Distinction between myocardial infarction patients with and without history of ventricular tachycardia based on wavelet transformed signal-averaged electrocardiogram

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Original Article

Abstract

BACKGROUND: There are varieties of electrocardiogram-based methods to predict the risk of ventricular tachycardia in patients. New extracted features from the signal-averaged electrocardiogram (SAECG) and its wavelet coefficient as a distinction index are used in this study.

METHODS: Signals of orthogonal leads from 60 myocardial infarction (MI) patients with or without the history of ventricular tachycardia were selected from the national metrology institute of Germany (PTB diagnostic database). They were filtered and the discrete transformed wavelet was exerted on them. New and conventional features introduced in this study were extracted from signal-averaged electrocardiogram and its wavelet decompositions.

RESULTS: Extracted features: QRS-d, Entropy-w, Maxhist, and ZeroC have acceptable statistical criteria ($P < 0.05$) for the mentioned groups, comparing QRS duration, in MI patients which is longer than MI + VT, and for other features it is Vice versa. In wavelet decomposition analysis, the entropy feature has higher precision for detection and diagnosis of MI and MI + VT.

CONCLUSIONS: Entropy of wavelet coefficients is a useful feature in distinguishing myocardial infarction patients with or without ventricular tachycardia.

KEYWORDS: Discrete Wavelet Transform, Electrocardiogram, Myocardial Infarction, Ventricular Tachycardia

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Introduction

In signal-averaged electrocardiogram, orthogonal leads, such as vectorcardiogram, are utilized which are more detailed than the conventional electrocardiography (ECG). This procedure takes approximately 20 minutes, and evaluates several hundred cardiac cycles to detect subtle abnormalities which increase the risk of cardiac arrhythmias.

In 1981, Simson studied the end of QRS wave (late potential) in order to find the myocardial infarction patients prone to ventricular tachycardia.[1] In fact, Simson was the inventor of a method that revealed a significant distinction between the signal of infarction patients with and without the history of ventricular tachycardia at the end

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of QRS wave by performing three pairs of Frank leads with high-resolution electrocardiogram (HRECG) and averaging the obtained signals. Afterwards, some researches were performed by the short-time Fourier transform on HRECG.[2] In recent years, the use of Wigner-Ville distributions and wavelet transform has been suggested to measure the frequency characteristics in HRECG as a function of time.[3-6]

However, the precision of wavelet transform in the frequency interval and the power of extraction feature in ECG signal are more tangible. Therefore, the wavelet transform role in processing ECG signal is increasing every day.

In the field of myocardial infarction identification in patients with ventricular tachycardia potential, Couderc et al. gained good results by using orthogonal wavelet transform which are offered on HRECG.[7] Recently, Subramanian et al. conducted some studies to detect and identify the late potentials (LP) by using a discrete wavelet and neural networks.[8] Most of the previous studies to distinguish myocardial infarction patients with and without ventricular tachycardia were reviews of the potential delay. In the past few years, wavelet transform is used for a better extraction of this feature.

The problem is that in ventricular tachycardia, due to myocardial infarction, potential delays do not necessarily occur in all cases and if they do they will be difficult to detect. It is therefore important that new features be extracted, so they can be used as complement for detecting the individuals prone to ventricular tachycardia.

In this regard, Yodogawa et al. have compared the groups of patients with myocardial infarction and ventricular arrhythmias. In this study the continuous wavelet transform was used and five new features were extracted from the wavelet transform applied on SAECG in addition to the potential delay characteristics, while examined in different groups.[9]

In 2011, Tsutsumi et al. extracted features of components with high-frequency in QRS complexes by using morlet wavelet transform, and introduced as new index and feature to predict those prone ventricular arrhythmia.[10]

Furthermore, using morlet wavelet transform, Takayama et al. brought in the turbulence characteristics of wavelet coefficients as new criteria for these patients.[11] In this paper, from the applied signal-averaged electrocardiography (SAECG) and Haar discrete wavelet transform, new features are extracted and statistically analyzed for the two given groups.

