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Stationary wavelet transform based technique for automated external defibrillator using optimally selected classifiers

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A R T I C L E I N F O

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A B S T R A C T

Early and accurate detection of ventricular fibrillation (VF) and rapid ventricular tachycardia (VT) is vital for defibrillation therapy. Various techniques have been proposed based on various parameters extracted from the electrocardiogram (ECG), which are mostly slow and requires comparatively wider ECG segment. The proposed technique requires a 4.1 s segment of ECG which results in an early detection and thus proposed to help in timely diagnosis and treatment of these life-threatening arrhythmias. Stationary Wavelet Transform (SWT) has been used for decomposition of the signal followed by calculation of sample entropy of the wavelet bands selected using filter-type feature selection procedure. Sample entropy of these bands, working as attributes for the classifier was fed to three different classifiers, Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), and Random Forest Algorithm (RFA) and their performance was analyzed with variation in their key model parameters. The proposed technique has been analyzed in two scenarios; VFVT vs Non-VFVT and VF vs Non-VF. The Sensitivity ($Se\%$), Specificity ($Sp\%$), Positive Predictivity ($+P\%$), Accuracy ($Ac\%$), and area under Receiver Operating Characteristics Curve ($Roc\%$) analyzed over Creighton University Ventricular Tachyarrhythmia (CUVT) database were used for performance analysis and comparison. As per observations of the results, under VFVT vs Non-VFVT scenario SVM has highest $+P\% = 96.53$ and $Sp\% = 97.08$, RFA has the highest $Roc\% = 98.10$, and k-NN has the highest $Se\% = 95.64$ and $Ac\% = 96.01$. For VF vs non-VF classification, SVM gives best $Sp\% = 96.86$, RFA has the highest $Roc\% = 98.00$, $Se\% = 95.74$ and $Ac\% = 95.80$, and k-NN gives best $+P\% = 96.52$.

1. Introduction

Cardiovascular diseases are dominating reason of mortality and this trend is seen globally, including the low and middle-income countries [1,2]. In 2013, an estimated 595,000 (395,000 out-of-hospital and 200,000 in-hospital) sudden cardiac arrest (SCA) cases were reported in the United States of America [3]. SCA is an abrupt failure of heart function, most often caused by a rapid ventricular tachycardia (VT) that quickly degenerates into ventricular fibrillation (VF) which requires emergency medical treatment. A competent treatment for VF is the electrical defibrillation of the heart using a device called automated external defibrillator (AED) which delivers a high energy electrical stimulus to the heart. This has led to the development of techniques that analyze the surface electrocardiogram (ECG) signal and warn/deliver a shock whenever is required.

Different algorithms have evolved out of research, such as techniques based on threshold crossing criteria [4,5], autocorrelation function [6], artificial neural networks [7], support vector machine [8], wavelet transform [9,10], semantic mining approach [11], methods based on complexity measures [12], phase-space reconstruction method [13], K-nearest neighbor rules [14], and Hilbert Transform based method [15]. For each algorithm, different detection scenarios have been considered, such as VF vs non-VF rhythms, VF vs VT, VFVT vs non-VFVT, VF vs Normal, VF vs Normal vs VT as three separate classes, makes it difficult to analyze or select an algorithm for the application [16]. In spite of research in the field, a reliable and fast detection of the life-threatening arrhythmias remains an open problem. A quicker detection of such potentially lethal rhythms may help with timely treatment.

Wavelet transform decomposes a signal, providing a time-frequency representation, which can be used for analysis of a non-stationary signal. The proposed technique uses stationary wavelet transform (SWT) for signal decomposition. SWT is selected for its time-invariant property and ability to contain same temporal information at different decomposition levels as that of the original signal. SWT overcomes the problem of robustness and repeatability by inserting zeros between taps of the filters instead of decimation, which exist in discrete wavelet transform [17,18]. Further, sample entropy calculated at selective bands was treated as attributes to the classifier. Filter-type feature

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selection strategy is used to rank the attributes according to their relevance. Finally, classification is performed using support vector machine (SVM), random forest algorithms (RFA) and k-nearest neighbor rules (k-NN). Supervised learning based machine learning algorithms are selected due to their ability to yield high accuracy, which is essential for correct functioning of an AED. For quicker detection a 4.1s window is used during segmentation. To implement SWT with L-levels ($L = 6$ in this work) on a signal, the length of signal should be multiple of 2^L. Due to this data length requirement and early detection, window length is selected to be 1024 ($1024/250 \approx 4.1$ s, here 250 is sampling frequency) long.

The proposed technique is analyzed on both VF vs Non-VF and VFVT vs non-VFVT scenario and is independent of QRS complex detection so it is free from QRS complex detection error. A widely accepted Creighton University Ventricular Tachyarrhythmia (CUVT) database, which is a benchmark for ventricular tachyarrhythmia related algorithms, has been used for performance analysis of the proposed technique.

The paper is organized as follows. After an introduction, Section 2 presents the proposed methodology. Section 3, discusses the results followed by conclusion in Section 4.

2. Methodology

2.1. Pre-processing

The raw ECG signal is segmented after every 1024 samples, say this signal be $y[n]$. The segmented ECG is passed through a SavitzkyGolay (SG) smoothing filter to smoothen out the noisy raw ECG signal, say this SG-filtered signal be $x[n]$. SG filter functions superior than standard averaging FIR filters by minimizing the least-squares error in fitting a polynomial to each frame of noisy data. The SG filter order, the coefficients and the frame size are selected as described in [19,20]. Fig. 1(a) and (b) shows raw and SG-filtered ECG for normal, VF and VT segments. A section of normal ECG smoothen out using the SG-filter is shown in Fig. 2 overlapped over the corresponding raw ECG section. Similarly, a section of VF ECG is shown in Fig. 3.

