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Analysis of ST Segment Variability Dynamics and Detection of Myocardial Infarction

S. Thulasi Prasad
Dept. of Electronics and Communications Engineering
Sree Vidyanikethan Engineering College
Tirupati, India
stprasad123@yahoo.co.in
S. Varadarajan
Dept. of Electronics and Communications Engineering
Sri Venkateswara University College of Engineering
Tirupati, India
varadasouri@gmail.com

Abstract

In recent years, cardiovascular disease has become the number one killer. The early detection of cardiac related deceases is essential to save a patient from death. The ECG signal plays a key role in the primary diagnosis, prognosis and has a philosophical influence on the practice of medicine. This paper deals with the detection of QRS complexes and ST segments variability of ECG signals using Independent Component Analysis (ICA). Analysis of ECG is not easy if signal is embedded in noise. We performed our analysis in three steps. At first the noisy ECG signal is firstly decomposed into a Set of Orthogonal Functions (SOFs) using ICA method. In the second step the noise free ECG signal is reconstructed from desired Independent Components. Finally QRS complexes and ST segments were found using suitable algorithms to perform statistical analysis such as finding ST variability. This method is evaluated on ECG signals available in MIT-BIH Arrhythmia database. The proposed method gives better results with improved Signal to Noise Ratio (SNR) than the commonly used Wavelet Transform based denoising technique.

Keywords: Arrhythmia; ECG; QRS; RR interval, SA node; AV node; ICS; STV; MATLAB.

Introduction

In present day scenario the bioengineering is becoming an essential course in engineering programs as it can be used to solve several difficulties which are being faced by the researchers and doctors in diagnose ailments. Signal processing in

bioengineering deals with the analysis of signals such as filtering, smoothing, digitization, feature extraction, prediction, in either discrete or continuous time, to dig out useful information from those signals. Now days there is a great interest in ECG signal processing in order to detect symptoms of cardiovascular disease in advance as it has become the number one killer.

The ECG is an acronym of Electro Cardio Gram and is used to represent the electrical activity of human heart. The deviations in the normal electrical patterns indicate various cardiac disorders. During the cardiac cycle of human heart the bioelectrical action potentials are transmitted through the various parts of the heart to perform contractions and relaxations of cardiac muscles in a rhythmic way. These electrical potentials are recorded as an ECG from surface of the chest near the heart [1], [2]. It is used as a basic investigative and major diagnostic tool for the cardiologists in cardiology to detect and analyze the Heart Rate Variability, Auricular and Ventricular Hypertrophy, Myocardial Infarction (heart attack), Arrhythmias, Pericarditis and Coronary Artery disease in patients with chest pain syndromes[2], [3]. The information pertaining to these imperfections and defects are concentrated in intervals and magnitudes of the P wave, QRS complex, T wave, PR segment, QT interval, ST interval, PR segment, and ST segment of the ECG signal. Based on the above data, doctors can correctly diagnose human heart diseases. Therefore, analyzing the ECG signals of cardiac Myocardial Infarction is very important for doctors to make correct clinical diagnoses and to take right decisions in right time.

The portion of the ECG that lies between the J-point end of the S wave and beginning of the T wave is known as ST segment [4]. This is not always flat instead it is elevated or depressed. It is not always easy to determine the duration of the ST segment if noise is present by using normally existing noise removal techniques. The most commonly used method in the real world applications are Pan-Tompkins QRS detection algorithm and its modification introduced by Hamilton and Tompkins [5], [6]. Pan-Tompkins and its modification Hamilton-Tompkins algorithms are based on patient specific detection threshold. These algorithms are well suitable to enhance the positions of QRS complexes and not for enhancing the locations of onset and off set of ST segment. To overcome this difficulty we proposed a procedure to estimate ST segment accurately using Independent Component Analysis (ICA) and inturn to perform ST analysis [7]. In our procedure the Pan-Tompkins QRS detection algorithm is used to locate peaks of QRS complex and JADE algorithm to find Independent Components (ICs) [8].

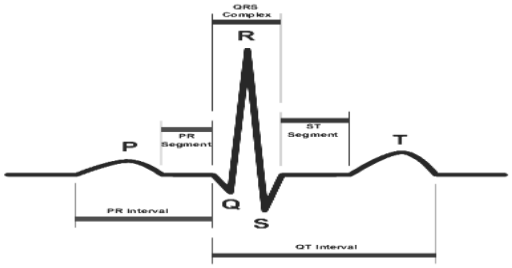

Figure 1: ECG Wave of A Heart Beat

Background

In 1901, Willem Einthoven used a string galvanometer to measure ECG and assigned letters P, Q, R, S and T to the various deflections. The parts of ECG waveform are the P wave, PR interval, QRS complex, ST segment, T wave and QT interval. These parts are shown in the Fig-1. These parts represent the rhythm of polarization of atria and ventricles when the heart beats in cyclic manner. 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. The physiology of heart and development of ECG are discussed next section.

A. Physiology of Heart

The heart (Fig. 1.5) is a 4 chamber cone-shaped muscular pump located in the cavity of the thorax between the lungs and beneath the sternum [1], [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. 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].

