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Diagnosis of shockable rhythms for automated external defibrillators using a reliable support vector machine classifier

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ABSTRACT

Sudden cardiac arrest is mainly caused by ventricular fibrillation and ventricular tachycardia, which are known as shockable rhythms. In this paper, a detection algorithm of shockable rhythms including support vector machine (SVM) model uses the public electrocardiogram (ECG) databases for training and testing. The databases are the Creighton University Ventricular Tachyarrhythmia Database (CUDB) and the MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB). At first, to compose a set of good features, we extend a well-known set of 2 good features such as Count2 and VF-filter Leakage Measure (Lk). We supplemented 5 more good features, selected based on a binary genetic algorithm-based feature selection, among 11 new input candidate features. All the combinations of 7 good features are estimated for their performance on the training and the testing data using the SVM models to identify 6 combinations of the final feature pool. 5-Folds cross validation is then implemented carefully to validate the performance of the SVM classifier using final feature pool on separated and entire 5s-segment databases. The final combination of 4 features, which includes Count2, Lk, Threshold Crossing Interval (TCI), and Centroid Frequency (CF), is addressed by the highest validation performance of the corresponding SVM model. The Count2 shows the proportion of the signal, which is above the mean absolute values of the output of an integer coefficient recursive bandpass filter computed for every 1 s time interval. The Lk represents the output of a narrow bandstop filter, which is applied to the ECG signal with the central frequency being the mean signal frequency. The TCI shows the average time between the fixed thresholds, which are computed for every 1s-segment using the pulses converted from the ECG signal. The CF is the frequency, which bisects vertically the area under the power spectrum. For the proposed algorithm, the average accuracy of 95.9%, sensitivity of 91.7%, and specificity of 96.8% are archived on the evaluation data of the entire database. Comparing to the performance of the SVM model using a combination of the Count2 and the Lk, we report a significant improvement for the accuracy of the SVM model using the final feature combination in average, i.e. 2.6%, 22.4%, and 2.7% on the evaluation data of the entire database, the CUDB, and the VFDB, respectively. Furthermore, existence of ventricular ectopic beats in the input data shows a negligible influence on the final performance of classification.

1. Introduction

Sudden cardiac arrest is mainly caused by ventricular fibrillation (VF) and ventricular tachycardia (VT). VF and VT are primary arrhythmic events which are also known as shockable rhythms. Rapid detection of these dangerous rhythms for delivering the electrical shocks or intervening with cardiopulmonary resuscitation is crucial for potential survival [1].

Most of the recent algorithms for shockable rhythm classification are mainly based on electrocardiogram (ECG) signal processing [2–6,8–13,28,29]. For the threshold-based method, the ECG signal is transformed into the 0/1 bit string using a certain threshold [2,3]. In [2], from the binary bit string, the complexity measure, which reflects the rate of new pattern arising with the increase in the length of binary sequence, is computed as the proportion between the number of different substrings and its asymptotic behavior for a random string. In [3], the ECG segment is divided into consecutive 1s-segments for which 20% of maximum absolute values of individual 1s-segments are used as thresholds to generate binary signal if the ECG samples are over the thresholds. The time intervals are then measured by comparing the start and the end of the

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considered 1s-segments with the ends of last pulses and the starts of the next pulses. Another efficient algorithm is based on the percentage of time for which the ECG signal remains outside a certain threshold [4]. The authors of [5] use a feature of the mean absolute value (MAV) to distinguish the shockable from the non-shockable rhythms based on the fact that the MAV of the shockable rhythms is comparatively larger than that of the non-shockable rhythms. The combinations of an advanced filter technique and segment by segment time varying thresholds are applied and shockability is then classified by numbers of samples over these thresholds [6]. Two dimensional phase space plots of ECG signal and its time delayed signal deployed on a specific grid is proposed as a time-delay algorithm in [8] while the maximum ECG signal amplitude of a segment is considered as the starting point to deploy an exponential curve to count the number of crossing points [9]. The center of gravity of the amplitude spectrum and different ratios of areas contained within various frequency bandwidths are calculated in the range of first 20 harmonics with peak frequency [10]. Wavelet transform in combination with fuzzy neural networks is proposed in [11]. Moreover, the non-linear methods using support vector machines (SVM) are used in [12,13]. A wide variety of machine learning classifiers are used to investigate the performance of the detection algorithm on public databases and out-of-hospital cardiac arrest databases [28]. Random forest (RF) classifier is suggested as an efficient algorithm using variational mode decomposition technique for feature extraction [29].

