An Adaptive Filtering based Approach for Cardiopulmonary Resuscitation Quality Assessment

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Abstract

Cardiac arrest is the leading cause of deaths for thousands of people every year. Immediate treatment of cardiac arrest can help reducing cardiovascular mortality rates. One of the most common approaches for treatment of cardiac arrest is cardiopulmonary resuscitation (CPR) that provides chest compressions. Quality of chest compression is considered as one of key indicators for CPR performance assessment. In this study, we present an approach for CPR quality evaluation using ECG and thoracic impedance signals via a least mean square based adaptive filter. Then, CPR quality evaluation is performed based on analyzing the spectra and frequencies of input ECG and estimated CPR signals. The proposed approach is applied for a dataset including 526 segments from patients presenting with asystole. The results are then compared with those derived from the compression depth used as reference CPR signals. Experimental results show performance of the proposed approach for assessment of CPR quality.

Keywords: Cardiopulmonary resuscitation, Spectrum analysis, Thoracic impedance, Cardiac arrest, Adaptive Filter

1. Introduction

The importance of providing high quality chest compressions during cardiopulmonary resuscitation (CPR) has been emphasized in resuscitation guidelines [1]. It has been proved that good quality of CPR can help increase the survival rates. For improvement of CPR quality, it is important to know the chest compressions in the heart rhythm. The compressions should be at least 5 cm depth at 100 to 120 compressions per minute, allowing full chest recoil and minimum interruptions in compressions [1]. In order to improve the delivery of CPR, the quantitative evaluation of CPR quality is essential [2]. In fact, several studies showed that CPR delivery is suboptimal both in- and out-of-hospital [3].

To evaluate the quality of the CPR, a vast number of researches have been introduced in the literature. Abella et al. [3], used accelerometer interface between the rescuer and the patient's chest to measure the presence and frequency of chest compressions. Lo et al. [4] used Empirical Mode Decomposition (EMD) and autocorrelograms to automatically quantify the chest compression quality from ECG signal recorded by ADEs. Ayala et al. [5], the authors used the compression depth and thoracic impedance signals acquired from defibrillators for characterizing the chest compression. To quantify the chest compression performance, Ruiz et al. [6], and Ayala et al. [7] analyzing the rhythm during ventilation pauses.

In this study, we propose an automatic method to detect the chest compressions using the ECG acquired via defibrillation pads and the thoracic impedance (TI) signal. The ECG and TI are used as the input signal and reference signal for the Least Mean Square (LMS) based adaptive filter to estimate the CPR. Based on spectral analysis of the ECG and estimated CPR signals, the CPR quality is assessed.

2. Background

2.1 Electrocardiogram and cardiac arrest

Electrocardiogram (ECG) is a representation of electrical activity of the heart muscles as it changes over time. Heart muscles contracts in response to electrical depolarization of the muscle cells. The chest compressions create noise in the ECG signal and should be stopped while the automated external defibrillators (AED) analyses the signal. In cardiac arrest, the heart stops the normal pumping of blood and the normal sinus rhythms of ECG will be changed and called as mentioned before an arrhythmia.

2.2 Thoracic impedance signal and chest compression

The electrical impedance of biological tissue is found by passing a current through the tissue and measuring the voltage drop. Ohm's law can then be

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used to find the impedance. The impedance changes with the distance between electrodes, and with redistribution and movement of fluids contained in the tissue. The impedance signal is sensitive to the movement, the CPR cause artifact in analyzing the heart rhythm.

Pressure signal is the information we get from the sensor fitted on the extra pad of the defibrillator. The sensor is sensitive to the movement of the chest and delivering the information on a card fitted to the defibrillator. The chest compressions are done by pressing the chest between the breastbones from 4 to 5 cm. These compressions should be repeated with rate of 100 compressions per minute. Chest compressions are necessary to provide the vital organ with circulation of blood.

2.3 Empirical Mode Decomposition

The Empirical Mode Decomposition (EMD) [8] is an adaptive signal analysis algorithm for analysis of nonstationary and nonlinear signals. EMD has been widely applied in many fields, i.e., medical image analysis [9], pattern recognition, signal processing, etc [8]. The EMD can decompose a signal into intrinsic mode functions (IMFs) that satisfies two conditions: (1) the numbers of extrema and zero-crossings must either be equal or differ at most by one, and (2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. The EMD is implemented via a "sifting process" [8], that allows extracting the data $x(t)$ into IMFs expressed as:

$$x(t) = \sum_{\lambda=1}^{L} c_{\lambda}(t) + r_L(t) \tag{1}$$

where $c_{\lambda}(t)$ is the λth IMF (or the λth -mode) $(\lambda = 1, \cdots L)$, and $r_L(t)$ is the residue.

