Signal Processing Techniques for Atrial Fibrillation Source Detection

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Abstract **– In clinical practice, Atrial Fibrillation (AF) is the most common and critical cardiac arrhythmia encountered. The treatment that can ensure permanent AF removal is catheter ablation, where cardiologists destroy the affected cardiac muscle cells with RF or Laser. In this procedure it is necessary to know exactly from which part of the heart AF triggers are originated. Various signal processing algorithms provide a strong tool to track AF sources. This study proposes, signal processing techniques that can be exploited for characterization, analysis and source detection of AF signals. These algorithms are implemented on Electrocardiogram (ECG) and intracardiac signals which contain important information that allows the analysis of anatomic and physiologic aspects of the whole cardiac muscle.**

I. INTRODUCTION

Atrial Fibrillation (AF) is a supraventricular arrhythmia in which heart muscles shows chaotic and uncoordinated atrial depolarization and repolarization. Atria affected by AF tend to form blood clots which increase the risk of stroke [1]. Cardiologists believe Catheter ablation as the treatment thus far capable of achieving cure in substantial proportions. It has the greatest efficacy as a stand-alone procedure in patients with AF. Catheter ablation is a medical procedure in which a series of catheters which are basically thin, flexible wires are inserted into a blood vessel through the arms or thighs, to reach heart [2]. A special device connected to catheter sends RF energy to destroy particular cells of cardiac muscle from where abnormal heart beats (electrical impulses) might have originated [2]. The targeted destruction of these tissues ensures that AF is suppressed permanently [2].

Normal sinus rhythm of heart is maintained by periodic contraction and relaxation generated from the Sinoatrial (SA) node [3]. Under abnormal conditions another electrical impulse is generated from atrium which also tries to control the cardiac cycle. In this case, heart is controlled simultaneously by two types of electrical impulses, first is electrical impulse from SA (normal) and other is the generated from somewhere in the atrium (abnormal) [3]. The study proposes algorithms useful in detection and characterization of this second type of impulse, helpful to track its origin. For this analysis two types of signals are taken into consideration.

1. *ECG:* reflects global electrical activity of the heart, including respiratory components and muscular noise components [3].
2. *Intracardiac Electrogram:* records fluctuations in electrical potential of specific cardiac tissue with the help of catheters that are inserted in the heart.

Studying both these types of signals helps in understanding AF characteristics better. Many research papers [1-2, 4] have considered either ECG or intracardiac signals for AF analysis. In this work both the signals are taken into consideration so that the results can be verified. Also, in this work the cross-correlation properties of signals are exploited to find out the delay in terms of number of samples, so that AF signal origin can be located.

II. METHODOLOGY

The basic algorithm in the form of block diagram for characterization of AF source and its detection is as shown in Fig.1.

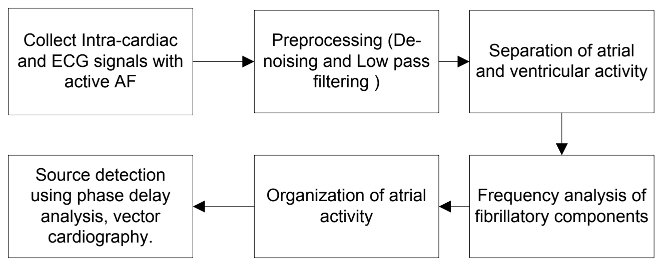

Fig. 1: Block diagram for a single source identification.

A. Data Collection

Data used in this research comes from PhysioNet ATM [5]. PhysioNet is a free web access to vast number of physiologic signals. Number of bio-physicists and medical practitioners worldwide rely on PhysioNet data signals for experiments and consider as de-facto standard for benchmarking and comparing algorithms. Intracardiac data base used in this work consists of endocardial recordings from the right atria of 8 patients in AF. It is collected by placing 5 bipolar catheters in each of the 4 separate regions [4]. Signal data is sampled at 1 kHz. Catheter bipoles are named as CS12, CS34, CS90 [5]. For ECG signals, the data is a one-minute recording of AF and contains two ECG signals. The data is digitized at the rate 128 samples per second. These records are small segments extracted long term ECG recordings. Normal Sinus rhythm (NSR) ECG signal consists of components P, Q, R, S and T. P wave corresponds to atrial activation. QRS complex corresponds to activation of the ventricles and T wave corresponds to ventricular recovery. In AF, P waves are replaced by fibrillatory F waves as can be seen in Fig. 2.