A SVM classifier is constructed in [13] based on two phases of design. In the development phase, the authors extract 14 candidate features of the ECG signals in 5s-segment length. Afterwards, 9 good features are selected using the binary genetic algorithm (BGA) feature ranking approach with the root mean square error (rMSE) of a multivariate logistic regression (MLR) as a fitness function on the training set. The individually good features and every possible combination of them are put into SVM models to train and test their performance on the training and testing data. For each number of features ranging from 1 to 9 in the combinations, a feature combination corresponding to its SVM classifier, which results in the best accuracy, is selected and therefore the final feature pool includes 9 feature combinations on which the number of features in each combination is different. In the validation phase, 5-folds cross validation (CV) is performed on the entire database with different segment lengths ranging from 1 s to 10 s to evaluate the SVM classifiers using the final feature pool. The classifier with final feature combination of two features, namely Count2 and VF-filter Leakage Measure (Lk), in the 5s-segment length exposes the best performance. The main contribution of [13] is to apply a statistically valid manner to estimate the performances of previously published features and their combinations. The final feature combination of Count2 and Lk, which is claimed using the statistical method, is significantly reliable for the practical diagnosis of shockable rhythms.

It is obvious that more exhaustive features are to be explored since the authors of [13] consider only a group of 14 input candidate features, which is not a full set to represent the characteristics of the ECG signal. Furthermore, the entire database is used for the performance evaluation of SVM classifiers employing different feature combinations without evaluating these classifiers on the separated databases. For that reason, we consider an expansion of candidate features. In addition, the combination of Lk and different time and frequency features are used effectively for shockable rhythm detection purposes [14]. Consequently, we firstly reuse 2 features of the final feature combination given by [13]. Moreover, a set of other candidate features, in which each single candidate is a separated classification algorithm and proves its adequacy for shockable rhythm detection with relative high accuracy [3–6,9], are chosen. Further, the candidate features, which represent the spectral characteristics of signal, are paid intensive attention [13,15–18] due to a clearly separated spectrum of shockable and non-shockable signals under equal conditions. As a result, a total of 13 candidate features are extracted from the 5s-segment of the ECG signal for this research.

Basically, we follow the process presented by [13] to identify a SVM classifier, which shows the highest validation performance, associated with a novel feature combination. This final feature combination consists of the Count2, Lk, Threshold Crossing Interval (TCI), and Centroid Frequency (CF) features in terms of comparison with a combination of Count2 and Lk as proposed in [13]. The reason behind the use of two phases, which are development and validation, is the limited databases. We use a fixed amount of training and testing data to estimate the performance of feature combinations on an entire database. However, because there is no extra database, we reuse the same database with different amounts of training and evaluation data to verify the performance of selected feature combinations. This is a reliable method to address the final feature combination which can be applied for practical applications.

The rest of the paper is organized as follows: The target databases and preprocessing are described in Section 2, followed by descriptions of the proposed classification method in Section 3. Section 4 presents the details of classification method and results while the additional discussion is provided in Section 5. The remarkable conclusion is expressed in Section 6.

2. Data and preprocessing

We use two ECG public databases, which are the Creighton University Ventricular Tachyarrhythmia Database (CUDB) and the MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB), and the preprocessing techniques which are proposed in [13] for this research. It is noteworthy that one more filter which is five-order moving average is added in the data preprocessing step to make the ECG signal smooth in comparison with the preprocessing techniques in [13]. Indeed, five-order moving average filter is a good choice for reduction of random white noise while keeping the sharpest step response [19]. It is obvious that R-peaks of non-shockable rhythms are better sharpened and enhanced while noise is not increased significantly by applying this filter. This leads to an improvement in overall classification in terms of presence or absence of QRS complexes.

2.1. Data

The CUDB consists of 35 single-channel records, each of them being about 8 min. The signals in this database are annotated as VF, VT, and non-VF. The VFDB includes 22 double-channel records of 35 min. The annotations of signal in VFDB database are ventricular flutter, VF, and VT for shockable rhythms; normal sinus rhythm, nodal rhythm, paced rhythm, and arrhythmias such as atrial fibrillation, ventricular ectopic beats (VEBs) for non-shockable rhythms. All the records are sampled with a frequency of 250 Hz. There are 57 records with 79 channels of the entire database, which are then divided into non-overlapping 5s-segments of 29 odd records for training set and 28 even records used for testing set. The VFDB is separated into 11 odd records for training and 11 even records for testing sets, while 18 odd records and 17 even records are used for training and testing sets of the CUDB. The number of shockable and non-shockable 5s-segments is presented in Table 1. The total database, which is comprised of the segments of two separated databases, is also split into the training and testing sets. In order to estimate the characteristics of each database and the adaptability of various feature combinations as the input of the SVM classifiers, the CUDB and the VFDB are also considered as training and testing