Proceedings of the 5th WSEAS Int. Conf. on Signal Processing, Computational Geometry & Artificial Vision, Malta, September 15-17, 2005 (pp238-243)

A Noninvasive Method for Identification of Independent Components of Fibrillation in the Heart Muscle Cell

S.HOJJAT SABZPOUSHAN, AHMAD AYATOLLAHI, PENNY NOBLE, FARZAD TOHEEDKHAH
Department of biomedical engineering
Iran university of science and technology (I.U.S.T)
Tehran, Narmak, 16846-13114
IRAN

Abstract: - Fibrillation is a dangerous episode in cardiac muscle and so any new work towards the understanding of this process is important to the development of new methods in diagnosis and therapy. In this work we have used surface and intra cardiac ECGs of patients with chronic atrial fibrillation (AF). By means of the blind source separation (BSS) algorithm, which is a well-known method in signal processing, the AF process has been deconstructed into its independent components and we can show that from the point of view of these components the surface ECGs contain the same information as the intra atria electrogram. Then the important components have been related to the ionic currents of the cell. We show that one of these independent components can be influenced by the sodium-calcium exchange current, (iNaCa) and hence by controlling iNaCa we may be able to control the fibrillation process. This new idea can bring about new strategies in drug therapy .

Key- Words: Noninvasive method, Fibrillation, Independent component, Ionic current .

1 Introduction

fibrillation is a dangerous episode in cardiac muscle. Ventricular fibrillation, (VF), is the most common arrhythmia which directly leads to sudden cardiac death. Atrial fibrillation, (AF), while not usually lethal, also causes significant fatality. So any new work towards the understanding of this process may lead to the development of new methods in prevention, diagnosis and therapy and save many people's lives. Most studies in this context have been done by using invasive data from human or animal heart muscle. Invasive observations are burdensome and expensive and the required equipment is not available to every researcher especially biomedical engineers, therefore noninvasive methods are preferred. Firstly in this study we carry out our method by the use of the surface ECG of patients with AF, then redo the study with intracardiac electro gram of the same patients. Since the results are the same, we conclude that our noninvasive method can be used instead of the invasive method and this is an advantage of our study.

The nature of fibrillation is a mater of controversy [1], some authors believe that it is a random process and others believe that it is deterministic but chaotic. Our method has no dependence on these beliefs but adds a new point of view to this phenomenon.

The surface ECG is an observation on a dynamic system; heart muscle. A sufficiently long time observation on a dynamic system contains enough information for its characterisation [2]. A dynamic system is characterised by its state variables. State variables are independent variables, which combine to create the behavior of the system. The mechanical activity of heart results from the action potential and action potential occurs as a result of ionic currents so it is evident that state variables of heart i.e. independent dynamic variables can be connected to ionic currents. Arrhythmia in heart can be interpreted as changes in heart dynamics and so heart diseases could be called dynamic diseases [4]. The dynamics of a system is influenced by its state variables and so identification of state variables can lead to identification of normal and abnormal behaviors and better controlling of arrhythmia. Fig (1) illustrates the action potential and two main currents in the rabbit atrial cell [3].

In this study we first investigate the independent components of the atrial activity of normal subjects. The results show that the calcium current (iCa) may be the main independent component in normal

activity. We next consider the surface ECG of patients with AF; these results show that the sodium-calcium exchange current (iNaCa) may be the main independent component in the AF case. As a test for these conclusions from the surface ECG and in order to justify of our noninvasive method we repeat our study with intracardiac electro gram of the same patients. We get the same results, hence our noninvasive method works as well as an invasive method and is a more favourable choice.

2 Methods

We have used the ECG records of normal subjects from lead II, the specifications of these records are in [5]. From approximately two seconds of recorded single lead ECG data, we make Toeplitz observation matrix as described in [6]. (see appendix A). A typical eigenvalues (EVs) spectrum of several normal subjects of either sex and a variety of ages is illustrated in fig(2). It is evident from fig (2) that EVs are separated into three distinct levels; of course the biggest EV is related to the most powerful component i.e. ventricular activity. The second component reflects atrial activity and the third includes possible noises and other weak components.