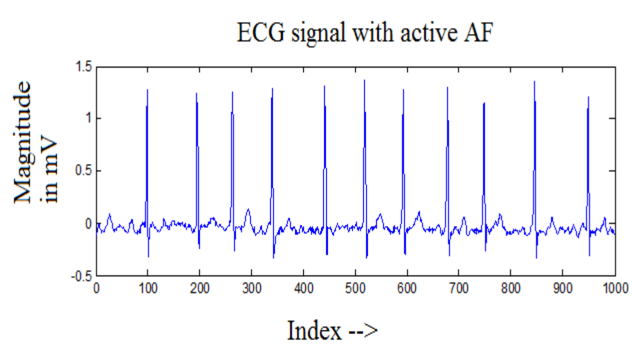

Fig. 2: AF signal as measured by ECG [5].

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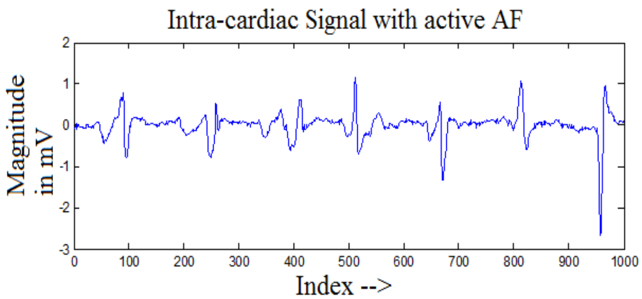

Fig. 3: AF signal as measured by Catheters inside the heart [5].

B. *Pre-processing*

Data obtained in the form of ECG and intracardiac signals is a measure of hearts electrical potential versus time. Data also contains unwanted components. There are various types of noises that are responsible for contamination such as baseline wander (BW) noise, electromyographic (EMG) interference, and 50 or 60 Hz power line interference [6]. In the case of intracardiac signals various noises such as respiratory interference, muscular noise is blended in the signal of interest. Hence it is really important to de-noise these signals.

1. *De-noising using Discrete Wavelet Transform*

Heart signals are non-stationary and hard to de-noise. Thus discrete wavelet transform (DWT) can be efficiently used for noise reduction. In this study Bi-orthogonal 3.5 wavelet is used for de-noising intracardiac signal and Daubechies wavelet is used for de-noising the ECG signal.

In DWT, the original signal is transformed using predefined wavelets [7]. DWT is computed by passing the discrete time-domain signal through successive low pass and high pass decomposition filters. Filtering takes place in several levels until the noise components are totally eliminated. The series of high pass filters are responsible for detail information analysis of the signal, while the series of low pass filters analyses the coarse approximations. Decimation by a factor of 2 at each level of filters produces signals giving half the frequency band. Thus frequency resolution is doubled as the uncertainty in frequency is cut down by half [7].

The resultant signal is passed through reconstruction filter which is opposite process to decomposition filter [7]. In this stage before high pass and low pass filtering (synthesis filters) the signal is up sampled by two, and they are added together to get the final resultant signal.

In Fig.4 and Fig.5, signal component shown in red (output) shows the smoother version of signal in blue (input). DWT algorithm works well on both types of signals. Thresholding can be really helpful in efficient de-noising of sampled signal. According to Donoho's method, the threshold estimate δ for de-noising with an orthonormal basis is given by $Th = \sigma\sqrt{2 \log N}$ where, σ = standard deviation of the Gaussian noise and N = the number of samples of the processed signal. Threshold can be estimated by calculating approximation coefficients vector and detail coefficients [7].

2. *Low Pass Filtering and Fourier Transform*

According to various researches in this field AF frequencies lie in the range of 5 to 25 Hz [4]. Thus signals obtained in Figs. 4 and 5 are passed through the low pass filter with a cutoff frequency of 50 Hz. Frequency response obtained using fast Fourier transform is plotted in Fig. 6 which clearly shows that the signal has been filtered successfully and all other components above 50 Hz have been removed.

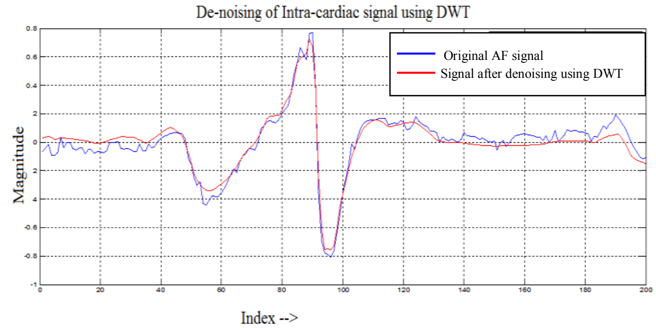

Fig. 4: Daubechies wavelet coefficients for analysis of ECG signal.

