# Slope Analysis Based Methods for Detection of Ventricular Fibrillation and Ventricular Tachycardia


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***Abstract*—Ventricular fibrillation (VF) and ventricular tachycardia (VT) are among the life-threatening cardiac arrhythmias and their in-time and accurate detection are very significant. In this paper, the capability of slope to detect cardiac shockable arrhythmias as a feasible time-domain feature of the electrocardiogram signal (ECG) is discussed. Several slope analysis methods were investigated and an innovative algorithm which works in real-time is introduced. Furthermore, slope analysis is employed in one of the genuine methods of VT and VF detection as a pre-processing step instead of the conventional amplitude thresholding and it is shown that it can better reflect the shockable cardiac arrhythmias irregularities. Finally, the validity of all the methods were assessed by 231 records collected from CCU of the Royal Infirmary of Edinburgh, MIT-BIH arrhythmia database, CU ventricular tachy-arrhythmia database (including 91 normal rhythm, 82 VT and 58 VF), all annotated and verified by expert cardiologists. The classification accuracy results showed a robust and reliable performance in discrimination between normal, VT and VF rhythms.**



***Keywords*—Slope analysis; arrhythmia detection; ventricualr fibrillation; ventricualr tachycardia***


## I. Introduction

Cardiac arrhythmias diagnosis and classification is a crucial task for cardiologists. VT and VF are among the most serious ventricular arrhythmias which if not properly handled can lead to death. Ventricular fibrillation (VF) as the most commonly identified rhythm in the cardiac arrest, is a condition in which ventricles quiver rather than contract and as a result, the heart muscle fails to pump the blood in the body properly and manifests a disorganized chaotic rhythm. Ventricular tachycardia also is a type of tachycardia that originates from the fast improper electrical activity of the ventricles and is known as a potentially life-threatening arrhythmia, because it may lead to VF, asystole and finally death. Since VF and VT are counted as shockable rhythms, they may be reversed and restored to normal sinus rhythm if cardio-pulmonary resuscitation (CPR) is performed and a sufficient amount of electrical current is passed through the patient's heart. Therefore reliable and fast detection of these rhythms possess a particular importance for any medical device or system which deals with cardiac arrhythmias [1]

The VF detection methods proposed and discussed in the literature mainly belong to one of these groups: (1) Time-domain methods consist of correlation analysis [2], [3], sequential hypothesis testing [4], [5], auto-regressive model [6], and empirical mode decomposition (EMD) based algorithm [7]. (2) Frequency-domain: Since frequency characteristics of the VF is mostly concentrated in the range 1.7-9 Hz in comparison to the normal ECG which covers a wide-band range up to 25 Hz [8], many spectral and frequency analysis methods were also presented. VF filter algorithm [9], spectral algorithm [10], coherence method [11], and Hilbert transform method [12] are placed in this category. (3) Time-frequency analysis which decomposes the signal into different elementary building blocks and looks for the suitable features in a proper level of decomposition [13], [14]. (4) The dynamics methods: while the rhythms are considered to become more complex from normal to VF, taking over the thought of a dynamical system, this complexity can be computed quantitatively. Consequently, many methods were developed based on dynamical features [15], [16], [17]. (5) Hybrid methods in which two or more of the previous methods are utilized [18], [19].

Slope defined as the first derivative of the signal always has been taken into account as an important feature in ECG analysis [20], [21], [22]. For example, because the waveforms with largest slopes are judged to be the QRS complexes in an electrocardiogram, this feature became so popular in many QRS detectors. In this paper a simple slope analysis algorithm in real-time is presented and then employed as a basis technique in several arrhythmia detection methods. It is also utilized as an initial step for the complexity measure method and indicated that it can reflect the complex and irregular characteristics of VT and VF better than amplitude thresholding step presented in the original method.

The rest of this paper is organized as follows: first the datasets used in the current study and the preprocessing step are described. In section 3, the methods developed and implemented in this paper are introduced. The results are showed in the fourth section and are discussed and interpreted in the conclusion section.

## II. Database and preprocessing

The main part of our experimental data was gathered from the MIT-BIH arrhythmia database, the MIT-BIH malignant ventricular arrhythmia database and the CU ventricular tachyarrhythmia database available in the physiobank website [23]. These datasets were annotated and verified by experienced cardiologists and 8-s records including 60 normal sinus rhythms

(NSR), 52 VT and 38 VF were extracted. The other part was collected from CCU of Royal Infirmary of Edinburgh which contains ECG records of 81 subjects including 31 NSR, 30 VT and 20 VF [24]. Hence, totally we have an ECG dataset of 231 subjects containing 91 NSR, 82 VT and 58 VF, all 8-s long. In order to have a fair comparison, all the data were resampled to 250Hz and filtered using the filtering scheme presented in [25] to eliminate high-frequency noise, power-line interference and baseline wandering artifact.

