise component. Then, the remaining ICA components are divided into 10 nonoverlapping blocks, each of one-second duration. The variances of the 10 segments for each component are calculated as shown in Eq. (5), then the variance of these 10 variance values is obtained as the parameter x_{var} . The component whose x_{var} value is above a predetermined threshold is marked as an abrupt change component. Finally, the required ECG can be obtained using equations (2) and (3).

C. Heart Rate Detection

To find heart rate (HR) [8]-[9], detection of QRS complex [9]-[10], in turn identification of R-Peaks is essential. An automated QRS detection algorithm structure which involves QRS enhancement is used to detect QRS complex.

1. The ECG signal is filtered with Derivative filter
2. Moving average filter is designed and used on squared ECG signal from derivative filter.
3. Signal is integrated and set a threshold
4. QRS complex is detected with the help of Pan-Tompkins algorithm [11]

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Since R-wave is positive waveform and highest peak in ECG signal, the time interval between two successive R-wave peaks is used to calculate HR (beats/minute) [10]-[11] as follows

$$HR = \frac{60}{RR\,Interval}\text{beats/minute} \quad (6)$$

IV. RESULTS

We tested our procedure on the ECG signal that is obtained from MIT/BIH database. According to our proposed procedure, first the signal was split into Independent Components using fastICA algorithm [7]-[8]. The two ECG signals and the ICs derived from fastICA algorithm were shown in the Fig. 5(a) and Fig. 5(b) respectively. Later the order of Independent Components was determined to identify normal ECG, noise and abrupt alterations. Based on the value of kurtosis and variances of the ICs, the desired ICs were selected [12]. From these the selected ICs, the desired ECG was reconstructed by using equations (2) and (3) shown plotted in Fig. 5(c).

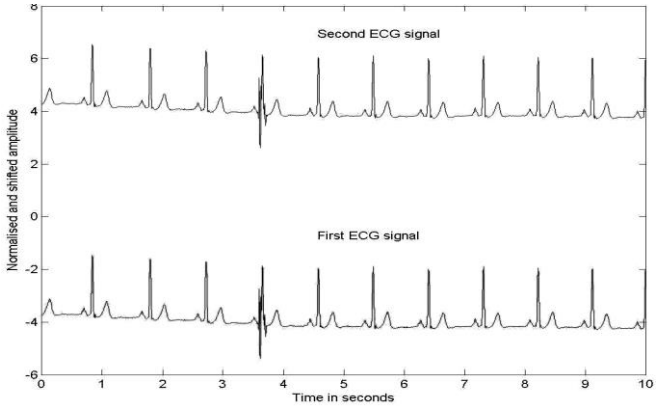

Fig. 5(a) Two separate ECG signals to be mixed

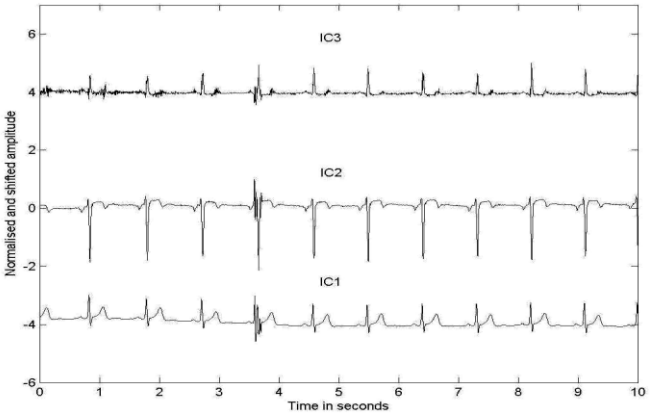

Fig. 5(b) Extracted ICs from mixed ECG

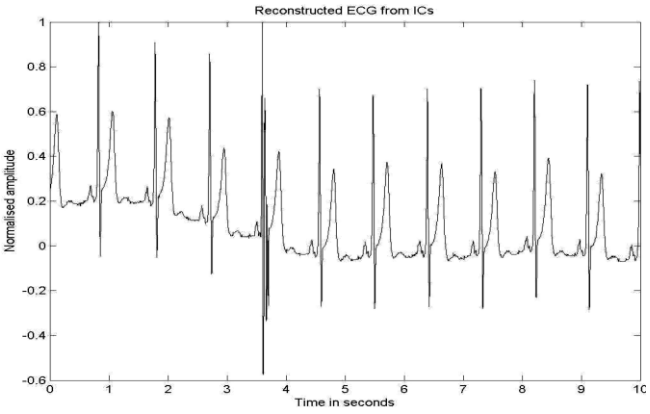

Fig. 5(c) Reconstructed ECG from selected ICs

The reconstructed ECG signal is processed for the QRS complexes to determine the temporal locations of the R-wave using a combined maximum/minimum search of a simple algorithm. Once the R-Peaks are located, the Heart Rate signal is determined from the separation between consecutive R-Peaks and plotted. Fig-6(a) shows the reconstructed ECG signal with identified QRS complexes, R-Peaks and other peaks. Fig. 6(b) shows the Heart Rate signal as a histogram.

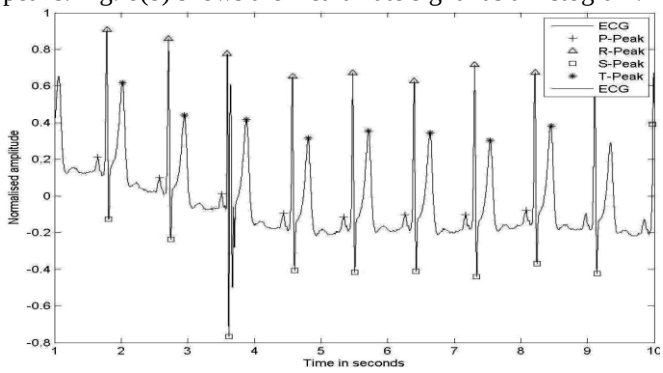

Fig. 6(a) ECG with QRS complex and other peaks

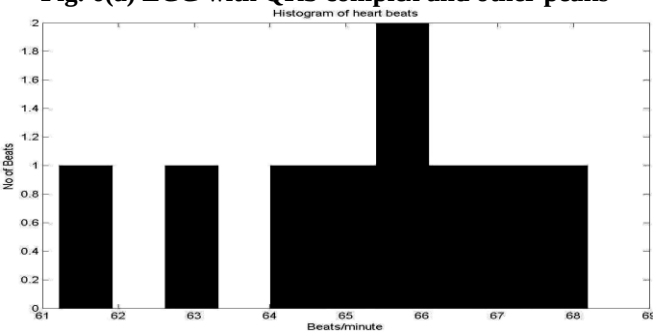

Fig. 6(b) Histogram of Heart beats

V. CONCLUSION

In our analysis we found that the overestimation as well as underestimation of ICs can be easily avoided by using the threshold-based method. As the noise is identified by using kurtosis and abrupt changes by using variance, we can achieve easily higher accuracy, automaticity and better correction of electrocardiogram. It is also observed the feature classification from the reconstructed ECG is also matching very closely to clinical investigations by the experts.

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The approache, such as one we proposed here, will tend to create interests in students and enhance their practical learning in multidisciplinary applications including analysis of ECG signals acquired from various sources. We used fastICA algorithm on the single channel ECG data to identify and remove noise or artifacts. The same approach can be used on multi-dimensional ECG signals in the future work.

ACKNOWLEDGMENT

We gratefully acknowledge the Sree Vidyanikethan Engineering College, Tirupati for providing Laboratory facilities. We also extend our sincere thanks to SVRR hospital's (Tirupati), personal for providing basic clinical information regarding ECG.

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