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Research paper

Detection of ventricular tachycardia and fibrillation using adaptive variational mode decomposition and boosted-CART classifier

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ABSTRACT

Rapid ventricular tachycardia (*VT*) and ventricular fibrillation (*VF*) are serious life-threatening ventricular arrhythmias. Correct detection of *VT/VF* is crucial for the rescue of cardiac arrest patient. In this paper, we proposed a new method for improving the detection effect of *VT/VF*. An adaptive variational mode decomposition (*adaptive-VMD*) algorithm was presented to decompose the electrocardiogram (*ECG*) signal into five band-limited intrinsic modes (*BLIMs*). Then, a total of 6 features were extracted from these *BLIMs* to characterize the details of *VT/VF*. Last, a boosted classification and regression tree (*Boosted-CART*) classifier that combines feature selection and recognition was used to detect *VT/VF*. Three annotated public *ECG* databases were used as the training and testing datasets. Ten-fold cross-validation was implemented to assess the performance of the method. An accuracy (*Acc*) of 98.29% ± 0.18%, a sensitivity (*SE*) of 97.32% ± 0.12% and a specificity (*SP*) of 98.95% ± 0.84% were obtained. In comparison with the existing state-of-the-art methods for *VT/VF* detection, the proposed method demonstrated better overall performance.

1. Introduction

1.1. General introduction

Rapid ventricular tachycardia (*VT*) and ventricular fibrillation (*VF*) are lethal cardiac arrhythmias which are caused by the disorganized electrical activity in the ventricles. This disorganized electrical activity causes the ventricular muscle fibers contract independently and results in obstacle of blood pumping. It can occur due to coronary heart disease, valvular heart disease, or cardiomyopathy. An *ECG* showing irregular unformed PQRST complexes without any clear P waves is usually a sign of *VT/VF*. As the onset of *VT/VF*, the patient may be in the danger of cardiac arrest with losing consciousness and no pulse. If left untreated, collapse and sudden cardiac death would happen in minutes [1,2]. Cardiopulmonary resuscitation (*CPR*) and electrical defibrillation (shock) are the main clinical treatments for cardiac arrest. *CPR* can help maintain blood flow to the organs and then an electrical shock is applied to the patient's heart region to help restore the heart rhythm to normal. Implantable cardioverter defibrillators (*ICD*) and automated external defibrillators (*AED*) are two kinds of widely used defibrillators [3]. After detecting the signs of *VT/VF*, these devices deliver a high-energy electrical shock to the heart. However, if a normal sinus rhythm (*NSR*) was misclassified as *VT/VF*, leading unnecessary shock delivery, it would damage the heart or even cause death. Therefore, correct and prompt detection of *VT/VF* is of pivotal importance for increasing the survival rate of patients with cardiac arrest [4].

1.2. Related works

In the last decades, varieties of methods had been proposed for the detection of *VT/VF*. The *ECG* features of *VT/VF* were also extensively been studied in these methods such as morphology analysis [4–6], spectral analysis [7,8], time-frequency analysis [9], complexity measure [10,11], wavelet analysis [12–14], empirical mode decomposition (*EMD*) [15,16] and sequential detection methods [17,18]. However, these methods were mostly considering each feature individually, and been tested on the specific datasets in their papers. When being tested under the same conditions of using open published annotated databases, they could not achieve the proclaimed performance [22].

Recently, some methods which combined the *ECG* features with machine learning techniques had been proposed to detect *VT/VF* [19–21]. The testing results of these methods on public databases

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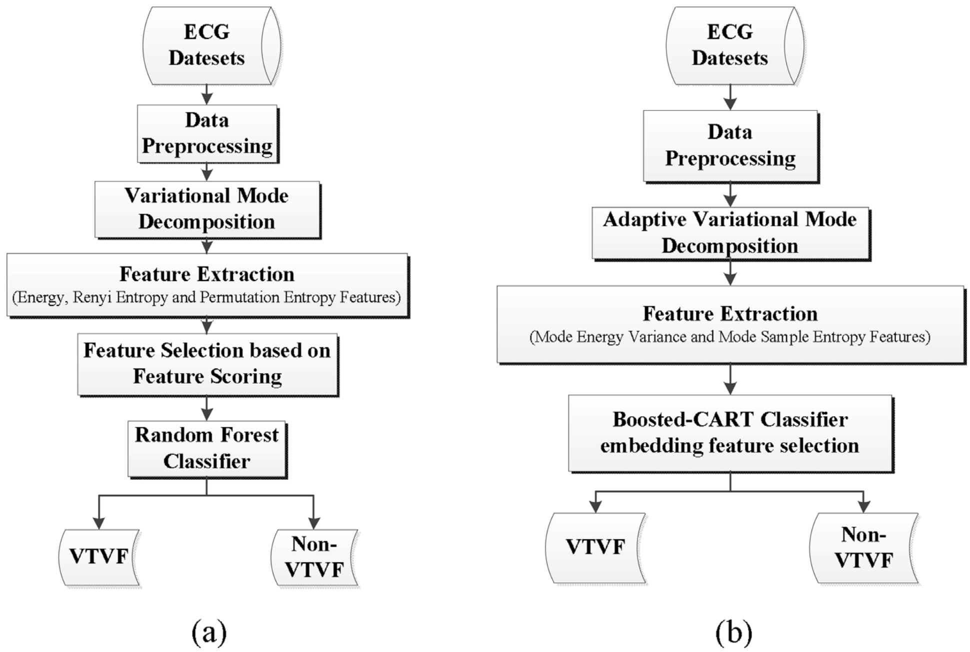

