35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

Blind Source Separation in Characterizing ECG Pre-shock Waveforms During Ventricular Fibrillation

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***Abstract*— Ventricular Fibrillation (VF) is a cardiac arrhythmia for which the only available treatment option is defibrillation by electrical shock. Existing literature indicates that VF could be the manifestation of different sources controlling the heart with different degrees of organization. In this work we test the hypothesis that the pre-shock waveforms of successful and unsuccessful shock outcomes could be related to the number of independent sources present in these waveforms. The proposed method uses Blind Source Separation (BSS) to extract independent components in frequency direction from a pig database consisting of 20 pre-shock waveforms. The slope of the energy capture curve was used as an indicator to demonstrate the number of independent sources required to model the pre-shock waveforms. The results were also quantified by performing a linear discriminant analysis based classification achieving an overall classification accuracy of 75%. The results indicate that successful cases can be modeled with less number of independent sources compared to unsuccessful cases.**

***Index Terms*— Ventricular Fibrillation, Cardiac Resuscitation, Blind Source Separation, Independent Component Analysis, Singular Value Decomposition**

I. INTRODUCTION

Ventricular fibrillation (VF) is a cardiac arrhythmia that can lead to sudden cardiac death. It is especially lethal in out-of-hospital VF incidences if medical attention is not available within few minutes of its occurrence. Some factors that could improve the success of resuscitation are cardiac stimulant drugs and cardio pulmonary resuscitation (CPR) followed by electrical shock. Many existing works[1][2] have shown that there is a correlation between the characteristics of pre-shock VF waveform and defibrillation outcomes. These works have attempted to provide feedback to the emergency medical staff in aiding them to choose appropriate sequence of action or timing of the shock in optimizing the shock outcomes.

From a mechanistic point of view there are studies that indicate the possibility of VF being maintained by few organizational centers called rotors [3]. It has also been shown that early VF signals are more organized and with time VF waveform degenerates indicating a transition from rotor to multiple wavelet mechanism [4]. This motivates us to believe that there might be a relation between the number of underlying sources maintaining VF and the characteristics of the pre-shock waveforms that results in successful or unsuccessful shock outcomes. If the influence of varying number of underlying sources during VF is reflected in the surface electrograms obtained during VF, it would be possible to associate them with the characteristics of pre-shock VF waveforms and thereby shock outcomes. To test this hypothesis in this paper, we present a blind source separation (BSS) methodology to extract independent sources (IS) from the pre-shock waveforms. BSS is the extraction of underlying signals from their linear mixture with minimum a priori knowledge. Single mixture source separation is a well- known approach to estimate underlying independent signals from one linear mixture of them. There exist many works in the field of music and biology[5][6] which use BSS techniques to extract independent sources from one single mixture.

In the proposed method we attempt to extract independent sources from the pre-shock VF electrocardiograms and establish a relation with the shock outcomes. BSS was performed in a sequence of steps which includes time-frequency transformation, singular value decomposition (SVD) for dimensionality reduction, and independent component analysis (ICA) for extracting the sources. Once the sources were extracted, feature extraction and pattern classification were performed to quantify the observations between the successful and unsuccessful groups. The block diagram and sequence of processing steps are presented in Fig.1. The paper is organized as follows; Section II presents the details of the methodology, results are presented in Section III, followed by discussion in Section IV and conclusions in Section V.

II. METHODOLOGY

In this section we provide details on the various steps involved in extracting independent sources from the pre-shock VF electrograms.

A. Database

The database used in this study consisted of 20 pre-shock ECG traces obtained from VF experiments on pigs. The protocol was approved by the Animal Care Committee at St. Michael's Hospita. VF was induced and left untreated for 4 minutes. At the end of this period, chest compressions were started and continued for 3 minutes. At the end of this period, defibrillation was attempted. The pre-shock waveforms used in this study were of 10s duration extracted right before the shock. All the pre-shock segments were down-sampled from 1kHz to 250 Hz and filtered with a bandpass filter which eliminates any high and low frequency which does not lie in the 3 to 15 Hz. The criteria for successful defibrillation is defined as sustained ROSC (at least 12 normal heartbeats) within one minute post shock. The 20 pre-shock ECGs used in this study consisted of nine successful and eleven

Thanks to HSFC and CIHR for funding this work.