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 structure and conducting system of heart are shown in the Fig. 2(a) and Fig. 2(b) respectively.

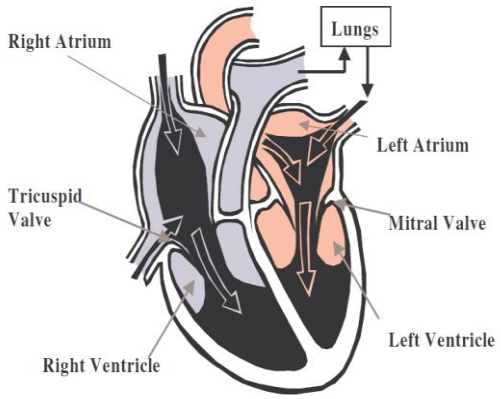

Figure 2(a): Structure of Human Heart

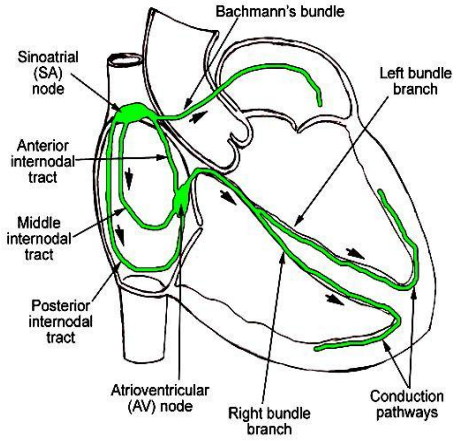

Figure 2(b): C conduction system of Human Heart

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. 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 P-R interval should terminate on the onset of Q-wave although it would still be labeled as P-R interval.) Atrial contraction typically lasts longer than the P-R 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 S-A node comes through the atrioventricular node and spreads through the ventricular conduction system to the myocardium.

B. ECG Basics

In both the 5- and 12-lead configurations, leads I, II and III are called limb leads [2]. The electrodes that form these signals are located on the limbs one on each arm and one on the left leg. The limb leads form the points of what is known as Einthoven's triangle. Lead I is the voltage between the (positive) left arm (LA) electrode and right arm (RA) electrode: I=LA-RA. Lead II is the voltage between the (positive) left leg (LL) electrode and the right arm (RA) electrode: II=LL-RA. Lead III is the voltage

between the (positive) left leg (LL) electrode and the left arm (LA) electrode: III=LL-LA. There are two types of leads known unipolar and bipolar. Bipolar leads have one positive and one negative pole. In a 12-lead ECG, the limb leads (I, II and III) are bipolar leads. Unipolar leads also have two poles, as a voltage is measured; however, the negative pole is a composite pole (Wilson's central terminal, or WCT) made up of signals from multiple other electrodes. In a 12-lead ECG, all leads except the limb leads are unipolar (aVR, aVL, aVF, V1, V2, V3, V4, V5, and V6). Wilson's central terminal V_W is produced by connecting the electrodes RA, LA, and LL together, via a simple resistive network, to give an average potential across the body, which approximates the potential at infinity (i.e. zero): V_w = (RA+LA+LL)/3. Leads aVR, aVL, and aVF are augmented limb leads (after their inventor Dr. Emanuel Goldberger known collectively as the Goldberger's leads). They are derived from the same three electrodes as leads I, II, and III. However, they view the heart from different angles (or vectors) because the negative electrode for these leads is a modification of Wilson's central terminal. This zeroes out the negative electrode and allows the positive electrode to become the "exploring electrode".

Methododlogy

Independent Component Analysis (ICA) is one of the best solutions to the Blind Source Separation problems (BSS) [8]. In ICA a set of signals are extracted merely based on their mixtures. In our proposed method of analysis ICA is used to remove noise and artifacts first and followed by reconstructing the noise free ECG by setting ICs, which are embedded with the noise and artifact, set to zero in (2) [9], [10] . This may be achieved with the help of kurtosis and variance of ICs. ICA is a quite powerful technique and is able (in principle) to separate independent sources linearly mixed in several sensors. Finally the fiducial points are determined and the ST episodes are analysed using suitable algorithms & MATLAB.

A. Extraction of ECG signal

In particular let us consider ECG, which is a mixture of signals from nodes presented in the heart and various artifacts and noise. Basic ICA model assumes linear combination of source signals (called components)

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

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

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

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 [8], [9], [10]. 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

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

Where, **V** is the matrix of derived independent components with the row representing the noise or artifacts set to zero.

After getting ICs it is necessary to determine the order of the independent components in order to identify normal ECG, 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 [9], [11]. For a signal ***x*(*n*)**, it is classically defined as in (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 non over lapping blocks, each of one-second duration. The variances of the 10 segments for each component are calculated as shown in (5), and 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 (2) and (3).

