Computer Methods and Programs in Biomedicine 141 (2017) 111–117

Contents lists available at ScienceDirect

Computer Methods and Programs in Biomedicine

journal homepage: www.elsevier.com/locate/cmpb

A method to differentiate between ventricular fibrillation and asystole during chest compressions using artifact-corrupted ECG alone

Guang Zhang[a], Taihu Wu[a], Zongming Wan[b], Zhenxing Song[a], Ming Yu[a], Dan Wang[a], Liangzhe Li[a], Feng Chen[a,*], Xinxi Xu[a,*]

[a] Institute of Medical Equipment, National Biological Protection Engineering Centre, Tianjin, China
[b] Department of Pharmacology, Logistics University of Chinese People's Armed Police Forces, Tianjin, China

ARTICLE INFO

Article history:
Received 20 April 2016
Accepted 29 January 2017

Keywords:
Cardiopulmonary resuscitation (CPR)
Chest compression (CC)
Ventricular fibrillation (VF)
Asystole (ASY)
Least mean-square (LMS) filter
Amplitude spectrum area (AMSA)
Automated external defibrillator (AED)

ABSTRACT

In recent years, numerous adaptive filtering techniques have been developed to suppress the chest compression (CC) artifact for reliable analysis of the electrocardiogram (ECG) rhythm without CC interruption. Unfortunately, the result of rhythm diagnosis during CCs is still unsatisfactory in many studies. The misclassification between corrupted asystole (ASY) and corrupted ventricular fibrillation (VF) is generally regarded as one of the major reasons for the poor performance of reported methods. In order to improve the diagnosis of VF/ASY corrupted by CCs, a novel method combining a least mean-square (LMS) filter and an amplitude spectrum area (AMSA) analysis was developed based only on the analysis of the surface of the corrupted ECG episode. This method was tested on 253 VF and 160 ASY ECG samples from subjects who experienced cardiac arrest using a porcine model and was compared with six other algorithms. The validation results indicated that this method, which yielded a satisfactory result with a sensitivity of 93.3%, a specificity of 96.3% and an accuracy of 94.8%, is superior to the other reported techniques. After improvement using the human ECG records in real cardiopulmonary resuscitation (CPR) scenarios, the algorithm is promising for corrupted VF/ASY detection with no hardware alterations in clinical practice.

1. Introduction

Early defibrillation in conjunction with chest compression (CC) is crucial for the return of spontaneous circulation (ROSC) in patients suffering from cardiac arrest [1,2]. The current application of an automated external defibrillator (AED) requires CCs to be interrupted during automatic rhythm analysis, as the mechanical activity from the CCs introduces artifact components into the electrocardiogram (ECG) signal and causes inaccuracy of the shock/nonshock decision of the AED [3]. However, the interruption of CCs compromises circulation and further adversely affects the ROSC probability [4–6]. The American Heart Association (AHA) keeps emphasizing the importance of minimizing the hand-off intervals and the continuation of the compressions [7,8].

In recent years, numerous adaptive filtering techniques have been developed to suppress CC artifacts for reliable classification between shockable rhythms (Ventricular Fibrillation (VF) and Ventricular Tachycardia (VT)) and non-shockable rhythms (Pulse-generating Rhythm (PR), Pulseless Electrical Activity (PEA) and Asystole (ASY)) during cardiopulmonary resuscitation (CPR) [9–14]. Unfortunately, the result of rhythm diagnosis during CCs is still unsatisfactory, despite these sophisticated adaptive filtering methods. Although good sensitivity after adaptive filtering is achieved, the specificity which is less than 90% is considerably lower than the value recommended by the AHA in most of the present studies. In recent years, several studies indicated that low specificity values after filtering primarily resulted from false identification of filtered asystole (ASY) rhythm [12–16]. During CPR, ASY signals are seriously corrupted by CCs. After filtering, the high frequency residual of corrupted ASY episodes is disorganized and resembles low-amplitude ventricular fibrillation (VF). Mistaking filtered ASY for VF rhythm permits the traditional AED to perform unnecessary shocks, which could have adverse effects on survival. It is obvious that the correct diagnosis of corrupted VF/ASY will considerably improve the specificity of shockable heart rhythm detection during CPR and thus provide a boost to the survival rate of patients with cardiac arrest.

