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# Shockable Rhythm Detection Algorithms for Electrocardiograph Rhythm in Automated Defibrillators

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**Abstract**

The quick and accurate detection of shockable rhythms is important in real application of automatic external defibrillator or implantable cardioverter defibrillator to save lives. The crucial component in automatic defibrillator is the detection algorithm for shockable rhythms, including ventricular fibrillation and pulseless ventricular tachycardia. We summarized the main development of the algorithms, including the time-field detection method, frequency-field detection method, time-frequency analysis detection method and dynamics analysis method. Furthermore, the key issues for further study are also presented.

## 1. Introduction

Sudden cardiac arrest is a major public health problem and one of the leading causes of mortality in the whole world. For example, from the website of the American Heart Association (AHA), we know that each year about 295,000 emergency medical services-treated out-of-hospital cardiac arrests occur in the United States.

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Usually, cardiac arrest is classified into "shockable" versus "non–shockable", based upon the electrocardiograph (ECG) rhythm. The two shockable rhythms are ventricular fibrillation (VF) and pulseless ventricular tachycardia (VT) while the non–shockable rhythms include sinus rhythm (SR), supraventricular tachycardia (SVT), premature ventricualr contraction (PVC), atrial fibrilation (AF) and so on. Cardiac arrest with shockable rhythms may be reversed if cardiopulmonary resuscitation (CPR) is performed or a defibrillator is used to shock the heart and restore a normal heart rhythm within a few minutes. Thus, AHA recommends defibrillation response within 5 minutes for out-of-hospital events, and 3 minutes for in-hospital events.

Now, besides manual defibrillation by an emergency paramedic, bystander defibrillation with automatic external defibrillator (AED) or implantable cardioverter defibrillator (ICD)) is becoming more and more widely available, especially for public assess defibrillation in out-of-hospital. In order to detect the shockable rhythms fast and correctly, a crucial component in automatic defibrillator is the appreciate detection algorithms. Thus, a brief review on the detection algorithms is given in the present paper.

## 2. Algorithms

For an electrocardiogram signal from body-surface, after a prefiltering process, there are many software methods for fibrillation detection, including the time-field detection method, frequency-field detection method, time-frequency analysis detection method and dynamics analysis method [1].

### 2.1. Time-field detection method

Using slope, amplitude and width information of a ECG signal, tompkins algorithm [2] gives a real-time VF detection based on a QRS complex search. After that, Chen et al. [3] proposed autocorrelation function (ACF) algorithm. The main idea is to analyze the periodicities within the ECG and the basic assumption is VF signals are more or less aperiodic and SR signals are approximately periodic. For a given ECG signal, the short-term ACF with a rectangular window is first calculated and then performs a linear regression anlaysis of the ACF peaks. After that, the index of variance ratio VR is defined and calculated acoording to the linear regression equation. Finally, SR and VF can be detected based on the index VR.

The threshold crossing intervals (TCI) algorithm [4] is based on the number and position of signal crossings through a certain threshold. For each 8s ECG signals, the main ideas of the algorithm is given a threshold value and obtain a binary signals according to the position of the signal above or below the threshold. Then the index TCI is calculated for each 3s episode of the binary signals, and SR, VT and VF can be sparated based on the calculated values of the TCI indices.

Aim to the automated VF detection in cardiac care devices, the indicators of triangular-like components with a waveform representation of heart function, an area encompassed by the waveform representation indicative of heart function and their ratio were calculated in the invention [5]. According to these indices, the (minimum) ventricular fibrillation indices can be calculated and used to assess the likelihood of ventricular fibrillation based upon waveform representation of heart function. The results indicate that the invention can enhance the sensitivity and selectivity of the automated detection of arrhythmias within even highly chaotic waveform representations of heart function.

Based on ECG waveform factor and its irrrgularity, the invention [6] provide an improvement algorithm for the detection of cardiac arrhythmia, wich is capable of reliably and efficiently differentiation VT, VF, and nonshockable SVT and AF. Especially, the algorithm is easily implement and has a minimum amount of computation complexity, thereby can distinguish these kinds of signals in real time in either an external (AED) or an internal (ICD) antitachyarrhythmia device.