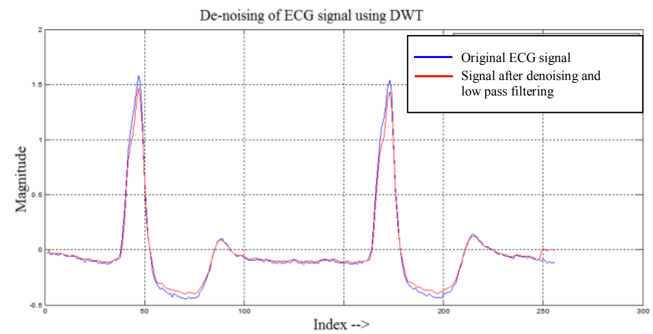

Fig. 5: De-noising of ECG signal using DWT.

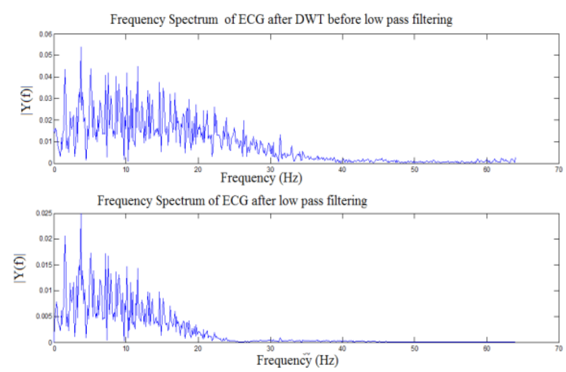

Fig. 6: Frequency spectrum before and after low pass filtering.

C. *Separation of Atrial and Ventricular Activities*

Ventricles are more massive than the atria, generating QRS complex considerably larger in amplitude than the P wave while contraction. The combination of atrial and ventricular contraction wave component is not a linear. Also the atrial repolarization wave an inverse P wave, is hidden the QRS wave because atrial repolarization wave is smaller in amplitude. The only useful component in diagnosing atrial fibrillation and characterization of abnormal electrical impulse is P waves (in the case of AF P waves are replaced by F waves.). So it is very necessary to separate ventricular components from overall signal and get rid of it. It can be done using two nonlinear signal analysis methods, 'Principal Component Analysis' and 'Removal of the QRS-T interval'.

1. *Principal Component Analysis (PCA)*

PCA is a dimensionality reduction algorithm used to reduce a complex data set to a lower dimension so that most correlated hidden components in data set are revealed [8]. Assuming that atrial and ventricular activities are uncorrelated during AF, two intracardiac signals with largest contribution of atrial components are chosen. They are first subjected to preprocessing steps. In this study signals from the catheter near atrial free wall and superior vena cava are chosen. They generally show most prominent F waves. Two-dimensional signal is created using data points from these two catheters. It is necessary to normalize the data before applying the actual algorithm so that mean of the signal is zero [9]. The covariance matrix for the above signal is then calculated. Since the data is 2-dimensional, the covariance matrix will be of size 2 by 2 [9]. Then eigenvectors and eigenvalues of this matrix are calculated. Next step is to find the highest eigenvalue and eigenvector corresponding to that value. This gives the most significant component. Lesser significant components whose eigenvalues are relatively small can be ignored and not much information is lost [9]. Transpose of the most significant vector is multiplied to the original data set. In Fig.7, the signal in red shows the resultant fibrillatory signal after PCA. It can be seen ventricular peaks are almost removed and thus the processed output signal basically represents the F waves from atrium.

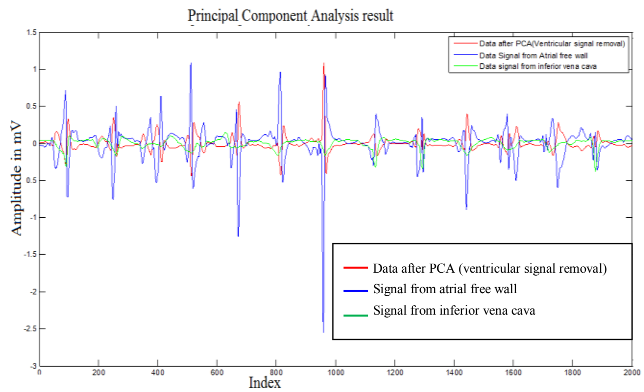

Fig. 7: Result of PCA.

To verify and confirm the results, Fourier transform of the resulting signal is plotted. The frequency contents of the result are as shown in Fig. 8. It can be observed that the frequency components of the dominant signal are located in the range of 6.3 Hz to 18.55 Hz.

