Prediction of ventricular fibrillation using complexity analysis of T Wave from surface electrocardiogram

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Abstract

Ventricular Fibrillation (VF) is the major cause of triggering sudden cardiac death (SCD). Efficient prediction of ventricular fibrillation is very important for clinical purpose, as this is the most serious cardiac rhythm disturbance and can be life threatening. A reliable predictor of an imminent episode of VF, could be incorporated in an implantable cardioverter defibrillator (ICD) would be capable of delivering preventive therapy. The aim of this study is to investigate the possibility of predicting VF from surface electrocardiogram (ECG) signal by beat to beat tracing of the signal and using a dynamic thresholding method. As VF arises from the lower pumping chambers of the heart (ventricles), it is expected to find some changes in the ventricular activity part of the ECG signal before its occurrence. In this paper, we focused on the T-wave of ECG signal which shows the repolarization of ventricles and tried to present an online predictor by finding an entropy-based pattern in T-waves of ECG signal that can effectively maps the irregularity of this wave before VF. We have also used an Empirical Mode Decomposition (EMD) method to reduce the high frequency noises of T-waves before predictive index extraction in each beat. We found that proposed predictive pattern can be considered as a useful index for probability occurrence of VF. It reached the sensitivity of 89% and specificity of 95% in online VF prediction method. Presented method is simple, computationally fast and has high prediction quality and hence is well suited for real time implementation.

Keywords-Ventricular Fibrillation, Prediction index, Approximate Entropy, Empirical Mode Decomposition.

I. Introduction

Sudden cardiac death (SCD) is the cause of millions of death worldwide and has no significant symptoms earlier than one hour before occurrence [1]. Ventricular Fibrillation (VF) is the most common causes of SCD. VF is characterized by uncoordinated contractions of ventricles and it is crucial for the patients to receive immediate electric shock when VF occurs. If this arrhythmia continues for more than few seconds it may lead to SCD. Despite recent advances in medicine, VF has been difficult to manage within clinical practice. As a consequence, the prediction of VF will surely contribute to increasing the survival rate of patients with heart problems and is still a major challenge. Even though several methods have been reported previously for predicting VF, there is no reliable and clinically useful system to predict VF. Some previous methods tried to solve this issue as a classification problem and introduced different features that can discriminate between normal episodes and before VF.

MP Bonomini et al. [2] applied the concept of "allometry" for evaluating the probability of VF based on the ST-segment deviation values. Allometry, in general biology, measures the relative growth of a part in relation to the whole living organism. They tried to calculate coefficients of a linear equation which describes the probability of VF occurrence based on ST segment deviation from isoelectric line. Prolongation of the QT interval (QTI) was also widely accepted as an indicator of ventricular arrhythmia that can lead to syncope or sudden cardiac death [3]. E. Pueyo et al. [4] investigate the ionic mechanisms of QTI and its relationship to arrhythmic risk. T-wave alternans (TWA) also has been linked to the heightened risk of ventricular tachyarrhythmia (VTA) and SCD during the last decade. Theoretical, experimental and clinical research efforts have focused primarily on TWA, by examining its mechanisms [5]. Ph Maury et al. [6] investigated the feasibility of detection of TWA preceding the onset of VF and ventricular tachycardia (VT) in ICD-stored intracardiacelectrograms (IEGM). They found that TWA can be detected before VF/VT onset in more than half of episodes using a simple time-domain technique and multiple T wave measurements. Some other researchers also predicted VF/VT by detecting TWA using wavelet transform based method before VTA [7]. H.S. Dong et al. proposed an algorithm based on the Hilbert marginal spectrum analysis of short term heart rate signal prior to the onset of VTA. The low-frequency amplitude, high frequency amplitude, very high

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frequency amplitude, total amplitude and the low-to-high frequency amplitude ratio were extracted from frequency marginal spectrum and considered as the features. They found out that high frequency amplitude, very high frequency amplitude, and total amplitude of heart rate signal before the onset of VF/VT are significantly higher than normal sinus rhythm, but the low-to-high frequency amplitude ratio significantly is lower [8].