3. Methodology

3.1 Data and Preprocessing

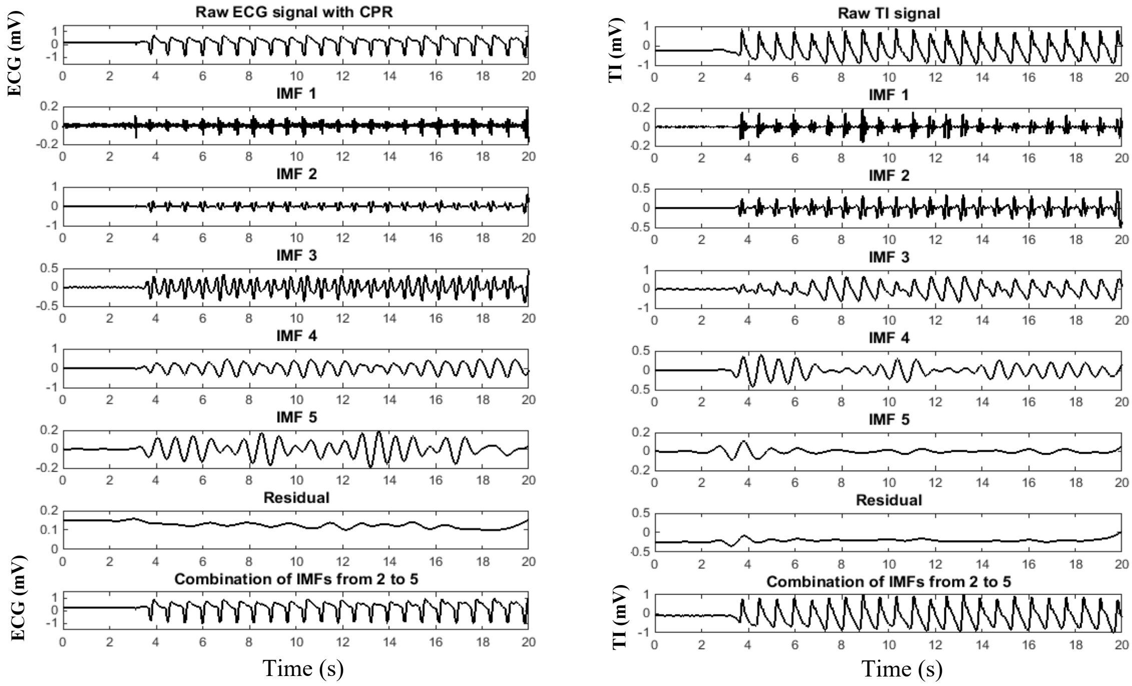
We have applied the proposed approach to the data set acquired from 50 patients presenting Asystole with 526 segments, each segment lasts 5 seconds. The dataset used in this study was a subset of an OHCA database provided by Tualatin Valley & Fire Rescue (Tigard, Oregon, USA) collected using the Philips HeartStartx MRx monitor/defibrillator. The data also includes the ECG, transthoracic impedance (TI) and the compression depth (CD) signals. The reference CPR is manually annotated by medical experts.

Since the acquired signals are often with noise, we need to remove baseline wander and filter out the noise from the ECG which is corrupted with CPR artifacts, and TI signals. For suppression of baseline wander and noise, we perform the EMD on the raw ECG and TI signals. The purpose of using EMD is to decompose a signal into several IMFs and residual component. We first remove the first IMF that is with very high frequencies, and the residual component, then combine the remaining IMFs and to get the reconstructed signal that is less noises and artifacts than the original one. An example presenting the results of this step is given in Fig.1.