In [7], Amann et al. proposed three new algorithms in the time domain, including standard exponential algorithm (STE), modified exponential algorithm (MEA) and signal comparison algorithm (SCA). Using a suitable exponential curve decreasng on both sides through the absolute maximum value of the investigated sequence of the ECG signal, STE can count the number of crossing points of the ECG signal. This number is an index to decide whether it is shockable, include SR, VT and VF. Comparing with STE, the MEA lifts the decreasing exponential curve at the crossing points onto the following relative maximum, which can improve the detection effect of SR, VT and VF. With four predefined reference signals (three sinus rhythms containing one PQRST segment and one ventricular fibrillation signal), SCA calculate the residuals in the L1 norm to separate SR and VF.

Though bystander CPR can greatly increase the chance of survival for heart attack victims, continuous chest compression can induce the presence of large amplitude artifacts on victim's ECG signals and affect the accuracy of the detection on VF in AED. The traditional treatment is advise the rescuer to stop chest compression and to "stand back" away from the patient for many seconds to preclue shocking the rescuer and to stop adding chest compression artifacts to the ECG signals so a "clean" signal can be analyzed. However, the invention [8] point out that the cessation of compressions by as little as 10 seconds reduces the probability of successful defibrillation by as much as 50% in the prior studies, this interruption of chest compressions adversely affects the survival possibility of the victim. Based on the indices of average amplitude, slope, the time between the peak signals and so on, Young et al. proposed an algorithm to detect VF and QRS in the presence of chest compression artifacts through crosscorrelation and autocorrelation. As a result, the invention provides a method for operating an AED by a rescuer who can provide chest compressions without the need for a extended interruption. Similarly, the invention [9] provides a method for detection of a shockable rhythm by the calculation of mean slope, median slope, slope deviation and rate for CPR-filtered ECG signals, which can continuously provide recommendation regarding action to be taken in order to minimize required pauses in the treatment.

Recently, based on the empirical mode decomposition (EMD) algorithm, Arafat et al. [10] proposed a algorithm for VF detection. Concretly, EMD obtained the first three consecutive intrinsic mode functions (IMFs) of normal sinus rhythm (NSR) and VF, and then found that the IMFs of VF are orthogonal whereas the IMFs of NSR are not. For the digitized ECG signals in MIT-BIH arrhythmial database, according to the orthogonality indices, the EMD algorithm can offer a good detection of VF for a window length of 3s.

## 2.2. Frequency-field detection method

The VF filter algorithm [11] is one of the earliest method in the frequency domain. A narrow-stop filter is applied to the signal with central frequency being equivalent to the mean frequency of the considered ECG signal and the calculated output is the index of VF filter leakage. Since VF signals are approximately sinusoidal waveform, VF can be detected. Furthermore, Aramendi et al. [12] proposed a new adaptive filtering method to recover the VF waveform in the presence of CPR artefacts in the surface ECG signal, which enable CPR to continue during AED rhythm analysis and increase the likelihood of resuscitation success.

Note that the normal ECG is a broadband signal with major harmonics up to 25 Hz and it will becomes concentrated in a band of frequencies between 3 and 10 Hz if VF occur [13, 14]. There are different energy contents in different frequency bands to normal ECG and VF signal. Therefore, based on Fourier analysis, the normalized first spectral moment and the sum of amplitudes in different bands can be calculated and used to detect VF. These are the main principle of Spectral algorithm (SPEC) in [15].

Recently, aim at the use of AED, Amann et al. [16] proposed a new algorithm (HILB) based on the Hilbert transform for a window length of 8s. Comparing with other frequently-used algorithms, HILB algorithm yield the best sensitivity for any given specified specificity and it is the fastest of all aogorithms.

## 2.3. Time-frequency analysis detection method

The time-frequency analysis detection method can use the signal strength in time and frequency domains at the same time and there are a number of methods for transforming the signal [17, 18].