In fig (3) a two second ECG record of a normal case is illustrated. We have used the blind source separation (BSS) method in [7] for independent source computations (see appendix B). In fig(4) to fig(6), the first, second and third independent components (sources) have been depicted respectively and from the morphology of the second component it is reasonable to relate it to the ionic current iCa.

Now we investigate lead II ECGs of patients with AF. The specifications for them are in [8]. We make an observation matrix as above. The typical EVs spectrum for three patients is depicted in Fig (7). We see that EVs are separated into three distinct levels but the distribution of the third level is more than Fig (2), i.e. it seems that the third level itself is composed of two close levels.

Fig (8) illustrates a lead II surface ECG of a patient with AF. Fig (9) shows the first component, which is indicative of ventricular activity. The second component is depicted in Fig (10) which clearly has a triphasic morphology and it is completely different from Fig (5). Fig (11) shows the third component. It does not have clear morphology but it seems to be biphasic and certainly different from Fig (6). The triphasic morphology of Fig (10) together with the fact that the ECG originates from the action potential and the action potential originates from ionic currents leads to this conclusion that: in AF iNaCa which has a triphasic morphology is the main state variable but in normal ECG iCa is the main component.

Now for confirmation of the above results, which were based on noninvasive data (surface ECGs), we repeat our study by using intracardiac data from the above patients which have been recorded from the interior of their right atrium [8]. We make an observation matrix as mentioned beforehand and obtain EVs spectrum. A typical EVs spectrum is illustrated in Fig(12). It can be seen that in this case, unlike Fig(7), the separation of the last levels i.e. levels two and three is more obvious .

Fig (13) shows the recorded electrogram from the interior wall of the right atrium of a patient with AF and Fig (14) illustrates its first independent component. It is clear that the first independent component has a triphasic morphology (here we use electrogram, so we do not have ventricular activity). Fig (15) shows the second component, which has a biphasic morphology. Fig(16) shows the third component which represents possible noises and other weak components. Considering the above results we conclude again: In AF the sodium – calcium exchange current (iNaCa) may be the most powerful independent variable i.e. when atrial muscle is affected by fibrillation, its dynamics are influenced more by iNaCa. This finding is in agreement with previous findings about fibrillation. The previous studies apart from randomness or chaotic nature of fibrillation, show that when a muscle encounters fibrillation, its dynamics become more complex. Reasoning as above we can conclude that in fibrillation, iNaCa which has more complex dynamics, affects the dynamics of the muscle.

3 Conclusions

In this study we showed that for blind source separation purposes we can use surface ECG instead of electrogram**.** So we have proposed a noninvasive method. In this study we showed that in normal subjects iCa could be the most powerful state variable of the atrial activity. We also showed that in patients with AF (and maybe VF) iNaCa is the most powerful independent component. According to these results it seems that we may control AF (or VF) better by means of iNaCa and this may lead to new drug therapies.

References:

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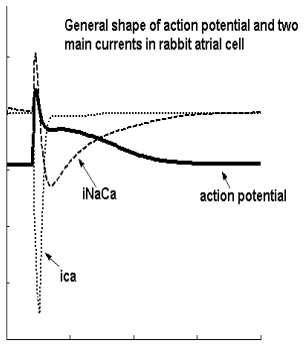
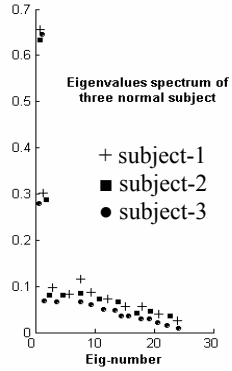
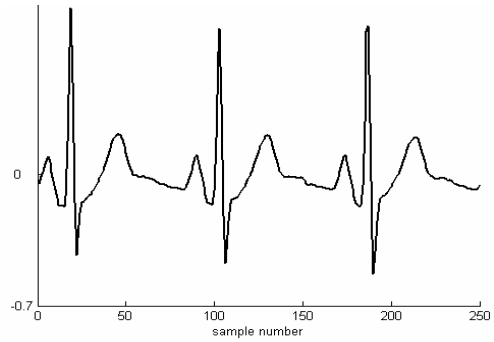


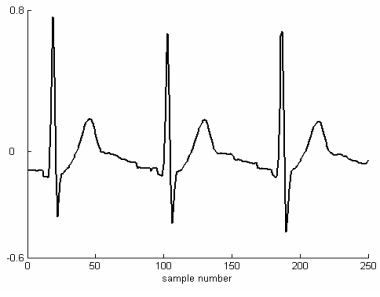
Fig(1).action potential and two main ionic currents in rabbit atrial cell [3].
ica **,** iNaCa have bi- and tri- phasic dynamics respectively.