## III. METHODS

The slopes in the ECG signal are of a small value and varies smoothly as the signal forwards in time except of the QRS complexes in which an abrupt change is seen. However there are lots of signal variations in VT and VF and their slopes are permanently changing during time. This fact stimulates the motivation to use slope as a discriminative feature for cardiac arrhythmias detection. Slope is defined as the first derivative of the signal as depicted in

$$m = \frac{f(n) - f(n-h)}{h} \tag{1}$$

where $h$ represents the distance between two samples used in derivation. If $h$ is selected large, the slope may miss signal fast transitions and if selected small it may be affected by high frequency noise. Therefore, in order to make a trade-off, five point differentiation was performed and the slope signal was achieved as $M = \{m_j | j = 1, ..., WL * f_s/h\}$ where $WL$ is the window length in second and $f_s$ is the sampling frequency. Based on this initial step, three methods were developed as follows:

### A. Slope Histogram

In the window length of 7-sec, all the slope values in the range between the maximum and minimum values of the slopes are quantized into 10 different levels between 1 and 10. The histogram of the rhythms are depicted in Fig.1. Since NSR is smooth with abrupt slope variation in QRS segments, its distribution is close to a super-Gaussian while the VF and VT distributions covers a wider range and are seemed to be Gaussian or sub-Gaussian. As a measure of tailedness in probability distribution functions (PDF), kurtosis is utilized which is generally defined as

$$Kurt[X] = \frac{\mu_4}{\sigma^4} = \frac{E[(X-\mu)^4]}{(E[(X-\mu^2)])^2} \tag{2}$$

where $\mu_4$ is the fourth moment about the mean and $\sigma$ is the standard deviation. Hence, kurtosis as a feature was calculated and utilized to distinguish the rhythms. In addition, variance as another feature was also used for comparison.

### B. Slope Count

The other method developed for the purpose of arrhythmia detection was an algorithm based on slope analysis. The pseudo code of algorithm which is suitable for real-time applications is described in detail in the following:

1) Initialization: Put $count = 0$ and take the first 1-sec of the original signal and calculate all the slopes $PrSL = \{m_i | i = 1, ..., f_s/5\}$;

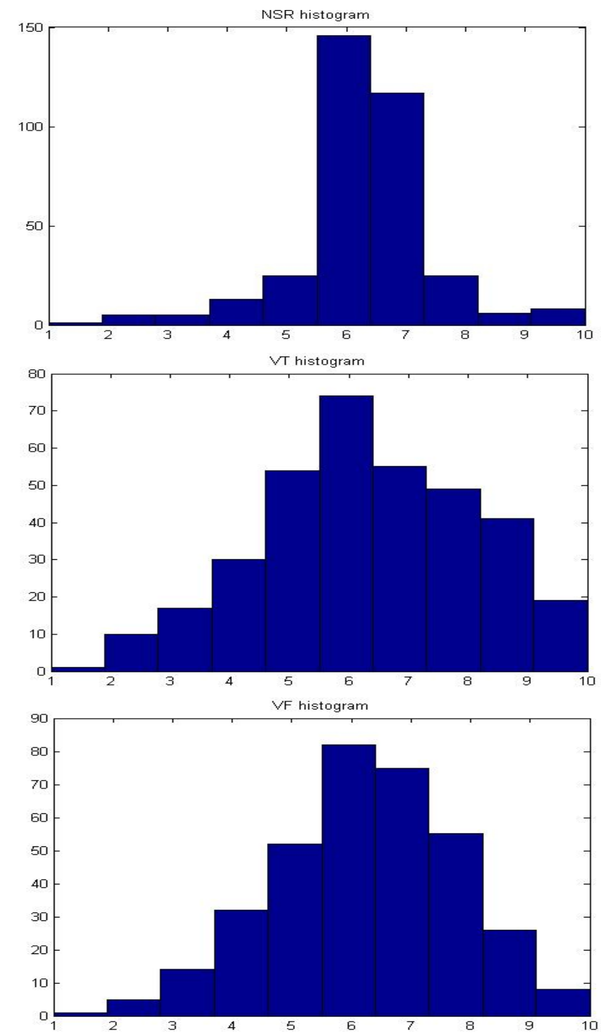


Fig. 1. Top to bottom - Histograms of NSR, VT and VF. It is clear that the histogram of NSR approaches a super-Gaussian, while the other two are sub-Gaussians.

2) Calculate the slopes in the next 1-sec segment of the signal (vector $SL$);
3) Concatenate $PrSL$ and $SL$ in order to have a 2-sec vector and find the peak $ms$ of the absolute value;
4) For each slope in the 2-sec vector, if it is positive and larger than a threshold of $0.2 * ms$, then if the last threshold crossed slope was negative, a one is assigned to the related bar segment of $h$ samples. The same procedure is performed for the slopes smaller than $-0.2 * ms$. Otherwise, if two sequent threshold crossed slopes have the same sign then a one is assigned to the segment, if their distance exceeds $7{*}h$. For either of conditions mentioned above, $count$ is increased one unit;
5) $PrSL = SL$ and go back to 2.

