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Analysis of electrocardiogram pre-shock waveforms during ventricular fibrillation

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ABSTRACT

Pre-shock waveform analysis for optimizing the timing of shock delivery could be immensely helpful to emergency medical personnel in treating ventricular fibrillation. For this purpose, our proposed method resolves the pre-shock surface electrocardiogram into independent sources using a blind source separation approach. The electrocardiogram pre-shock waveforms were transformed into the wavelet domain and the independent sources were extracted using component analysis. A database consisting of 50 pre-shock waveforms from 50 pigs was used in this study. The pre-shock waveforms were obtained using a controlled protocol. After ventricular fibrillation was induced and left untreated for 2–5 min, cardio pulmonary resuscitation was administered for 3 min, followed by defibrillation. Energy-based features were extracted from the independent sources and a linear discriminant analysis based pattern classifier was used to evaluate the features for their ability to discriminate between successful and unsuccessful shock outcomes. The proposed method achieved a classification accuracy of 68% ($P<0.02$), and the classification results were cross-validated using the leave-one-out method. A comparative study demonstrated that the proposed approach performed relatively well compared to existing methods for the given database.

1. Introduction

Annually, about 300,000 sudden cardiac deaths (SCD) occur in North America [1], most of which are related to ventricular fibrillation (VF). During VF, the lower chambers of the heart contract rapidly in an uncoordinated fashion, resulting in poor or no blood circulation. Without immediate medical attention within minutes of its onset, VF will result in fatality. In spite of decades of research, the mechanisms behind VF is not yet fully understood and hence there are no universally effective therapies for treating VF after its onset. Currently, the only available treatment option for VF is defibrillation by applying electric shocks to reset the heart, which may or may not restore normal rhythm. To improve shock success and thereby survival rates, research efforts have been directed toward identifying methods and markers that could help emergency medical staff (EMS) optimize defibrillation shock parameters and delivery, in addition to cardio pulmonary resuscitation (CPR) maneuvers and drug therapy.

At present, there are two prevailing theories that attempt to explain VF: multiple wavefronts theory and rotor theory [2,3]. In general it is believed during VF that many dynamic sources attempt to take control of the heart's rhythm, resulting in disorganized muscle contractions at high rates; this is in contrast to normal heart rhythm, where a single source (i.e. sinoatrial node) controls the heart's uniform contractions. These sources (mapped as spatio-temporal organization centers or breakthroughs [4,5]) degenerate as time progresses from the onset of VF, resulting in different manifestations of VF dynamics. Mechanistic studies often require extensive interventional multi-channel spatio-temporal cardiac data to track these sources and study VF in a research setup. However, in real world emergency situations, EMS personnel have to make appropriate choice of therapies to improve shock success using only single or few surface electrocardiograms (ECG). Hence, most of the existing works on prediction and improvement of shock success derive markers from fewer physiological parameters and/or electrocardiogram channels and do not have the luxury of multi-channel spatio-temporal data. From the surface

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ECG signals, these markers are often derived from capturing different characterization in temporal, spectral, and time-frequency domains, which may or may not have meaningful correlation with underlying sources.

A comprehensive review of some of the works in predicting defibrillation shock success are discussed in the literature [6,7]. Briefly, the amplitude and energy of the ECG were proposed by [8,9] from the viewpoint that the amplitude of the ECG during VF decreases with time, indicating deterioration of cardiac function. The centroid frequency (CF) of the ECG was proposed as a marker [10] since the CF decreases with time during VF, which correlates with the status of the heart over time. Amplitude spectrum analysis (AMSA) is another well-known marker derived from the spectral domain, which computes the spectrally weighted amplitudes and associates them to shock success [11,12]. Other works quantified the chaotic or self-similarity features in an ECG signal as markers that could be associated with the shock success. Two such markers include scaling exponent (SE) and logarithm of absolute correlation (LAC) [13,14]. Wavelet analysis has also been proposed on the ECG during VF [15] and markers in the wavelet domain, such as cardioversion outcome prediction (COP) [16] and wavelet entropy [17], were introduced. Our preliminary works have also explored wavelet features and arrived at a relative scale distribution width (SDW) feature in predicting shock outcomes [18,19], expanding the application of this feature to quantify CPR efficacy by indirectly measuring coronary flow during VF [20]. Although the aforementioned works did arrive at markers that correlated with shock success, there are no studies (to the authors' knowledge) that attempt to relate the mechanistic insights of underlying sources that maintain VF and their relation in characterizing VF for predicting shock success. In addition, since the EMS personnel only have access to the surface ECGs in out-of-hospital VF incidents, it is essential to resolve (or decompose) this single lead ECG to identify the underlying sources, otherwise this approach may not have practical benefits in cardiac resuscitation.