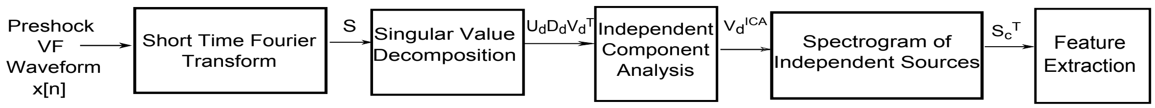

Fig. 1. Block diagram of the proposed method

unsuccessful cases. Only first three shocks were considered and each of the 20 tracings were obtained from individual pigs.

B. Blind Source Separation Algorithm

Independent Component Analysis (ICA) is one of the approaches in BSS to extract mutually independent signals from their linear mixtures. Applying Singular Value Decomposition (SVD) and ICA on matrix of spectrogram is an approach for independent source separation when there is only one observation (single channel source separation). Following sub-sections explain the steps to perform this algorithm on the studied database.

1) Step1: Short Time Fourier Transform (STFT) was used to map the signal $x[n]$ into time-frequency domain and the spectrogram was constructed as the squared modulus of STFT:

$$S[N,\omega] = |\sum x[n]\omega[n-N]e^{-j\omega N}|^2 \tag{1}$$

where w[n] is the window function (usually a Hann window) and $x[n]$ is the pre-shock segment of VF waveform that are, as stated before, segments of 10 s right before shock. The phase information of STFT is eliminated from the calculations and will be used in reconstructing the independent sources at the end of the complete process.

2) Step2: The spectrogram obtained in the previous step can be treated as a matrix. This matrix was then projected into another dimension using SVD to only retain the dominant components. SVD was performed on the transpose of spectrogram in which the columns represent time slices and rows frequency bins. The SVD operation is given by

$$S^T = UDV^T \tag{2}$$

where the columns of U are the right singular vectors of S (here time components) and columns of V are left singular vectors (frequency components) and D is a diagonal matrix with square root of Eigen-values in descending order.

All the columns in U (time basis) and columns in V (frequency basis) are ordered according to their relevant singular values. Each singular value shows the amount of information that its corresponding basis contain. First d singular values contain most of the information of the signal. Based on the observations 10 up to 25 dimensions can give sufficient information (more than 99% of information) for the separation. Fewer dimensions does not give a complete decomposition, while more dimensions increase the complexity with no improvements in decomposition. With this in mind, a good approximation of S could be achieved by

$$\bar{S}^T = U_d D_d {V_d}^T \tag{3}$$

Here U_d is first d columns of original matrix U, and V_d is first d rows of V^T, and D_d is a matrix which contains first d elements of D.

3) Step3: ICA was performed on the matrix ${V_d}^T$ to acquire independent frequency components. First d rows of V^T (d most significant frequency components) were treated as observations and JadeICA algorithm [7] was applied on them to acquire independent frequency components. The JADE algorithm was chosen since it is developed to process complex signals as well.

$${V_d}^T = M({V_d}^{ICA})^T \tag{4}$$

M is mixing matrix (a d by d matrix) and $M({V_d}^{ICA})^T$ is matrix of independent frequency components which is obtained by minimizing the mutual information between the frequency components and columns of $({V_d}^{ICA})^T$ are independent spectral components (this matrix has the same dimension as ${V_d}^T$). So the matrix of spectrogram can be written as

$$\bar{S}^T = U_d D_d M({V_d}^{ICA})^T \tag{5}$$

and the new matrix of time domain components is

$$\bar{U}_d = U_d D_d M \tag{6}$$

In other words, in this way the independence of frequency basis in guaranteed. In order to have a constant energy for S^T the columns of U_d were transformed to the new space to have a one by one correspondence with columns of new spectral matrix (V_d) using the equation 6.

4) Step4: The spectrogram corresponding to the independent sources were then calculated by multiplying the columns of $\bar{U}_d$ and rows of $({V_d}^{ICA})^T$ as given by

$${S_c}^T = \bar{U}_d({V_d}^{ICA})^T \tag{7}$$
$$c = 1, 2, ..d$$

From these spectrograms corresponding to the independent sources, we could reconstruct an approximation of the separated source signals in time domain using the phase information retained in Step 1. As an example illustration Fig 2 shows a successful and unsuccessful pre-shock waveforms and their two most significant sources obtained following the above described steps. Left column shows one successful case on the top row and its relevant dominant sources in second and third row. Right column is an unsuccessful case and its related sources are shown in second and third row.