Despite several researches on predicting VF, there are not many attempts to extract a predictive index which notify the occurrence of VF in near future. From this point of view, T Thong et al. [9-10] investigated R-R interval signal before VF/VT and used a particular monotonic heart rhythm acceleration pattern during sinus rhythm before an imminent episode of VTA and could achieve a sensitivity of 44% with corresponding specificity of 94%. They have also shown that this monotonic heart rate acceleration is common (83%) in the 1.8 hours before an episode of VTA but is less frequently seen (43%) in randomly selected time matched segments from ICD patients not preceding an episode of VTA [11]. This work was the most successful study for developing such a predictive index for VTA prediction.

Our main research objective is to introduce a reliable predictive index for VF prediction as a major cause of SCD. This index must be able to identify changes – if present – occur within minutes prior to VF. To this goal, we have focused on the ventricular repolarization that corresponds to the relaxing phase of the myocardium contraction that reflected as the T wave in the ECG signal. Due to the importance of ventricular repolarization and its direct relation with some severe heart diseases, such as VF [12], T-wave variability can be a potential feature for this arrhythmia prediction. Hence, approximate entropy (ApEn) is used to trace the complexity/irregularity of beat-by-beat changes of T wave before VF. In order to improve the quality of T wave, its fast oscillation mode was omitted and then T wave of each beat is reconstructed by using Empirical Mode Decomposition (EMD) method. We have used EMD to avoid Misdiagnosis of remained high frequency noises in calculating entropy of T-waves. We have found that the proposed predictive pattern which is based on the ApEn of T wave is observed more frequently before VF and can be considered as an effective tool for predicting imminent episode of VF.

The structure of this paper is as follows: Section II describes our database. Section III presents the brief review of the EMD and ApEn. The proposed method and the obtained results are presented in section IV and V. finally conclusion is given in section VI.

II. Database

The performance of the proposed method was evaluated using 58 ECG records which consists of 18 pre VF records and 40 normal records. Pre-VF records are belonged to CUDB who experienced episodes of sustained VT and VF digitized at 250 samples per second per channel. Each record covers a complete transition from the normal state until exactly before VF occurrence. Also 40 control records with length of at least 10 minutes are chosen from MIT-BIH Normal sinus Rhythm (nsrdb) with sampling rate of 128 samples per second and Cinc challenge database with sampling rate of 100 samples per second. From each record the lead II was only considered for analysis. All these databases are available in PhysioNet website [13].

III. Theoretical background

A. Emprical Mode Decomposition

Empirical mode decomposition is a new method in signal processing which is introduced by Huang et al. [14]. The EMD is appropriate for nonlinear and nonstationarity signals like biomedical signals and it is an alternative method for previous data analysis such as Fourier or wavelet. But its advantage is that the EMD is a fully data-driven mechanism and it does not need any a priori known basis. Among EMD's applications, it has been reported as a good tool for denoising and detrending purposes [15]. Artifact reduction based on EMD is usually performed by partial reconstruction, i.e. separating the IMFs identified as noise components from IMFs that are defined as signal components. Partial reconstruction is particularly appropriate in those cases, where signals consist of a mixture of very rapid variations with much slower ones. In these cases, the EMD allows efficient trend extraction. This method decomposes a signal into some subcomponents called Intrinsic Mode Functions (IMFs). The extraction of the IMFs for a given signal x(n), can be done through a sifting process[14] and as a result it can de expressed as follows:

$$x(n) = \sum_{k=1}^{N} h_k(n) + r_N(n) \quad (1)$$

where N is the number IMFs, h_k (t) is the kth IMF and r_N (t) is the residue signal [16].The lower order IMFs capture the fast oscillation modes while the

higher order IMFs typically represent the slow oscillation modes present in the underlying signal.

B. Approximate Entropy

Despite rapid growth of various complexity measures such as dimensions, Lyapunov exponents and entropies, there are limitations to experimental time series because of noise which prevent accurate estimation [17]. To overcome the problems of short and noisy recordings in physiological signals, approximate entropy (ApEn) was introduced by Pincus in 1991[18]. Higher values of ApEn indicate more irregularity and lower ones represent more regularity in a time series. For an N sample time series $\{u(i):1 \leqslant i \leqslant N\}$ ApEn is calculated as follow:

Consider vector sequences x_1^m through x_{N-m+1}^mas

$$x_i^m = \{u(i), u(i+1), \dots, u(i+m-1)\}, i = 1, N-m+1 \quad (2)$$

Where m is the length of a compared window.