B. ST segment Variability

In the second stage ST episodes are identified after finding fiducial points. To find out fiducial points such as P-peak, Q-peak, R-peak and S-peak more accurately, a well known QRS enhancement Pan-Tompkins algorithm, and derivative-based methods can be used. ST segment is the separation between J point and K point [12], [13]. The J-point is located at 60 ms after the R-peak in normal sinus rhythm case. In the case of RR interval less than 600 ms (tachycardia), the J-point is taken at 40 ms after the R peak. The K-point is the onset of T wave. These values are in general agreement with the recommendation of the European ST-T database. The ST segment elevation or depression is measured as the difference between the mean of ST segment in each beat and the isoelectric line. If the absolute value of ST segment deviation exceeds 0.08 mV, the beat is classified as ischemic beat. If the no of ischemic beats exceeds 75 % of total no of beats then the subject is prone to Myocardial Infarction. The variance of ischemic beats and all ST segments are calculated by using (6) and (7)

$$IST_{\text{var}} = \sum_{n=1}^{N-1} [IST(n) - \overline{IST(n)}]^2 \qquad (6)$$

$$ST_{\text{var}} = \sum_{n=1}^{N-1} [ST(n) - \overline{ST(n)}]^2 \qquad (7)$$

The ratio of IST_{var} and ST_{var} is taken as measure of severity of MI and called Myocardial Infarction Severity Index (MISI). If MISI is more than 0.7 the subject is classified as acute Myocardial Infarction and if MISI is less than 0.3 the subject is classified as mild Myocardial Infarction.

Results

We analyzed the ECG waveforms based on morphological differences between abnormal and normal ECG waveforms using our proposed algorithm. The proposed algorithm has been tested on MIT-BIH (Massachusetts Institute of Technology - Beth Israel Hospital) Long Term ST database. Two ECG records '**s20041m**' and '**s20045m**' are taken from MIT-BIH Long Term ST database and preprocessed by using Independent Component Analysis to obtain ICs as shown Fig. 3(a). To get ICs we used JADE algorithm. Later the cleaned ECG is obtained by choosing the relevant Independent Components based on kurtosis and variance of ICs. The cleaned ECG is shown plotted in Fig. 3(b). After getting cleaned ECG signal, we computed the R peaks, R-R intervals, QRS amplitudes, ST segment durations and amplitudes by using a simple algorithms. The peaks are shown in Fig. 3(c). The variance of ischemic beats, all ST segments and the value of MISI are calculated by using (6) & (7). The MISI is found to be more than 0.7 and classified as acute Myocardial Infarction.

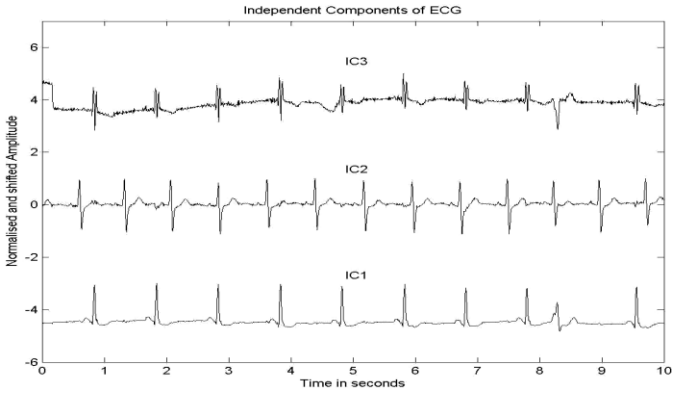

Figure 3(a): Extracted ICs from mixed ECG

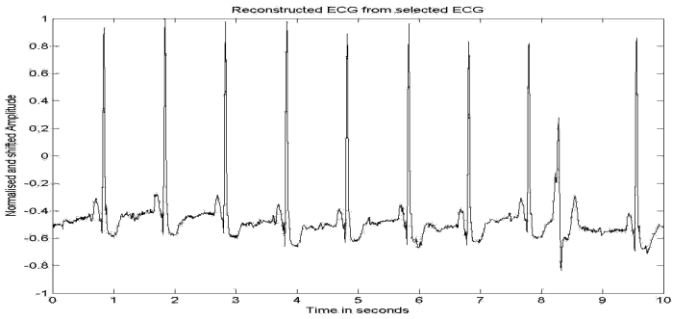

Figure 3(b): Reconstructed ECG from selected ICs

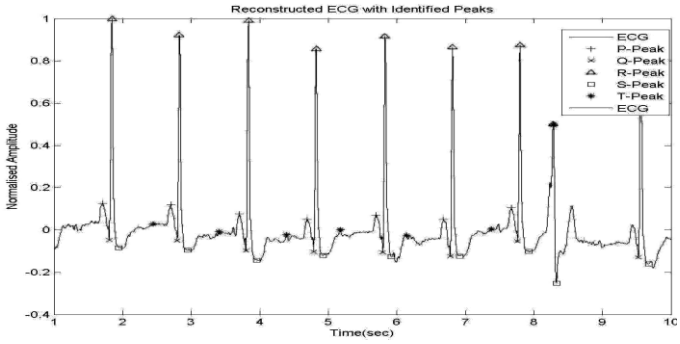

Figure 3(c): Reconstructed ECG from selected ICs with peaks

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