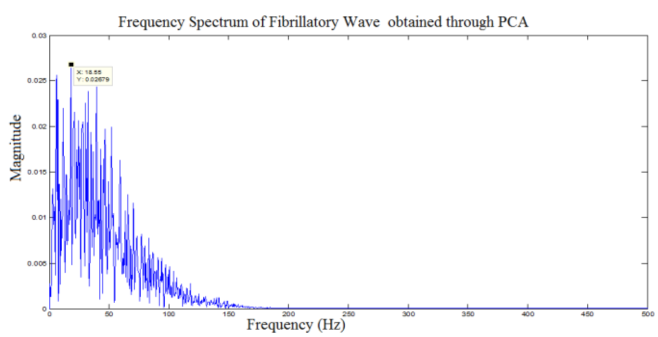

Fig. 8: Frequency spectrum of signal obtained through PCA.

2. *Removal of the QRS-T interval*

This algorithm is executed on ECG signals. The DWT of surface ECG is used for QRS-T interval removal. It involves the reconstruction of an approximation of a signal based on the local maxima and minima of its DWT [10]. ECG signal after preprocessing is passed through DWT algorithm. Finding the extrema of wavelet transform provides an iterative method of decomposition and synthesis which allows the estimation of signal after QRS-T interval removal. The result obtained through this filter is set for detection of the local extrema. Once all of them are known, only those extrema of the transformation are kept while the other values are set equal to zero. The QRS-T cancellation is conducted level by level. The extrema present around in the signals are eliminated. The signal reconstructed from the residual extrema by passing it through the reconstruction filters and then summing up. This contains only information outside the QRS-T interval as shown in Fig. 9.

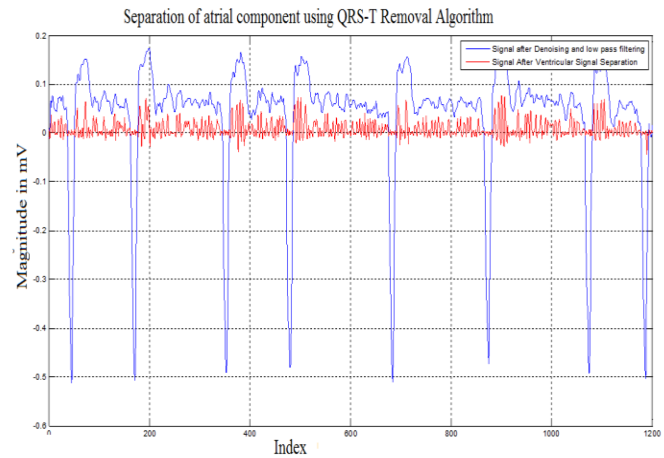

Fig. 9: Atrial component extracted through QRS-T removal.

After removal of QRS-T interval it can be seen that some of the higher frequency components are added to the signal [10]. This happens because the algorithm used is a nonlinear algorithm. It involves removal of samples from the signal and addition of zeroes inside the signal. Hence the signal needs to be lowpass filtered with a cutoff frequency of 50 Hz. For this purpose a fifth order Butterworth filter is designed.

D. *Analysis of Fibrillatory Component*

Linear Predictive Coding (LPC): The F waves signal obtained from ECG and intracardiac signals are passed through a 10^{th} order LPC filter and evaluated for dominant frequencies. This method provides the better resolution than any other method. The frequency response is plotted. This response shows a prominent peak in the frequency spectrum. This peak is the dominant frequency of the given AF signal. Fig.10 shows the frequency spectrum of the signal and also the dominant frequency component.

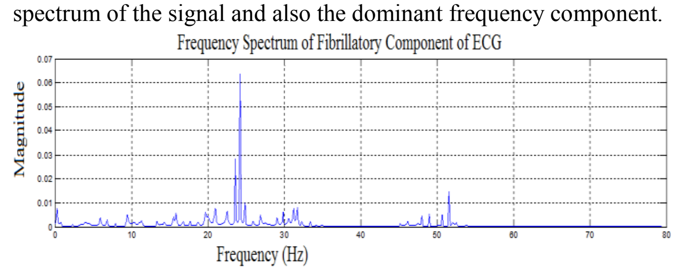

Fig. 10: Dominant peak for ECG.

LPC can also be used to estimate the number of stable sources [11]. Fig.10 shows more than one peak and hence can be concluded as AF with multiple triggers.