Methods

Study population

Real electrocardiographic signals provided by "PhysioNet" database were used to develop the written algorithm in our technique. We chose PTB Diagnostic ECG Database with sampling frequency of 1 kHz, resolution of 16 bit with 0.5 µV / LSB, and total duration of about 2 minutes.[12] Each ECG is made by 15 leads; the 12 conventional and 3 orthogonal (Frank leads). The study population consisted of 60 cases, including three orthogonal signals (Vx,Vy,Vz) from the Frank leads. 50 myocardial infarction (MI) patients with no history of ventricular tachycardia (VT) and 10 MI patients with history of VT were included in this study.

Filtering and Pre-processing

I . Two bidirectional Butterworth filters were used, a 4th order high-pass and a 5th order low-pass filter with cutoff frequencies of 25 Hz and 300 Hz, respectively, to remove DC component and the low frequency oscillation. They could be caused by patient's breathing and movement, and remain in interesting bandwidth limit.[1,13]

II. A 50 Hz notch filter was created by the filter design toolbox of MATLAB software

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(Version 7.11.0; Mathworks Inc., Natick, MA, USA) to remove power line interface noise.

Signal-Averaged ECG (SAECG)

Signal-averaged electrocardiography is a technique to detect the low amplitude and high frequency component of signals by improving signal to noise ratio (SNR).

Averaging

Averaging can be used either temporal or spatial by three pairs of orthogonal bipolar leads X, Y, and Z in SAECG. 150 to 300 beats are sufficient in most of the cases for averaging. For obtaining an averaged cycle, signals must be analyzed and fragmented into QRS complexes with different cycles. The ventricular premature beats signals, unusual conduction beats, or beats with detected noises were identified and excluded from the processing system. An automatic model recognition algorithm using several primary QRS complexes were utilized to generate a new pattern. Using this pattern, every beat was analyzed in terms of the appropriateness, and fitness beats were selected and averaged from selected beats along signal.[14]

Vector Magnitude (VM)

The filtered signals for the three leads were combined into a vector magnitude which quantifies the energy measured by the three bipolar leads.[1] Vector magnitude is defined as:

$$VM=\sqrt{X^2+Y^2+Z^2} \qquad (1)$$

Where X (t), Y (t), and Z (t) are the SAECG of the three leads that are shown in figure 1.

Wavelet Decomposition Analysis

The wavelet transform has emerged over recent years as a powerful time–frequency analysis. Its application to biosignal processing such as ECG has been at the forefront of these developments. The wavelet transform reveals the components in ECG that are hidden in the original signal.

The discrete wavelet transform (DWT) is used for analyzing, decomposing, and compressing the ECG signals. Based on the correlation between the wavelet of certain scales and the original signal, it generates some coefficients which correspond to a multi-resolution analysis that can reduce the redundancy of each filtered signal, so that the processing algorithm can be applied effectively to a small subset of the original signal.

The Haar wavelet was selected for this research. This wavelet better detects ECG, insures minimum signal degradation, and provides a convenient technique for QRS extraction.[15]