In addition to unsatisfactory classification between ASY and VF corrupted by CC artifacts, another deficiency of the most of the present adaptive filtering methods is strong dependency on additional reference signals, such as compression depth, compression acceleration and thoracic impedance [17]. These reference signals

* Corresponding authors.
E-mail addresses: chenfeng62037@hotmail.com (F. Chen), xuxinxi@hotmail.com (X. Xu).

http://dx.doi.org/10.1016/j.cmpb.2017.01.015
0169-2607/

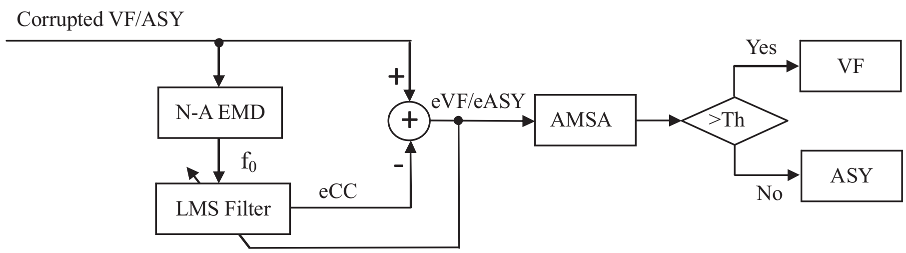

Fig. 1. Flowchart of the algorithm proposed in this study for the VF/ASY detection during chest compressions (CCs). f_0: the estimated CC frequency. N-A EMD: noise-assistant empirical mode decomposition. LMS: Least Mean Square. eCC: estimated chest compression. AMSA: amplitude spectrum area. eVF: estimated ventricular fibrillation waveform. eASY: estimated asystole waveform. VF: ventricular fibrillation. ASY: asystole. Th: threshold value for classification between VF and ASY.

cannot be acquired by most of the current AEDs, which record only the surface ECG signals. Therefore, the additional AED hardware alteration is necessary for these adaptive filters to obtain any reference signal. Additional hardware, which increases the cost of AEDs and makes the operation more complex, is a huge obstacle in the extension and application of techniques useful in detecting shock rhythm during CPR.

The present study was therefore undertaken to develop a novel method to differentiate between VF and ASY during CCs using artifact-corrupted ECG alone. In this proposed method, named LMS-AMSA, a least mean-square (LMS) filter and an amplitude spectrum area (AMSA) analysis were combined to suppress the CPR artifact and distinguish between two estimated rhythms (VF and ASY) after filtering, respectively. To evaluate the performance of the LMS-AMSA method, it was tested on ECG samples from cardiac arrest porcine models and later compared with six other algorithms.

2. Methods

The algorithm proposed in this study consists of three steps, as shown in Fig. 1. The first step is to determine the CC rate (f_0) using the noise-assistant empirical mode decomposition (N-A EMD) method, which can retrieve the CPR-related fluctuations. The second step is to reconstruct CC artifact with a least mean-square (LMS) filter and estimate original VF/ASY waveform by subtracting the CC artifact from the corrupted ECG signal. The last step is to perform amplitude spectrum area (AMSA) analysis for VF/ASY classification. If the estimated VF/ASY waveform has a value of the AMSA that is greater than the threshold, then its rhythm is VF; otherwise, the rhythm is ASY.