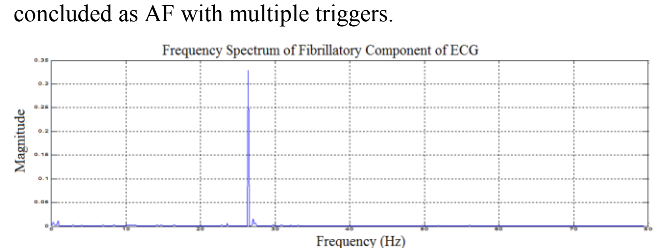

Fig. 11: Dominant peak for ECG.

Fig.11 shows one peak and hence can be concluded as AF with just a single AF trigger.

E. Source Detection Using Phase Delay for Intracardiac Signals.

This technique helps in understanding AF wave propagation in the heart tissue. The preconditions for this technique are
1. AF is triggered by a single source only (not multiple sources)
2. No re-entry or regenerative sites are present

This algorithm works well with intracardiac signals as the catheters are inserted inside the heart. Also the exact location of catheter inside the heart for the available test data is known. The relative phase difference between F-waves captured by each electrode is determined using cross correlation. Particular electrode signal with lowest relative phase value should most likely be closest to the location of the AF source. The difference obtained will be in terms of sample delay. For example, test data is available for 4 phase delays represented in Table 1 shown below.

Table 1. Phase Difference (Delay measured in number of samples)

	Delay					
CS34	0	0	0			
CS56	91			0	0	
CS78		-157		3610		0
CS90			-85		-160	-62

1. From the first column, lead CS34 lags behind lead CS56. CS34 is nearer to the AF Source.
2. From column 2, lead CS78 lags behind lead CS34. CS78 is nearer to the AF Source than CS34.
3. From column 3, lead CS90 lags behind lead CS34. CS90 is nearer to the AF Source than CS34
4. From step 1, lead CS56 can be eliminated and from steps 2 and 3, CS34 can also be eliminated.
5. Comparing CS78 and CS90 from the last column, lead CS90 lags behind lead CS78. So CS90 is nearest to the AF Source.

Hence it can be concluded that the source of AF lies closest to the lead CS90. As CS90 is at the annulus of the inferior vena cava, it can be confirmed that this may be the possible location for AF trigger.

F. Source Detection Using Vector Cardiography for ECG signals

Vector cardiogram is an efficient way of representing ECG signal accurately in the form of Electric Heart Vector (EHV) [12]. The vector-cardiograms (VCG) may or may not be measured from the heart directly but they can be calculated using ECG and orthogonal leads [13].The inverse Dower transformation is used to construct VCG from ECG lead signals. It is the most commonly used method for synthesizing VCG from the 12-lead ECG contains and 3 orthogonal signals using Dower's transformation matrix D [13]. The VCG signals thus obtained are of the dimension 3xN. The fibrillation signal can be classified into three planes: Sagittal, Frontal, and Transverse planes [13]. The parts of the atrium belonging to best plane of fit can be considered as the possible source of AF. The covariance matrix [3x3] for the VCG signal matrix [3xN] is calculated [14]. Eigenvalues and eigenvectors are calculated. Using Eigenvector values (v_1, v_2, v_3) corresponding to smallest eigenvalue are used for further analysis. Azimuth angle ϕ_{AZ} [14] and angle of elevation ϕ_{EL} [14] are as follows:

$$\Phi_{AZ} = \arctan(v3/v_1)$$
$$\Phi_{EL} = |\arctan(v_2/\sqrt{({}_{v1}{}^2 + v_3{}^2)})|$$

Φ_{AZ} is always in the range $-90 < \Phi_{AZ} < 90$ and the angle of elevation is always in the range $0 < \Phi_{EL} < 90$ [14]. To decide the source of origin of AF and to determine the best plane for fit the specific conditions are defined. For Sagittal plane: $-30 < \Phi_{AZ} < 30$ [14] and for Frontal plane: $60 < |\Phi_{AZ}| < 90$ [14]. Thus vector cardiograph can be effectively used in AF source detection.

III. Conclusion And Future Work

Electrocardiogram (ECG) and intracardiac signals provide important information which allows the analysis of anatomic and physiologic aspects of the whole cardiac muscle. The algorithms proposed in this research try to characterize the atrial activity in ECG as well as intracardiac signals using nonlinear methods. They also provide robust method for tracking the AF frequency in noisy signals. Cleaner versions of the signals are easy to read and eliminate unnecessary interferences. Separation of ventricular activity is carried out successfully.

Algorithms proposed in this project are tested on sample data signals obtained from 'Physionet ATM'. It is very important to test them on real time data. To find the location of AF source on cellular level, it is necessary to exploit these algorithms more extensively, using number of data signals extracted from large number of catheters and ECG leads.

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