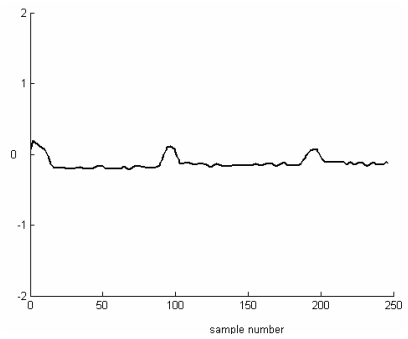
Fig(2).Eigenvalues spectrum of three normal subjects. Three distinct levels are observable.



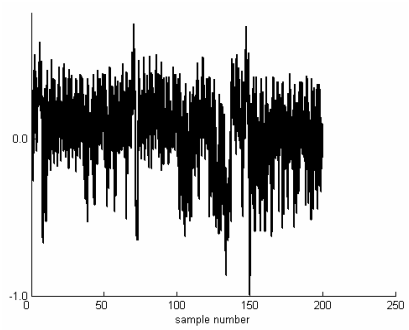
Fig(3).A normal ECG from lead II



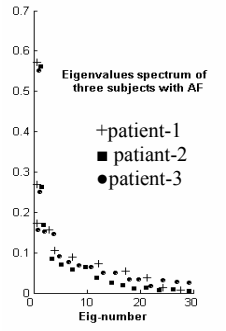
Fig(4).first component of normal ECG



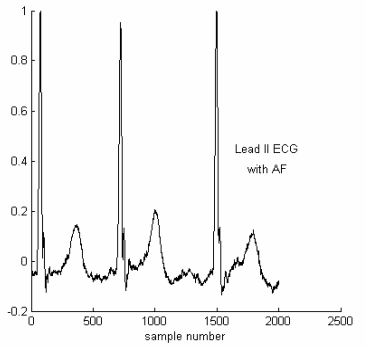
Fig(5). second component of normal ECG



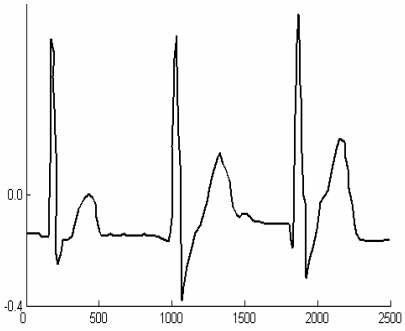
Fig(6).third component of normal ECG.



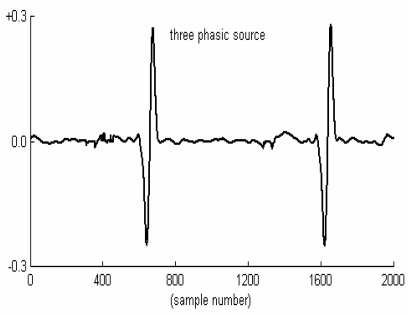
Fig(7).Eigenvalus spectrum of patients with AF. Dispersion of values in the last level is more clear than fig(2).



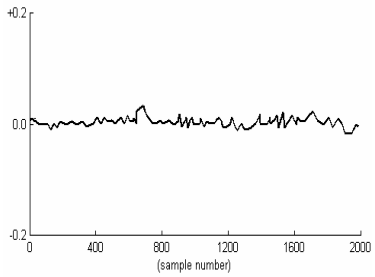
Fig(8).Lead II ECG of a patient with AF.



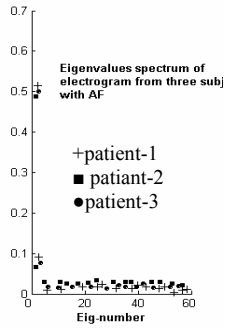
Fig(9).General morphology of first component of the fig(8) signal, which shows ventricular activity.