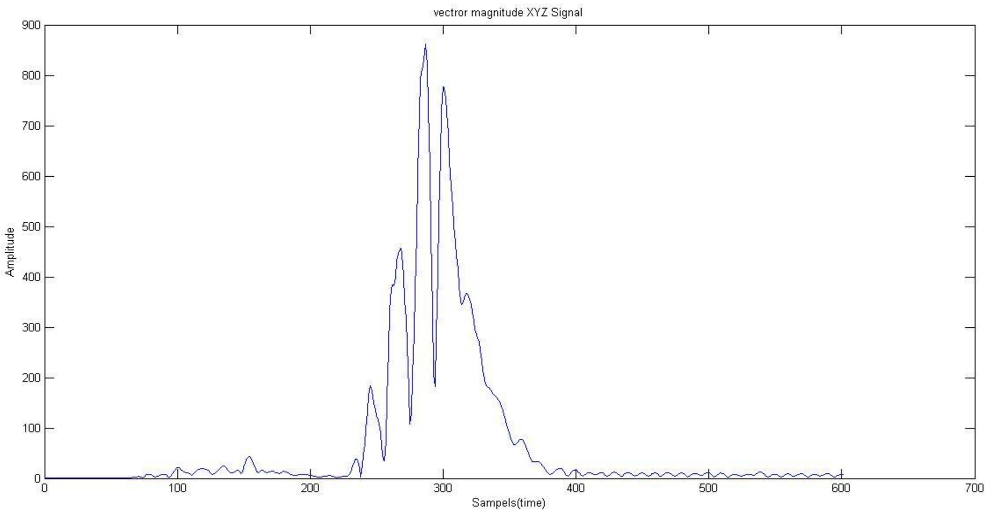

Figure 1. Vector magnitude of X, Y, and Z orthogonal leads

Statistical analysis

Data were expressed as mean ± standard deviation, and statistical analysis was performed using the Mann–Whitney test for unpaired variables. A P value of < 0.05 was considered significant.

The statistical software used in this study was SPSS (Version 16.0.0; SPSS Inc., Chicago, IL, USA).

Feature Extraction

QRS-d is the time duration of a filtered QRS, and SM is the smoothness magnitude of a curve.

Moreover, PeakMax is calculated by the amplitude of the maximum peak of signal.

The mathematical measurement for the smoothness of a function y (t) over an interval [0, n] by equation 2, where t is the number of samples (time) and f (t) is the signal amplitude (voltage):

$$\text{Curve Smoothness} = \int_0^n \left(y''(t)\right)^2 \qquad (2)$$

This equation was normalized to absolute maximum peak in all cases to obtain comparable criteria.

Entropy defines the complexity of a signal. Wavelet coefficients energy distribution is defined using Shannon entropy, the entropy of a discrete variable i with probability density function P_i is defined as follows:

$$E_{entropy}(s) = -\sum_{i=1}^{N} p_i \cdot \log_2 p_i \qquad (3)$$

MaxMin is the numerical differences between maximum and minimum peak. Maxhist is the maximum value of histogram for wavelet decomposed signal. NDP is the number of disarrangement points (number of positive and negative peaks). ZeroC is the number of crossing points on the horizontal plane as a criterion of signal disturbance.

Results

Statistical analysis of Extracted features:

The extracted features from 50 MI and 10 MI+VT patients were analyzed using the Mann-Whitney test, and its results are shown in table 1.

This table shows that the four features of QRS-d, Entropy-w, Maxhist, and ZeroC have acceptable statistically criteria (P < 0.05) for the mentioned groups. Comparing QRS duration of patients with MI or MI + VT showed that it was longer in patients with MI. However, the other features were greater in the patients with MI + VT.

ROC curves were plotted for each feature and the area under these curves was calculated (Figure 2).

The area under ROC curves for entropy, Maxhist, and Zeroc were 0.965, 0.936, and 0.871, respectively. In wavelet decomposition analysis, the entropy feature has higher precision for detection and diagnosis of MI and MI+VT than the two other features.

Table 1. Statistical analysis using Mann-Whitney test for two groups of MI and MI + VT

Features	MI n = 50	MI + VT n = 10	P
QRS-d	167.6 ± 15.1	208.6 ± 30.8	< 0.001
PeakMax-SA	526.2 ± 213.8	463.7 ± 213.7	0.275
SM-SA	0.2 ± 0.1	0.3 ± 0.3	0.114
Entropy-SA	6.6 ± 0.1	6.6 ± 0.2	0.413
PeakMax-W	65.3 ± 38.7	72.5 ± 34.8	0.938
NDP	16.4 ± 6.1	13.8 ± 3.7	0.598
Entropy-W	248.3 ± 28.0	324.3 ± 46.8	< 0.001
MaxMin-W	126.5 + 60.1	129.5 ± 49.5	0.892
Maxhist-W	32.8 ± 7.8	44.0 ± 7.2	< 0.001
ZeroC-W	41.6 ± 4.6	50.6 ± 7.6	< 0.001
SM-W	59.4 ± 18.5	55.9 ± 18.2	0.770

All the features are normalized to a QRS complex PeakMax-SA: Maximum signal peak;
VT: Ventricular tachycardia; MI: Myocardial infarction; ZeroC-W: Zero crossings; QRS-d: QRS duration;
NDP: Number of disarrangement points; SM: Smoothness in signal

Discussion

In this paper, new features were extracted using signal-averaged electrocardiogram and its wavelet transforms to discriminate and diagnose myocardial infarction patients with and without the history of ventricular tachycardia.