To achieve the above goal, a blind source separation (BSS) [21] based approach is suggested to resolve the single lead ECG into a combination of statistically independent sources (ISs), which can then be used to extract meaningful features from the ISs and associate them with the prediction of shock success for optimizing cardiac resuscitation. In order to identify these underlying ISs from a linear mixture, BSS is used to extract the underlying signals with minimal a priori knowledge. A well-known approach to estimating underlying independent signals from a linear mixture is single mixture source separation. A few works in the field of audio and biology [22,23], have used BSS techniques to extract ISs from a single mixture. In our initial study, we demonstrated the extraction of features from ISs (using the short-time-Fourier-transform) that could be related to shock outcomes [24]. In this work, we expand upon our previous work by using a larger database to arrive at features extracted from ISs and using the wavelet domain that relates to VF mechanism. This research may be used by EMS personnel to inform optimized cardiac resuscitation. Finally, this work also presents a comparative analysis with existing features.

2. Database

For the objective of predicting shock success, anonymous time series ECGs from a cardiac resuscitation study using pigs at St. Michael's Hospital in Toronto, Canada were obtained. Fifty ($n = 50$) previously healthy pigs of both genders were used. VF was induced and left untreated for 2–5 min. To induce VF, burst pacing was applied by giving 10 V of 60 Hz signal to the heart for 2 s. At the end of this period, chest compressions were started using a pneumatic device (Lucas, Jolife AB, Lund, Sweden) at 100 compressions/min, along with manual ventilation at 6 breaths/min using 5–6 L/min of 100% O_2 with an artificial manual breathing unit bag. CPR was continued at a rate of 30:2 (compressions to respirations) per minute for 3 min. After CPR, a defibrillation shock was first attempted at 150J. If the animal failed to respond, CPR was continued for 2 min followed by defibrillation at 200J. Upon failing again, the combination of CPR and defibrillation was repeated, but with a stepwise increase in the defibrillation shock energy to a maximum of 360J. The criteria for a successful defibrillation is defined as a return of spontaneous circulation (at least 12 normal heartbeats) within 1 min of the delivery of the shock. For the 50 deidentifiable pre-shock waveforms that were used for the analysis in the proposed work, 25 of them had successful shock outcomes and 25 had unsuccessful shock outcomes. The pre-shock waveforms used in this study were limited to be from the first 3 shocks (to eliminate time dependency), with 88% of the signals extracted from the first shock attempt. The protocol was approved by the Animal Care Committee of St. Michael's Hospital.

The VF time series ECGs obtained from the database were downsampled from 1 kHz (original acquisition sample rate) to 250 Hz to reduce the computational complexity. A bandpass filter was used to remove low (below 3 Hz) and high (above 15 Hz) frequency artifacts because most of the dominant components in pig VF falls within this frequency range [25]. The VF time series ECGs signals were normalized to remove the effect of the absolute amplitude. In cases where the CPR artifact had affected the pre-shock waveform, a notch filter was also implemented to mitigate this effect on the pre-shock waveform. The length of the pre-shock waveforms used in this study was 4 s for all the cases.

3. Methodology

In order to decompose these signals into ISs, a BSS approach was applied on the VF time series ECGs. In the first stage, the signal is projected onto the time-frequency plane using continuous wavelet transform (CWT). This is followed by the extraction of time and frequency basis components using singular value decomposition (SVD). Independent component analysis (ICA) of the time and frequency basis components ensures independence of each component. In the final stage of the BSS, the independent time and frequency basis components are combined to create a scalogram for each IS, and the inverse wavelet transform is then used to produce the ISs themselves. Features extracted from each IS were then used for the purpose of predicting the shock outcome. A flowchart outlining this process is illustrated in Fig. 1. The following subsection briefly presents the stages of BSS.

3.1. The blind source separation algorithm

The necessary steps needed to obtain ISs are illustrated using a sample ECG during VF in Fig. 2.

3.1.1. Projection of the data into the time-frequency domain

In order to perform ICA on a 1-dimensional ECG time series signal, the signal has to be transformed to a 2-dimensional representation. For this purpose, the signal was projected onto the time-frequency plane using CWT [26]. The CWT used to map the pre-shock waveform into the time-frequency domain is given by Eq. (1).

$$\mathbf{S}(a, b) = \sum_{n=1}^{L} x[n]\Psi^{*}_{a,b}[n] \tag{1}$$

The matrix $\mathbf{S}(a, b)$ is the matrix of wavelet coefficients, x is the ECG VF time series signal with L time samples and $\Psi^{*}_{a,b}$ is the