Note that wavelet transform contains the information not only the frequency distribution but also the time distribution of a signal. With a suitable mother wavelet, wavelet based algorithm [7] can be used to detect VF and search QRS complexes. The reference [19] is also based on wavelet analysis.

Furthermore, Jekova [20] proposed a set of 10 parameters, include the frequency characteristics, the variations, the complexity, the periodicity and the symmetry of the 10s ECG signals. After that, the stepwise discriminant analysis on the parameter set proved their adequacy for both shockable rhythm detection and shock success prediction. Thus, it is possible to achieve the decision for defibrillation not only the rhythm type but also the possibility for successful defibrillation in the future AEDs, which gives out a new orientation of the development of AED.

## 2.4. Dynamics analysis method

Beside the information from the time domain and/or from the frequency domain, dynamics analysis method is also available to detect shockable rhythms and the most extensively used algorithm is the complexity measure algorithm (CPLX). Specifically, the the main principle is as follows: taking over the thought of a dynamical system, the CPLX [21] introduce a complexity measure to quantitatively characterize the complexity of the transformed binary sequence from the investigated ECG signal, which can be used to separate SR, VT and VF.

Now, there are many extension on the CPLX. For instance, on the basis of symbolic dynamics for chaotic system, Zhang and Zhu [22] proposed a new index (complexity dispersity) to detect VT and VF. The results show that it is helpful to real-time analysis of cardiac pathological monitoring and detection. Though all of the cardiac data was obtained from implantable cardioverter defibrillator (ICD) in the literature, the qualitative analysis method may be extend to AED. Note that CPLX cannot perform real-time complexity analysis and avoid unneccessary therapy caused by SVT or high-frequency noise in ICDs or AEDs. The invention [23] proposed a system and method for real-time detecting shockable VF and VT based on ECG complexity analysis. Concretely, an easily calculating index, complexity measure (CM), was introduced and different kinds of tachyarrhythmia and high-frequency noise can discriminate based on the calculated index and three thresholds.

Recently, note that the slop and amplitude probability density for VF are relatively low, whereas, the slope and amplitude probability are relatively high due to the presence of a complete QRS wave for AF, AFL, SVT, and so on. The invension [1] modified the exiting complexity algorithm and incorporated a plurality of feature values, which make it more adapted to reflecting characteristics of the VF-related signals and produce some benefits, for example, it has a reduced calculation load, can more effectively differentiate various types of ECG signals and accurately distinguishes VF from VT, AF, AFL and SVT, and can fully satisfy the clinical needs. Thus, it has the potential to be used in the medical equipment for detecting VF more effectively, such as monitors, ICD and AED.

## 3. Conclusion

Though there are many algorithms to detect shockable rhythms in the literatures, most of the algorithms were tested by the segment of the whole BIH-MIT database, the CU database, and the files 7001-8210 of the AHA database. Thus, to assess the accuracy of the existing algorithms, testing should be done by using a large

amount of annotated data under equal conditions, such as the references [7, 24]. In addition, comparing with the signals in the standard database, there are measuring noises and specificities unavoidably during CPR, so the assessment of the algorithms should also be done in the presence of pathologic cases under frontline treatment.

Since the shortest possible window length to detect the shockable rhythms is important to increase the the successful rate of rescue, it is a valuable direction to study the fast algorithm, such as EMD algorithm can detect VF and NSR within 3s with high accuracy [10]. Moreover, to make the advantages of relevant algorithms complementary with each other so as to raise the robustness, we advise to consider the cooperation of different algorithms. For example, though the invention [25] was focus on the detection of cardiac rhythms produced by the heart in ICD, the idea that include a pluarality of discriminators for classifying cardiac rhythm may be useful in the field of AEDs.

What should to be point out is that the present is not offer the detailed process of the algorithms for the sake of simplicity. A comprehensive survey on the algorithms and their calculative process can be found in the corresponding references.

## Acknowledgements

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