In this way the slope threshold is selected for every 2-sec of the slope signal, but it is updated every one second. Thus, the analysis must be performed on 8-sec windows (i.e. one second of preprocessing and 7-sec of signal process). The parameter count as the number of threshold crossing is used

TABLE I. CLASSIFICATION ACCURACY FOR DIFFERENT METHODS

| Methods | NSR-VT | NSR-VF | VT-VF |
|---|---|---|---|
| Slope Histogram (kurtosis) | 0.9480 | 0.9463 | 0.5714 |
| Slope Histogram (variance) | 0.9191 | 0.8725 | 0.6571 |
| Slope Count | **0.9653** | **0.9799** | 0.6857 |
| Slope Complexity | 0.8439 | 0.9664 | **0.7714** |
| Complexity | 0.6185 | 0.8121 | 0.7286 |

for detection.

### C. Slope Complexity

A VF and VT detection method which uses Limpel-Ziv complexity feature is proposed and fully explained in [15]. In the very first steps of this algorithm a binary signal is produced based on amplitude thresholding. However, the binary signal produced from the slope analysis algorithm from the previous section seems to better represent the irregularities which exist in the VT and VF signals. Therefore, the amplitude thresholding was replaced with slope based binary signal.

## IV. RESULTS

In this section the classification results achieved by applying all the algorithms and methods proposed in this paper on NSR, VT and VF ECGs are presented. 70% of the available dataset of each class was selected for training and the rest was used for the test. Afterwards, all the methods including Slope Histogram with variance and kurtosis feature, Slope Count and Slope Complexity were applied to the records. In order to have a fair comparison, Complexity Measure algorithm was also implemented as explained in [15] and its accuracy results are shown in Table.1 along with other methods.

As illustrated, the results of the proposed slope analysis methods indicate the capability of slope as a reliable feature to classify NSR, VT and VF ECGs properly. Moreover, slope analysis is successful in improving the robustness of Complexity measure.

## V. CONCCLUSION

In this paper, the validity of slope as a simple and fast computing feature in distinguishing between the ECG arrhythmias was evaluated and a novel algorithm for real-time applications was developed and proposed. Besides, it was demonstrated that slope analysis as a low computational cost method can be combined with other methods to improve their accuracy.

Since, slope PDF of NSR is super-Gaussian, it is clear from Table.1 that kurtosis as a measure of gaussianity was able to discriminate among NSR-VT and NSR-VF well, but it showed a poor performance in discriminating VT-VF suitably because of the wide range of slopes that both of these rhythms cover. Whereas the kurtosis represents the fourth standardized moment, its performance was even worse than variance. Slope Count by employing a measure of rate, was the most successful method among all others in distinguishing NSR-VT and NSR-VF, but again while VT and VF are so close in rate it failed to distinguish between them. Slope analysis combined with complexity measure, showed the most promising result in classification of VT-VF records alongside with the convincing result in discrimination of these two and NSR. In addition, it was definitively superior in comparison with the complexity measure in all aspects.

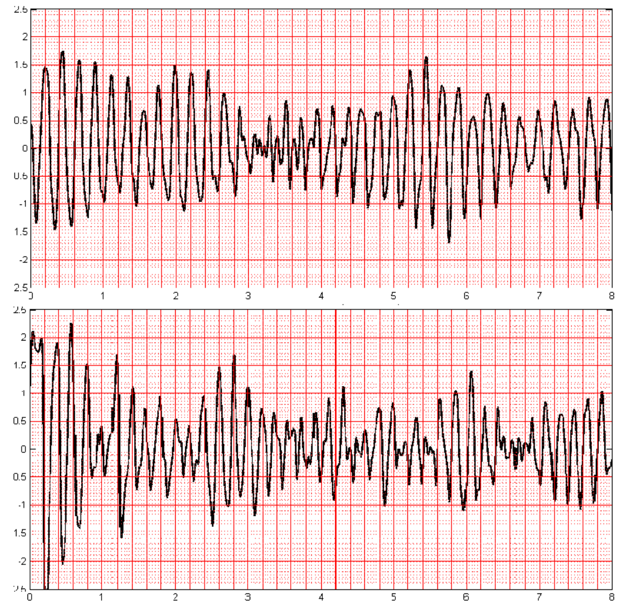

Fig. 2. A VT signal (torsade de pointe) depicted above is very similar to the coarse VF signal trial shown below.

In general, we can conclude that slope based methods performance is remarkable in VT and VF detection alongside with NSR and not convincing enough in discriminating VT and VF. As depicted in Fig.2 one of the major reasons for this weakness is the high similarity between VT and VF which occurs in many cases. Furthermore, the fact that VT consists a wide range of rhythms with different complexities leads to miss classification in several cases. However, since computational cost of slope based methods is low, they can be utilized alongside with other methods or take the place of amplitude thresholding in them.

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