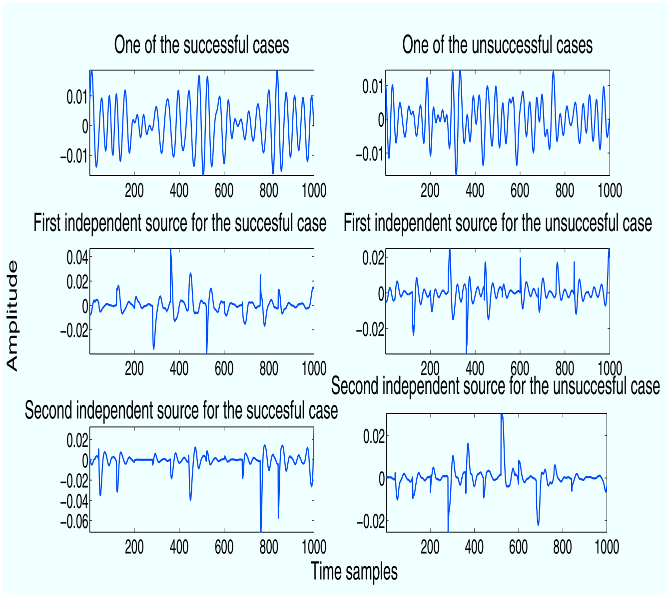

Fig. 2. Four seconds of an example of one successful and one unsuccessful pre-shock waveform with their two most significant independent sources

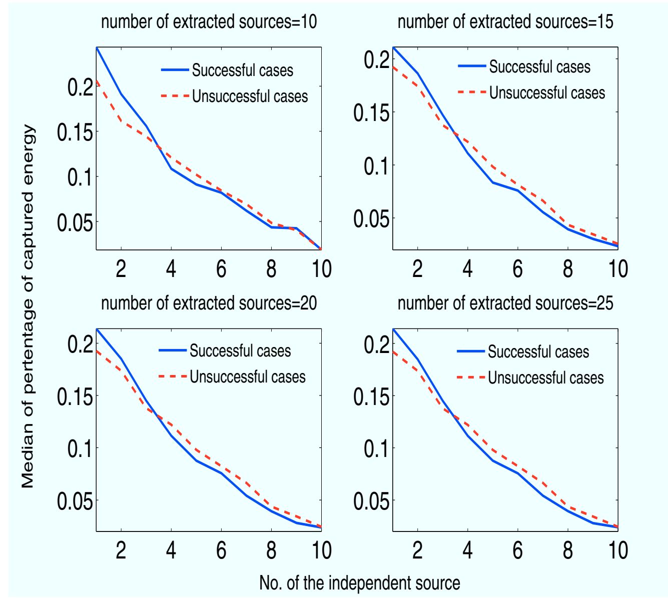

Fig. 3. Median percentage of energy captured by each independent source when the signals was de-mixied into 10,15,20 and 25 sources

C. Feature Extraction

After performing all the four steps on each ECG pre-shock waveform, the energy of all the sources was calculated and the percentage of the energy captured by each source was computed as shown below

$$E_i\% = E_i/E_{total}\times 100 \tag{8}$$

where $E_i\%$ is the percentage of energy captured by the i^{th} independent source, E_i is the energy of the i^{th} independent source , and E_{total} is sum of the energy of all the independent sources of the signal which is equal to the energy of the signal. In order to relate variation in number of sources to the successful and unsuccessful outcomes, we studied the amount and rate of energy captured by the identified sources between the groups.

Fig 3 shows the median percentage of energy captured by each independent sources when the signal was demixed into 10, 15, 20, and 25 sources. Energy capture curve is shown up to IS No.10 since the rest of the ISs contained less than 2% of total energy of signal. All 20 (9 successful and 11 unsuccessful) pre-shock waveforms were used in computing the median percentage of energy captured by each of the sources. The X-axis is the index of the sources and Y-axis is the median percentage of energy capture. Observing these plots it is evident that successful groups tend to capture more energy in the first few sources with a steeper slope than the unsuccessful group. It can also be observed that consistently around the source number 4, a cross over happens between the curves. Fig 4 is a magnified version of energy curve when signal was split into 10 sources. In order to show the difference of two curves the X-axis was restricted up to sixth IS . To quantify this observed difference, we computed the slope of the energy capture curve as

$$Slope = (E_i\%^{firstIS} - E_i\%^{sixthIS})/5 \tag{9}$$

$E_i\%^{firstIS}$is the percentage of energy for the first IS and $E_i\%^{sixthIS}$ is the percentage of energy captured by the sixth independent source.