Then, as represented in Fig. 4, the process flow diagram of the proposed technique, the filtered ECE segment is applied to SWT. The present technique, uses SWT to decompose the filtered ECG so that it can be analyzed at different frequencies and then the extracted features can be used for VF or VFVT detection. A tree-structure diagram of a 6-level SWT is shown in Fig. 5. In Fig. 5, $G(z)$ and $H(z)$ are high-pass and low-pass filters respectively, designed based on the wavelet basis function. As there are no set of rules for selecting a mother wavelet [21], 6-order Daubechies function is used in this technique.

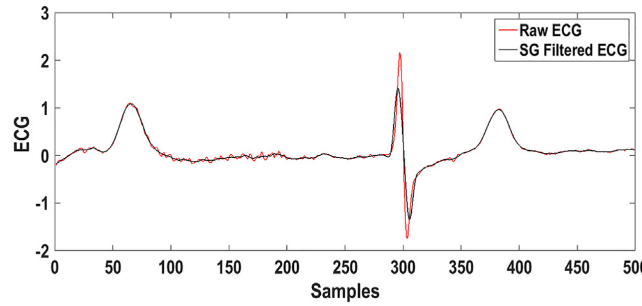

Fig. 2. Normal ECG, Raw ECG overlapped on its SG-filtered form.

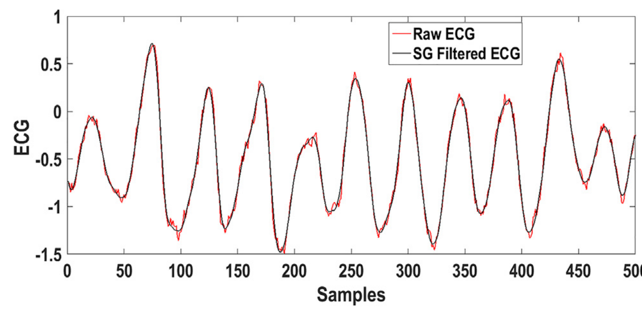

Fig. 3. Ventricular fibrillation ECG, Raw ECG overlapped on its SG-filtered form.

Hence, at the end of pre-processing step, a total of $(2*L)$ time series are generated (L = 6 detail coefficients and 6 approximate coefficients), where each coefficient time series has the same time resolution as the original signal. Since, both $x[n]$ and its squared form $x^2[n]$ are used in this technique, they are separately fed to the SWT and treated as a separate inputs to calculate their corresponding wavelet coefficients and also in further steps in the course. For annotations, $D(1,l)$ and $A(1,l)$ denotes detail and approximate coefficient of $x[n]$ at l^{th} level of decomposition, respectively. Similarly, $D(2,l)$ and $D(2,l)$ denotes detail and approximate coefficient of $x^2[n]$ at l^{th} level of decomposition, respectively.

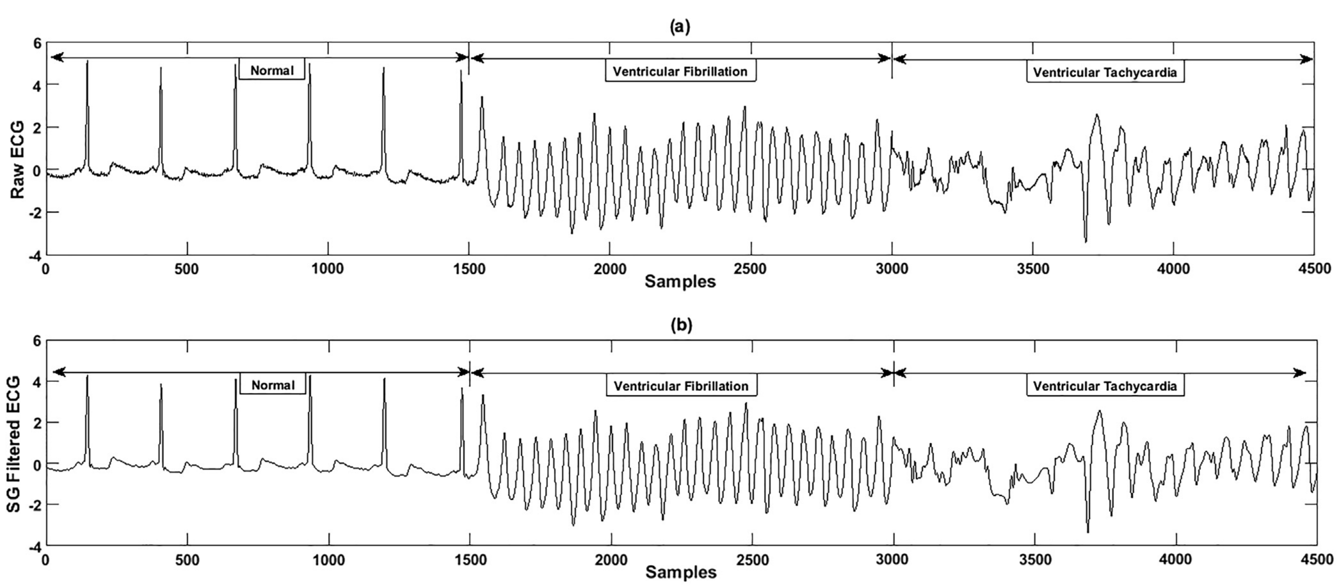

Fig. 1. (a) Raw ECG, (b) SG-filtered ECG.