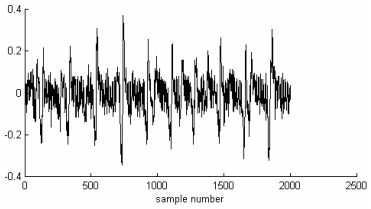
Fig(10).General morphology of the second component of fig(8) signal. Tri-phasic morphology is clear.



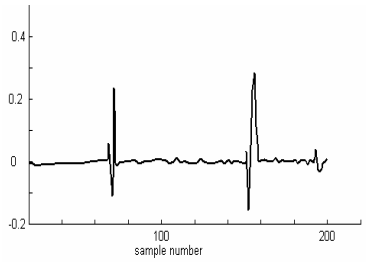
Fig(11) General morphology of third component of signal fig(8).It seems bi- phasic.



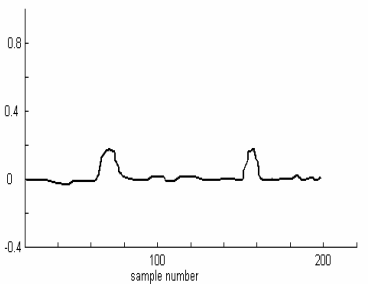
Fig(12).Eigenvalues spectrum of electrograms of patients with AF.last levels are more separate than Fig(7)



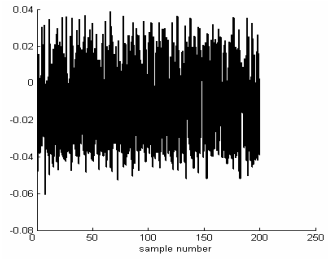
Fig(13).Recorded electrogram from right atrium of a patient with AF



Fig(14).First component of the fig(13) signal. Tri- phasic morphology is clear.



Fig(15).Second component of the fig(13) signal. Bi- phasic morphology is clear.



Fig(16).Third component of the fig(13) signal. This component has no clear morphology.

Appendix (A)

Blind source separation (BSS) algorithms relies on spatial diversity i.e. multi-lead (channels) observations, but if we have had sufficiently long time records, by building toeplitz observation matrix (we may use any linearly structured matrix such as Hankel) we can use tempolar diversity instead of spatial diversity. This reduces the need of multi- leads records .

Consider vector X which contains m times single lead ECG observation i.e.

X=[x (1), x (2), ……, x(m)] we make toeplitz observation matrix as:

$$X = \begin{bmatrix} x(n) & x(n-1) & ..... & x(1) \\ x(n+1) & x(n) & ..... & x(2) \\ \vdots & \vdots & \vdots & \vdots \\ x(m) & x(m-1) & .... & x(m-n+1) \end{bmatrix}$$

The above observation matrix is equivalent to observations from (n-m+1) channels each n points long. For making a toeplits matrix, we must decide on the number of rows which is an estimate of the number of independent sources responsible for generating the observation. We make covariance matrix $R_x = E(XX^t)$ and compute its singular values. A look at these values leads us to the number of rows.

Appendix (B)

Blind source separation (BSS) is an important subject in systems identification and signal processing. It consists of recovering unobserved signals or "sources" from several observed mixtures. Typically, the observations are obtained at the output of a set of sensors where each sensor receives a different combination of the source signals. The adjective "blind" stresses the fact that 1) the source signals are not observed and 2) no information is available about the mixture. The simplest BSS model assumes the existence of n independent signals $s_1(t),.....,s_n(t)$ and the observation of as many mixtures $x_1(t), \ldots, x_n(t)$ so that

$$x_i(t) = \sum_{j=1}^{n} a_{ij} s_j(t) \qquad ,i = 1,.....,n$$

This is represented compactly by mixing equation $X(t)=A.S(t)$ where $S(t)=[s_1(t),\ldots,s_n(t)]^t$ is an $n \times 1$ column vector collecting the source signals. Vector X(t) similarly collects the n observed signals, and the square $n \times n$ "mixing matrix" A contains the mixture coefficients. The BSS algorithm can be formulated as the computation of an $n \times n$ separating matrix B whose output Y(t)= B X(t) is an estimate of the vector S(t).

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