Fig. 1. Flowchart of the *VMD&RF* [21] method and the proposed method. (a) *VMD&RF* method. (b) The proposed method.

demonstrated that the multi-features-combining methods can dramatically enhance the performance of *VT/VF* detection. In [19], Atienza et al. evaluated 13 *ECG* features and presented a combining filter-based feature selection methodology to pick the useful features for improving the detection efficiency. The support vector machine (*SVM*) was selected as the classifier of *VT/VF* in their method. Li et al. [20] evaluated total 14 features and utilized the Genetic Algorithm to select the optimal feature combinations. They also used *SVM* to classify the ventricular arrhythmia episodes. Tripathy et al. [21] decomposed the *ECG* signal into 5 *BLIMs* by using variational mode decomposition (*VMD*) technique [23]. They found that the local variations of PQRST complexes due to pathology could be captured with these *BLIMs* for their characteristics in the time-frequency domain. A total of 9 features were extracted from the *BLIMs* in their study. Then the mutual information-based feature selection approach and random forest (*RF*) classifier were used for the detection of *VT/VF*. The flowchart of this *VMD&RF* method is given in Fig. 1(a). However, owing to the drawback of *VMD* on parameter setting [24], the *ECG* decomposition could not achieve the best effect in this method. Also, in these three multi-features-combining methods, feature selection technique was utilized to reduce feature dimension and then machine learning technique was employed to classify the cardiac rhythms. There was no method that combined feature selection and classification had been proposed for the detection of *VT/VF*.

In this work, a new multi-features-combining *VT/VF* detection method was proposed. Besides the *ECG* signal preprocessing and Feature extraction, this method contained several special stages: First, a novel parameter named mode energy and independence metric (*MEIM*) was presented as an evaluation index to judge the performance of *VMD* in *ECG* decomposition. Then, an *adaptive-VMD* algorithm was presented to optimize the effect of *ECG* decomposition. In this processing, the key parameter of *VMD* was online-optimized based on the *MEIM* through a global optimization algorithm. Last, to simplify the *VT/VF* detection procedures, a *Boosted-CART* classifier that embeds feature selection was given. The *Boosted-CART* classifier is an ensemble classifier of *CART* and been boosted by adaptive-boosting (*AdaBoost*) algorithm [26]. The flowchart of the proposed method is given in Fig. 1(b).

The rest of this paper is organized as follows. In Section 2, a brief introduction to the *VMD* technique for *ECG* decomposition and its drawback is given. Section 3 expands the proposed method in detail, including the *adaptive-VMD* algorithm and a *Boosted-CART* classifier. Then, a series of experiments for testing the proposed method performance are presented in Section 4. Finally, the conclusion is drawn in Section 5. Furthermore, most abbreviations in this paper are expanded at first use. For convenience, we have also provided a glossary in the Appendix A.

2. *VMD* for *ECG* decomposition

VMD is a newly developed signal processing technique proposed by Zosso et al. [23], using which an *ECG* signal can be decomposed into an ensemble of band-limited intrinsic modes (*BLIMs*). Each *BLIM* compacts around a center frequency $\omega_k$and its bandwidth is calculated with the *L2*-norm of the gradient of its Hilbert transformed signal. Mathematically, the *VMD* technique is a solution to the constrained variational problem which is given in [23]:

$$\begin{aligned}&\min_{\{u_k\},\{\omega_k\}}\left\{\sum_{k=1}^{K}\left\|\partial_t\left[\left(\delta(t)+\frac{j}{\pi t}\right)*u_k(t)\right]e^{-j\omega_k t}\right\|_2^2\right\}\\&\text{subjectto}\sum_{k=1}^{K}u_k=\mathrm{f}\end{aligned}\tag{1}$$

where K is the total number of *BLIMs*, u_k is the k^{th} *BLIM* and $\omega_k$is the corresponding center frequency. In order to address the constraint in (1), an augmented Lagrangian function is given:

$$\begin{aligned}\mathscr{L}(\{u_k\},\{\omega_k\},\lambda)=\alpha\sum_{k=1}^{K}\|\partial_t[(\delta(t)+\frac{j}{\pi t})*u_k(t)]e^{-j\omega_k t}\|_2^2\\+\|f(t)-\sum_{k=1}^{K}u_k(t)\|_2^2+\langle\lambda(t),f(t)-\sum_{k=1}^{K}u_k(t)\rangle\end{aligned}\tag{2}$$

where, α is the key parameter that represents the balancing of data-fidelity constraint, and λ is the lagrangian multiplier. The solution