If$n_i^m(r)$ indicates the number of vectors $x_i^m(r)$ within r (Euclidean distance) of $x_j^m(r)$, equation (3) will represent the probability that any vector $x_i^m(r)$ is close to the vector $x_j^m(r)$

$$C_i^m(r) = \frac{n_i^m(r)}{N-m+1} \quad (3)$$

In which ln is the natural logarithm. Equation (4) shows the probability of that consecutive data points will still remain close to each other when one more point is detected [19].

$$\varphi^{m+1}(r) - \varphi^m(r) \approx (N-m+1)^{-1} \sum_{i=1}^{N-m+1} \ln \frac{C_i^{m+1}(r)}{C_i^m(r)} \quad (4)$$

Finally ApEn is defined as equation (5):

$$ApEn(m,r) = \lim_{N\to\infty} (\varphi^m(r) - \varphi^{m+1}(r)) \quad (5)$$

IV. METHODOLOGY

The Presented algorithm consists of three steps: Preprocessing and noise removal, Extracting fiducial points of ECG signal including both R wave and T wave, and finally identification of a predictive index for VF forecasting.

A. *ECG Signal preprocessing and noise removal*

The aim of preprocessing step is to improve the general quality of the ECG for more accurate analysis and measurement. Noises may disturb the ECG and make measurements from the original signals unreliable [20]. Baseline wander (BW) is a low frequency activity in the ECG which mainly originate from respiration and it may interference with the signal analysis and rendering clinical interpretation inaccurate. As its

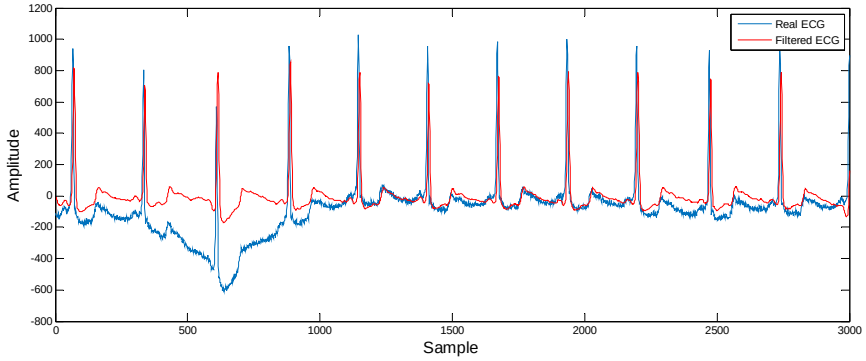

Figure 1. Blue waveform is a part of the record CU01 before preprocessing and red waveform is the same signal after preprocessing.

spectral contents is usually well below 1 Hz [21], to remove the BW we passed the signal from a low-pass filter with cut off frequency of about 0.7 Hz and then subtracted the output from the original signal. After removing BW, we tried to eliminate high frequency noises which caused by main interference (50 or 60 Hz), muscular activity, poor electrode contact and body movements by another low pass filter. As the highest frequency of ECG is belonged to QRS complex with maximum frequency of 30 Hz, the cut off chosen for the second low pass filter is around 31 Hz. Figure 1 shows the effect of preprocessing step on a Part of ECG signal.

B. Fiducial point detection

Since R-wave is the most important waveform in the ECG signal, the first step after preprocessing is finding the exact location of R wave. Different methods are proposed for detecting R-waves of ECG signals. Time variant and non-stationary

signals like biomedical signals often need a method which can describe frequency components of signal and their location on time axis precisely. Wavelet is the simplest and the most valuable method that can satisfy these requirements. Wavelet transform decomposes a signal into a set of coefficient. Each wavelet will have its own time duration, time situation and frequency band. In our algorithm, we used discrete wavelet transform (DWT) to extract R-waves. Selecting a good mother wavelet is depended on the intended signal and usually a wavelet similar to the main signal is considered. For ECG signals Daubechies mother wavelet gives the details of signals better than other ones and Daubechies 4 is more similar to QRS complexes [22].

Figure 2 shows an episode of the ECG signal with its related decomposition signals using daubechies 4. Since the second detail signal contains most of the QRS complex energy [22], it is used for the estimation of the QRS complex. It is worth mentioning that in wavelet decomposition, after passing the signal through a low-pass filter, half of the samples can be eliminated according to Nyquist's rule, since the signal has a highest frequency of half the frequency of the signal prior to filtering. Therefore once R-peak is detected in 2end level reconstructed signal, it must be cross validated in the actual signal and we should map the detected position of R peak to original signal by multiplying with 4. An important thing to remember is that down sampling process always deviate the signal position so R location in down sampled signal will never be on the original at a scale of 4 and we need search for the maximum value in a suitable window from the reference R point detected in the down sampled signal. Figure3 shows original signal, reconstructed approximation at 4 levels and detected R peaks in a part of ECG signal.