3.2. LMS-based adaptive filter for CPR estimation

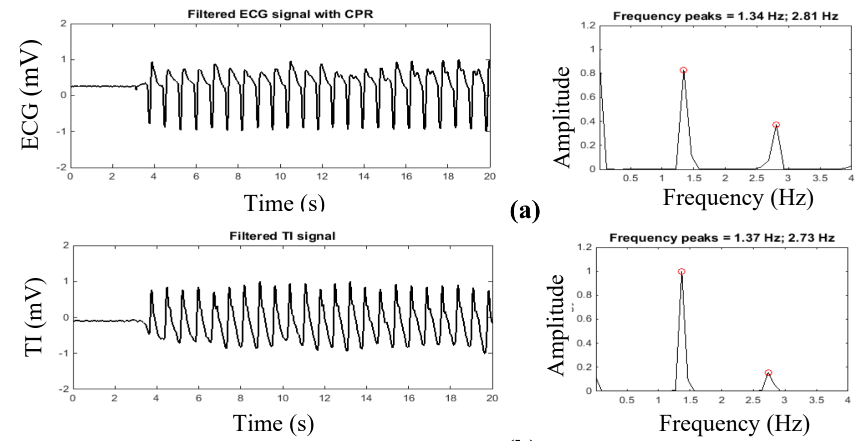
To estimate the CPR artifacts from the ECG signals, we proposed an adaptive algorithm using least mean square filtering methods to model the CPR. The ECG and TI signals are first preprocessed by EMD to remove baseline wandering and noise to obtain reconstructed ECG and TI signals. Then, the reconstructed ECG signal is used as the input signal, and reconstructed TI is used as the reference signal to the LMS based adaptive filter. The idea behind using TI signal as the reference for the LMS adaptive filter is that the TI signals can be used to estimate the compression rate of the CPR signals, while the CPR signals are not available in many cases. In addition, since we aim to estimate the CPR signal, which is corrupted in the ECG signal, the ECG is used as the input signal for the LMS adaptive filter, from that the CPR signal can be estimated. This can be observed from the representative epoch in Fig. 2, the fundamental frequencies of ECG (corrupted by CPR), and TI signals are approximately the same, 1.34 and 1.37 Hz. The diagram of the CPR estimation is shown in Fig. 3. The output signal from the LMS adaptive filter is then considered as the estimated CPR signal. The estimated CPR signal is then used for assessment of chest compressions and CPR quality evaluation.

To show the quality of estimated CPR signal in terms of waveform and frequency, we compare the results with the reference CPR signal derived by compression depth. As can be seen from Fig.4 (a) the waveform and spectrogram plot of estimated CPR signal is in good agreement with the reference CPR signal. The fundamental frequencies from the power spectral density of the two signals are also the same, 1.34 Hz, as in the bottom of this figure.



(a) (b)

Fig. 1. Representative illustration of the EMD-based baseline and noise removal on (a) ECG, and (b) TI signal on a 20-second epoch.



(b)

Fig. 2. Signals and the corresponding frequency distributions: (a) ECG, and (b) TI

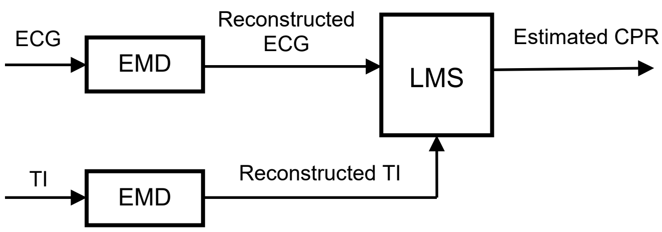


Fig.3. Diagram of the CPR suppression filter. LMS-based adaptive filter for CPR estimation and assessment

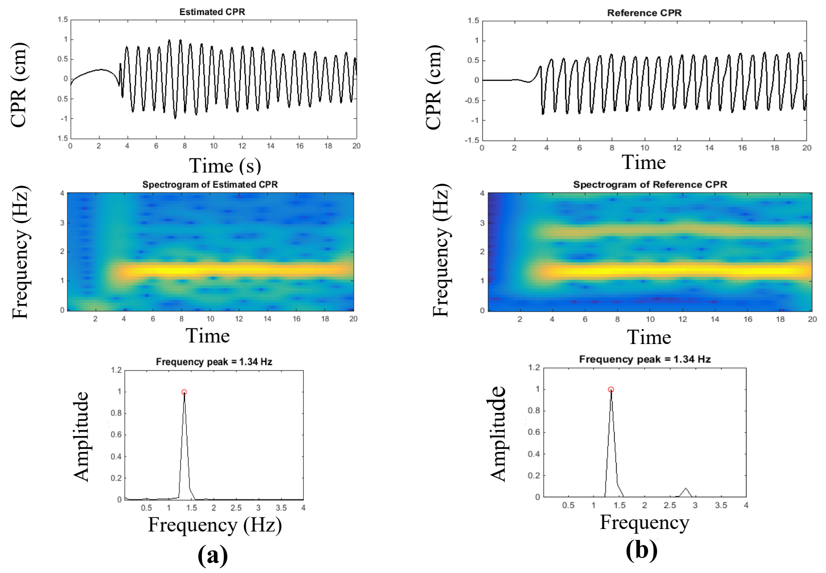


Fig. 4. Comparison of Estimated CPR with the reference CPR in an epoch: (a) Estimated CPR from LMS based-adaptive filter, and (b) Reference CPR signal. From top to down: Signal, Spectrogram, and Time-frequency plots.