Identifying patients prone to ventricular tachycardia in previous studies based on late potential detection that can be seen in most MI patients with history of sustained ventricular tachycardia.[1,4,7,16]

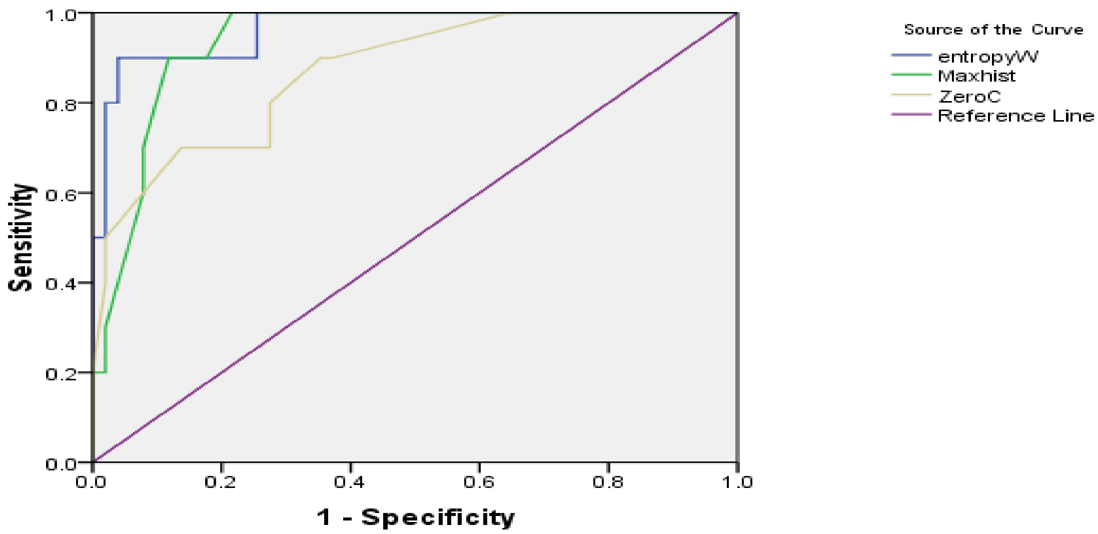

Figure 2. ROC curves for entropy features, maximum value of histogram and numbers of crossing from zero with Haar wavelet transform for two groups of MI and MI+VT

It should be noted, this potential is not observed in all mentioned cases, and this is a deficiency. Therefore, new features should be extracted to overcome this problem.

Among extracted features, QRS length from SAECG and three other features (entropy, maximum value of histogram, the number of zero crossings) from WTSAECG, comply with test conditions. This exhibits that SAECG cannot sufficiently distinguish between MI and MI+VT patients solely; thus, wavelet transform can extract new features and increase the discrimination ability.

Indeed extracted features show that signal disturbance in MI+VT is higher than MI patients; Entropy was particularly seen as an important feature. We conclude that there are reentry electric potentials around ischemic region or multiform ischemic region in MI patients prone to VT; hence, these factors are increasing signal disturbance in MI+VT group.

Conclusion

In conclusion, via the presented method in this paper, a significant difference was seen between the two study groups, and identifying and distinguishing between myocardial infarction patients with and without the history of ventricular tachycardia can be carried out with high sensitivity.

With implementation of wavelet transform, the recognition accuracy level of the two study groups increases greatly.

Entropy of wavelet coefficients is a useful feature in distinguishing between myocardial infarction patients with or without ventricular tachycardia.

Limitation

The low number of MI+VT samples is considered as a limitation of this research.

Suggestions

This algorithm is examined in the reliable global database and good results were gained; therefore, it is suggested that this algorithm and prepared auto-software be applied in health clinics and local data be checked.

Combining extracted features from published studies on this topic with research on other topics such as vectorcardiogram, LP, and conventional electrocardiogram will increase the recognition accuracy.

Conflict of Interests

Authors have no conflict of interest.

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