C. *Prediction index Extraction*

Since VF origins from ventricles, we believed that there would exist some irregularities and complexities in ventricular repolarization phase of ECG signal and we focused on the changes of T-waves before arrhythmia. Therefore, we initially improved the quality of T-waves

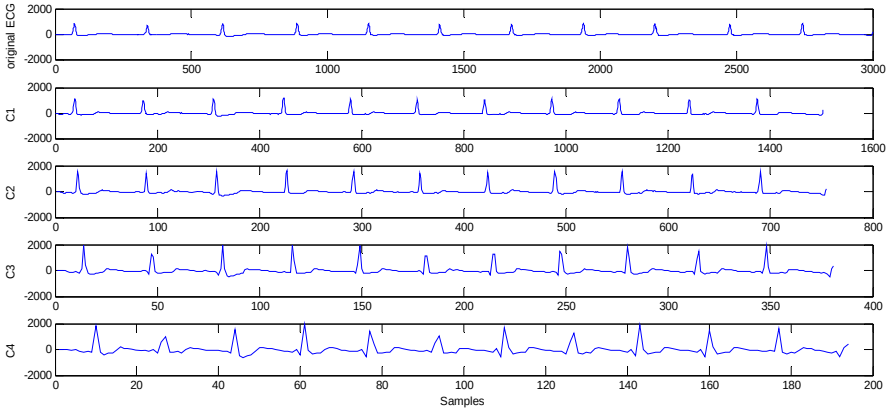

Figure 2. Wavelet coeffitients(C) of an episode of cu01 record of CUDB with dubechies 4.

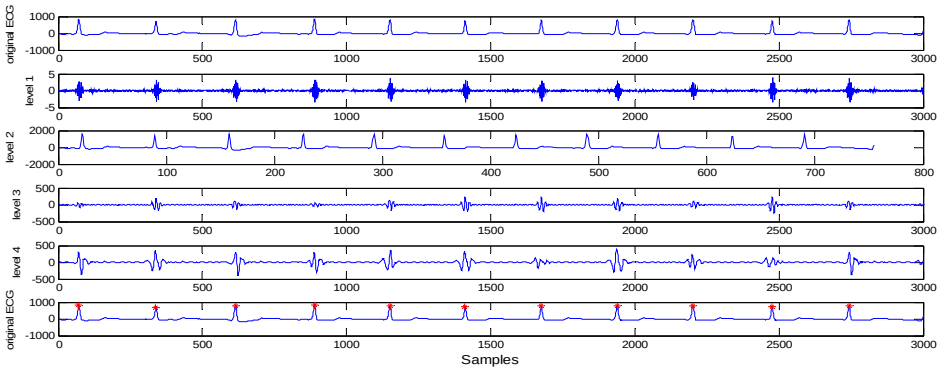

Figure 3. Original ECG signal of an episode of cu01 record from CUDB l and 4 levels reconstructed approximation signals and detected R peaks.

by separating the useful information of ventricular repolarization from noise and artifacts and extracted their trend before VF using EMD technique and then checked the T Waves irregularity before arrhythmia by computing its beat-by-beat entropy. To do so, we omitted the first IMF of T-wave for each beat which contains the fast oscillation of T-waves and reconstructed it from their remained IMFs. Figure 5 shows the EMD of a T-wave and its extracted IMFs. The reconstruction of T-wave by omitting the first IMF has been shown in figure 6. Then entropy of T-wave in each beat is computed as a marker of irregularity in repolarization phase. However *m* and *r*are critical in results of approximate entropy process, no references exist for optimizing their values. Actually by choosing short templates (small m) and wide tolerance (larger r) the accuracy of entropy estimate improves, but for larger r values too many details are lost. For this study, ApEn was calculated by choosing m=1 and r was set as 0.2 of the standard deviation (SD) of the samples of each T wave in each subject. Figure 7 shows changes of calculated entropy in a pre-VF and a normal record. For better indication of this change a straight line is fitted on the data. As we can see, in pre-VF event we have an up-going curve, however in normal record it remains nearly changeless. Based on this observed up-going pattern on T-waves entropy before arrhythmia, we searched for a predictive pattern which is related to the imminent episode of VF as follow: firstly the T-waves entropy of the first 30 seconds of each ECG recording were calculated and the average value of them was considered as a threshold level. Then the difference between this