D. Pattern Classification

In order to quantify the features obtained in a numerical manner, aA Linear Discriminant Analysis (LDA) based classifier was used to categorize the data in two groups with the slope of the energy capture curve as the feature. An LDA based classifier is preferable to nonlinear classifiers since it preserves more generalization. Since, the database was small, Leave-one-out Method (LOOM) [8] was performed on the features for cross validation. In LOOM classification method, each sample from the database is taken as test and the remaining samples are used to train the classifier. The algorithm keeps repeating this for all samples and then the accuracy of classification is calculated. The average of classification accuracies is later determined as the final classification accuracy.

III. Results

The slope of the energy capture curve for each of the 20 pre-shock waveforms were computed as explained in Section II-B and Section II-C. This was fed to an LDA based classifier and LOOM method was used to compute the overall classification accuracy. TABLE I shows the classification accuracy using the proposed feature when the total number of extracted sources was 10. Six out of the 9 successful cases and 9 out of the 11 unsuccessful cases were correctly classified based on the observed phenomenon that the unsuccessful cases need more number of sources to

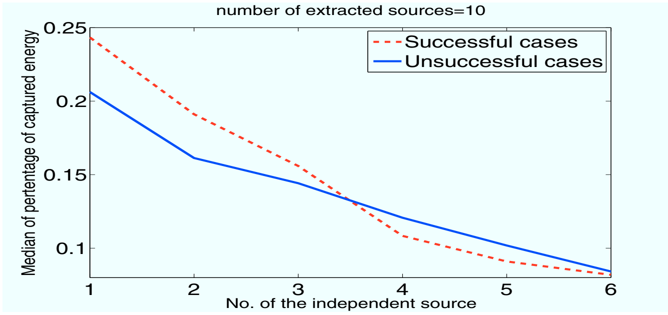

Fig. 4. Median percentage of energy captured by each independent source when the signals was de-mixied into 10 independent sources

TABLE I

CROSS VALIDATION RESULT FOR SLOPE OF ENERGY CAPTURE CURVE FOR FIRST SIX INDEPENDENT SOURCES

Number of extracted ISs=10				
Method	Group	Successful	Unsuccessful	Total
Cross Validated with LOOM	Successful	6	3	9
	Unsuccessful	2	9	11
Percentage of Classification %	Successful	66.7	33.3	100
	Unsuccessful	18.2	81.8	100

capture comparable signal energy with respect to successful group. While the identified difference in the slope of energy worked well in classifying the unsuccessful groups (81.8%), it did not yield good separation for the successful group (66.7%). An overall classification accuracy of 75% was achieved. A t-test was performed to compare the means of the two groups and found a p=0.1384. As the choice of demixing sources could influence the way the energy is decomponsed among the sources, we repeated the experiments by varying the choice of d (the number of sources). For 15, 20, and 25 independent sources the classification accuracy varied between 60% to 75% with the best classification accuracy achieved with 10 sources.

IV. DISCUSSION

Our objective was to evaluate the hypothesis that the number of the independent sources required to model a VF pre-shock signal has a meaningful correlation with their corresponding successful or unsuccessful defibrillation outcome. The results reported here are inclined towards supporting this hypothesis. As the observations show, the first six independent sources in successful cases grab more energy compared to the captured energy by the first six independent sources in the unsuccessful cases. Comparing the slope of energy capture curve we could observe a steeper slope for the successful cases which means the dominant components in successful cases capture a large portion of energy of the signal with fewer sources. This finding provides a different view point on source separation of VF and might have implications in augmenting existing theories on initiation and maintenance of VF. While the reported highest classification rate is relatively high, the p-value of 0.1384 obtained by the t-test does not allow us to reject the null hypothesis for the proposed feature, although this could be attributed to small size of the database. For small databases accepting the null hypothesis (equal means) when the means are different could involve making type II error [9][10]. Hence it is essential to increase the size of database to overcome this problem in future studies.

V. CONCLUSION

We have presented a methodology to test the hypothesis that there is a relation between the number of underlying sources and the characterization of pre-shock VF waveforms during cardiac resuscitation. Using a pig database it was shown that the shock outcome is related to the number of independent components needed to represent the pre-shock waveforms. Quantification of the difference between the groups resulted in a classification accuracy ranging from 60-75% for different sets of IS decompositions. Nevertheless we did not see statistical significance in testing of the hypothesis that the proposed slope of energy capture of two groups is different. In future works we will expand the databases to overcome the small sample size issue and also increase the feature dimensions to validate the robustness of the hypothesized relation between the number of independent sources and shock outcomes.

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