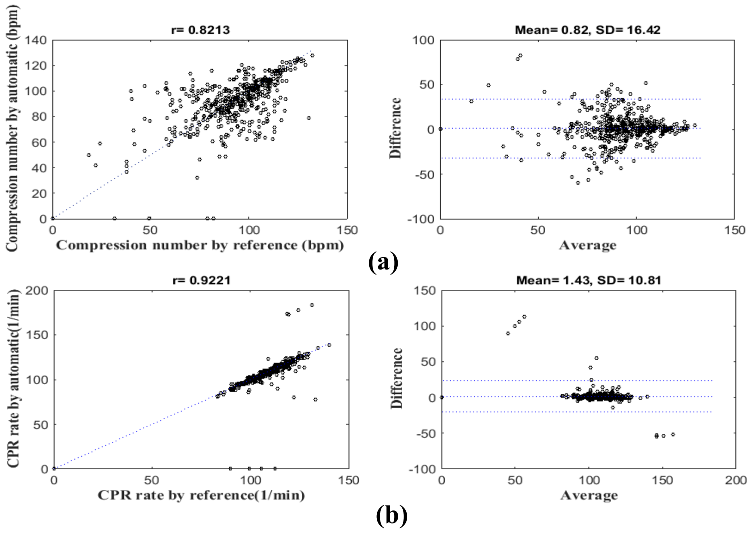


Fig. 5. Scatter plot and Bland-Altman mean-difference plot to examine the correlations between the compression numbers and compression rates by estimated CPR and reference CPR signal.

3.3. Assessment of CPR/ chest compressions

To assess the CPR artifact, the annotations of chest compressions from the estimated CPR signals are compared with annotations of chest compression from the reference CPR. The annotation of chest compressions provides us the reference to evaluate an automatic detection algorithm of chest compressions. For chest compression annotation, the spectrogram and probability density function (PDF) of CPR is performed. From the spectrogram and PDF, the fundamental frequency of compression is estimated, and the kurtosis value of the epoch are obtained. The CPR quality in each epoch is assessed based on the estimated fundamental frequency and spectral kurtosis values of the epoch. The epoch is considered good CPR if it satisfies the following conditions: (i) There exists a spectral peak, close to the estimated fundamental frequency with a deviation of 0.2 Hz; ii), The spectral kurtosis of the epoch is in a predefined range (i.e., 5 to 20) (i.e., not lower or higher than 50% the average of spectral kurtosis values in the segment).

4. Results

We have applied the proposed approach to the data set acquired from 50 patients presenting asystole with 526 segments, each segment lasts 5 seconds. Asystole is a state of no cardiac electrical activity. The EMD, LMS adaptive filter, and CPR quality evaluation are implemented using Matlab. The estimated CPR signal obtained from LMS adaptive filter is used for computation of the numbers of chest compression (shortly compression numbers) and chest compression rates. The chest compression rate is the inverse of the interval between two successive compressions.

The obtained values of CPR quality parameters are compared with those derived from the compression signal used as the reference. Especially, the correlations of various parameters of CPR quality by the proposed method and those derived from the compression signal using the scatter and the Bland-Altman mean-difference plots are presented in Fig. 5. As can be seen from the Bland-Altman plots, the CPR quality parameters obtained from the proposed automatic algorithm are in good agreements with those derived from the compression signal. The parameters are also with high correlation coefficients, 0.82 for compression number, and 0.92 for compression rate in in scatter plots. For compression rates, the average value by estimated CPR is 101.5 per minute, and the true CPR is 103 per minute. The compression rates in the database are therefore adequate since the values are close to the value recommended by CPR guidelines, 100 per minute as mentioned in the introduction section.

Table.1. Comparison of correlation coefficients for CPR assessment on the database

Parameters	**Lo method**	**Aramendi method**	**Proposed method**
Compression number	0.71	0.75	0.82
Compression rate	0.88	0.91	0.92

To evaluate the performance of the proposed algorithm, we reimplemented the two other state-of-the-arts, Lo et al. [4] and Aramendi et al. [10] methods and applied for the database. The correlation coefficients by the two methods in comparison with the proposed algorithm are provided in Table 1. As presented in the table, the proposed method obtained better correlations for both compression number and compression rate parameters.

5. Conclusion

We have presented a new approach for assessment of the CPR quality from analyzing the ECG signals retrieved from AEDs and thoracic impedance signals in patients presenting with Asystole. The proposed method is based on Empirical Mode Decomposition preprocessing, and Least Mean Squared based adaptive filter for estimating the CPR. The assessment of CPR quality on the ECG signal is evaluated using the spectrogram analysis and fundamental frequency of the estimated CPR signal. Experimental results with high correlation with those by reference compression signals demonstrates the performance of the proposed method.

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