2.1. Estimation of the CC rate using N-A EMD method

In the present algorithm, the CC-related fluctuations (CCF) are needed to estimate CC rate. The N-A EMD method, which can prevent mode mixing, is employed to decompose original VF/ASY signals into sequential intrinsic modes of oscillation. The relative power content of the artifact (%P) is then used to characterize a CC artifact. %P of each intrinsic mode is calculated as the fraction of the total signal power concentrated in the frequency band Δf(1 ~ 3 Hz) across CC frequency range. When the estimated value of %P exceeds the threshold value, the current intrinsic modes are suspected as the CCF. The final CCF is the sum of all CCF, as shown in (1).

$$Final - CCF = \sum imf_m \qquad P\_imf_m \geq 81\% \tag{1}$$

where imfm is the mth intrinsic mode which has the value of %P (P_imfm) greater than the threshold value. The optimal threshold of %P was defined as the intersection of the sensitivity and specificity curves which were obtained using a P% value from 1% to 100% as a detection threshold based on a training dataset. After the training process, the threshold value of %P for the CCF detection is optimally selected as 81%. As shown in Fig. 2, the instant of CC was marked by "☆" symbols in Final-CCF. The time interval of each CC was determined by the interval between adjacent "☆" symbols. The CC rate can be finally calculated by the inverse of the time interval.

2.2. Estimation of original VF/ASY waveform

Among many adaptive filters, the LMS filter is resistant to detailed artifact component losses and can filter CPR artifact satisfactorily using only the CC frequency [17]. Therefore, the LMS filter is employed by this study for artifact suppression.

During CCs, the CC artifact waveform is periodic and composed of K harmonics with variable periods determined by the CC rate. Therefore, the CC artifact with a time-varying period can be modeled as follows [17]:

$$\begin{aligned} Y(n) &= \sum_{k=1}^{K} c_k(n)\cos\left(\frac{2\pi k f_0(i) n}{f_s} + \theta_k(n)\right) \\ &= \sum_{k=1}^{K} v_k(n)\cos\left(\frac{2\pi k f_0(i) n}{f_s}\right) + w_k(n)\sin\left(\frac{2\pi k f_0(i) n}{f_s}\right) \end{aligned} \tag{2}$$

where Y(n) is the estimation of CC artifact, f_s is the sampling rate, $\theta_k(n)$ is the time-varying phase related to the *K*th harmonic. $f_0(i)$ is the rate of *i*th CCs estimated based on the final CCF. $v_k(n)$ and $w_k(n)$are the in-phase and quadrature components of *K*th harmonic, respectively. The CC artifact and original VF/ASY (E(n)) can be estimated as

$$Y(n) = \mathbf{u_1}(n)\mathbf{v^T}(n) + \mathbf{u_2}(n)\mathbf{w^T}(n) \tag{3}$$

$$E(n) = D(n) - Y(n) \tag{4}$$

where D(n) is the corrupted VF/ASY waveform. The in-phase and quadrature reference signals for K harmonics are expressed by the vectors $\mathbf{u}_1(n)$ and $\mathbf{u}_2(n)$, and the vectors $\mathbf{v}(n)$ and $\mathbf{w}(n)$ are the in-phase and quadrature coefficients at the time n, respectively, as presented by (5)~(8).

$$\mathbf{u}_1(n) = [\cos(\Phi(n)), \ldots, \cos(k\Phi(n))] \tag{5}$$

$$\mathbf{u}_2(n) = [\sin(\Phi(n)), \ldots, \sin(k\Phi(n))] \tag{6}$$

$$\mathbf{v}(n) = [v_1(n), \ldots, v_N(n)] \tag{7}$$

$$\mathbf{w}(n) = [w_1(n), \ldots, w_N(n)] \tag{8}$$

The vectors $\mathbf{v}(n)$ and $\mathbf{w}(n)$ can be recursively updated using the LMS adaptive filter algorithm, as shown by (9) and (10).

$$\mathbf{v}(n+1) = \mathbf{v}(n) + f(\mathbf{u_1}(n), E(n), \mu) \tag{9}$$

$$\mathbf{w}(n+1) = \mathbf{w}(n) + f(\mathbf{u_2}(n), E(n), \mu) \tag{10}$$