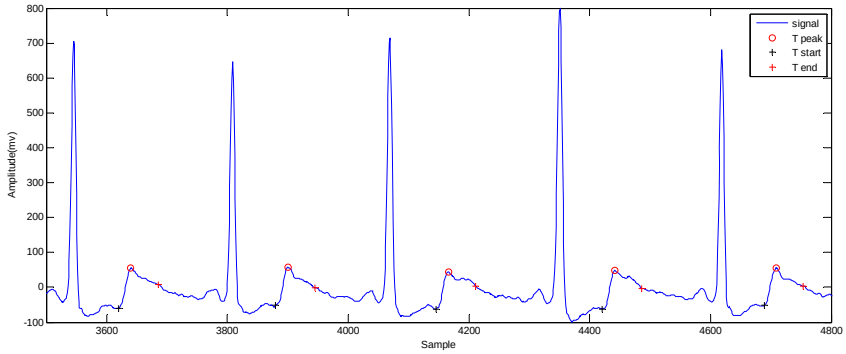

Figure 4. T-wave detection of a part of cu01 of CUDB record.

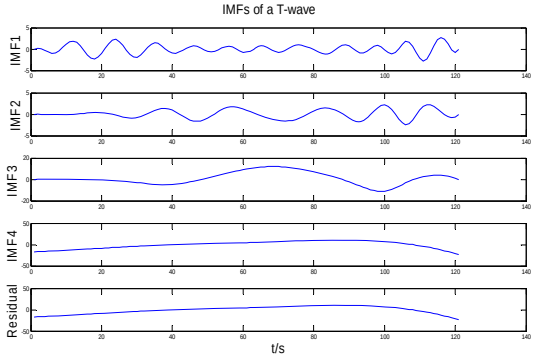

Figure 5. EMD decomposition of a typical T-wave from cu01 of CUDB.

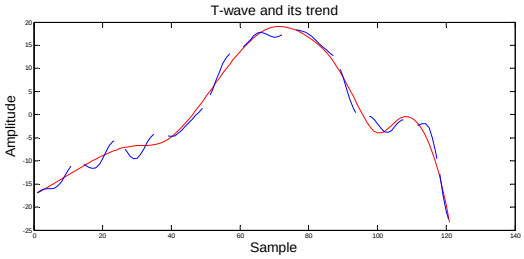

Figure 6. Typical T-wave from cu01 of CUDB (dashed line) and its reconstructed signal.

threshold value and the entropy of each reconstructed T-wave is computed. When this error signal was positive (T-wave entropy in each beat > threshold value) for more than 10 consecutive beats, we can expect an imminent episode of arrhythmia. Our investigation shows that such increasing of the T wave entropy, rarely occurs in the normal cases and consequently can be considered as an effective remark for VF events. It is worth mentioning that in the extraction of the predictive index, increasing of the Entropy in a single beat was not noted and the sequence of entropy increment is regarded to the prediction of VF.

V. Results and Discussion

We investigated 58 ECG records from different subjects in pre VF and normal records and found the above mentioned pattern in most of pre VF records, while entropy increase rarely last for more than 10 consecutive beats toward the threshold

during in a sinus rhythm. Thus we considered the increment of ApEn values which is seen in more than 10 consecutive beats as a useful pattern for VF prediction. Three parameters that are calculated to evaluate the performance of the proposed method are sensitivity, specificity and accuracy. These parameters are calculated as follows:

Sensitivity is the ability to predict VF and is given by

$$\text{Sensitivity}=TP/(TP+FN) \quad (6)$$

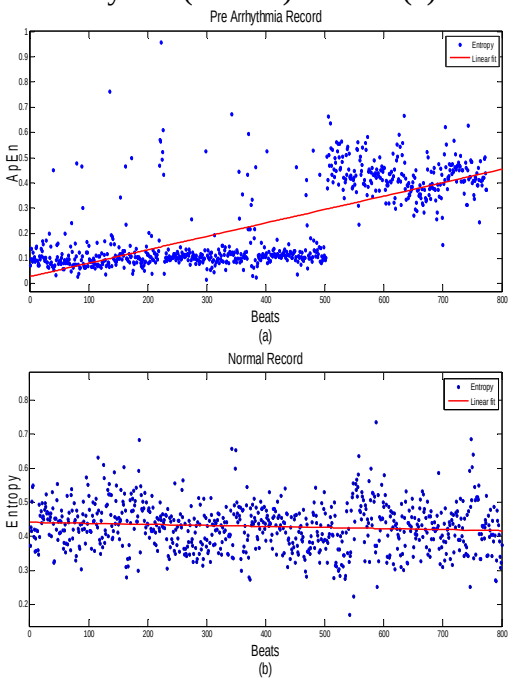

Figure7. (a) Entropy change of cu19 record before VF (b) Entropy change of a control record.

Specificity is the probability to predict no VF correctly and is given by

$$\text{Specificity}=TN/(TN+FP) \quad (7)$$

Accuracy is the probability to obtain a correct prediction and is given by

$$\text{Accuracy}=(TP+TN)/(TP+FP+TN+FN) \quad (8)$$

where TP is the number of true positive decisions, FN is the number of false negative decisions, TN is number of true negative decisions and FP is the number of false positive decisions. Table 1 shows the results of VF prediction. As it can be seen from this table, the extracted prediction index can be found in 16 out of 18 pre-VF episodes and it doesn't exist in 38 out of 40 normal episodes. The presented algorithm could achieve sensitivity of 89%, specificity of 95% and accuracy of 93% in predicting VF which is a reliable and acceptable result. As the time for receiving an aptly-timed shock is very important for patients, we also tried to evaluate the time of prediction for each subject. To do this, for those records which this pattern is met, the time from 10th stored beat to a point just before arrhythmia occurrence, is assumed as minimum prediction time. Figure 8 indicates minimum prediction time of VF prediction in the database. As can be seen, our proposed algorithm predicts occurrence of about 88% of arrhythmia records within at least 10 seconds before VF onset and in the vast majority of subjects (75%) algorithm is able to predict VF within at least 60 seconds before occurrence of these events.

Table1. Results of proposed algorithm in VF prediction

	Pre-VF Records	Normal records
Pre-VF Records	TP=16	FN=2
Normal records	FP=2	TN=38

Until now, various researches have been done to predict VF, but most of them convert the prediction problem to a classification problem and tried to extract some features which can separate normal and pre VF episodes. But in this paper we attempt to introduce a prediction index from ECG signal which its variability is a sign of occurrence of VF in each patient individually. This index is the increment of approximation entropy of T waves in a sequence of more than 10 beats which is related to the increase of complexity and irregularity of ventricular activity signal. The strength of this index extraction is that the entropy of each T wave is not compared with a predefined and constant threshold value and the criteria for this increasing is extracted from each subject independently. Therefore, by using such adaptive threshold, we will be able to introduce this index for each subject individually instead of extracting a constant index based on the behavior of the under study population. The obtained results also show that variability of this index is an applicable sign of VF occurrence.

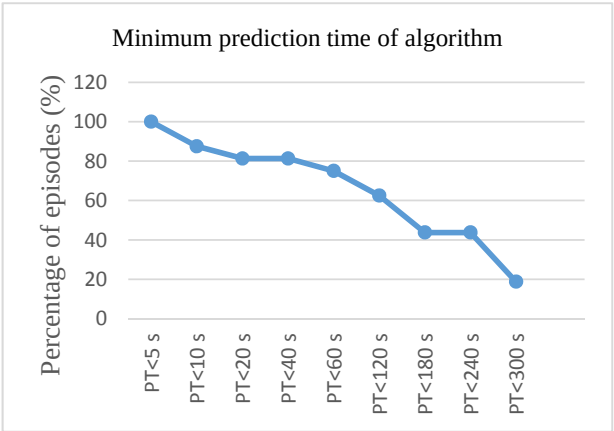

Figure 8. Minimum prediction time of presented algorithm.

VI. Conclusion

In this study, we investigated the changes in electrical activity of ventricles and presented a novel application of ApEn to predict VF in a suitable time. Our results show that the irregularity of T wave just before occurrence of VF have meaningful difference with normal subjects. Predicting this arrhythmia can provide physician more time for applying electrical shock to treat such patients and also can help Manufacturers to make more effective ICDs and AEDs, therefore it will save more patients who suffer cardiac disease.

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