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Improved Ventricular Fibrillation/Tachycardia Detection using NEWFM for Automated External Defibrillators

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Abstract

Ventricular fibrillation (VF) and ventricular tachycardia (VT) are life-threatening signals. Automated external defibrillators can decrease the fatality rate if the VF/VT detection is stable and quick. This thesis proposes improved VF/VT detection. For our experiments, we use the complete Creighton University Ventricular Tachyarrhythmia Database. Samples are analyzed under the same conditions in intervals of 7 s. Based on this data, we propose a time-delay transform. Then, we extract six shockable features, three known and three new, which are used to construct our Neural Network with Weight Fuzzy Membership Functions model (NEWFM). The result is better than the phase space reconstruction algorithm.

Keywords: *Shockable detection, VF/ VT, TDT, NEWFM, PSR.*

1. Introduction

There are hundreds of thousands of people dying of sudden cardiac diseases, which is primarily caused by ventricular fibrillation and ventricular tachycardia (VF/VT). VF/VT is a disorder of cardiac electrical activities, from which it is difficult to recover without intervention. When VF/VT occurs, the heart loses the pump function and the patient's life is at risk. Animal experiments and clinical experiments have proved that regulated electrical shocks can effectively terminate VF/VT. Moreover, the defibrillation success rate is closely related to defibrillation time. According to statistics, if defibrillation is delayed by one minute, the recovery rate decreases by 7 to 10 percent. Therefore, according to the American Heart Association, early defibrillation is an important chain of survival mentioned in American Heart Association (AHA) [6]. An automatic external defibrillator (AED) can quickly detect and classify VF/VT and other dangerous heart signals. An AED can quickly shock patients to recover the heart's pump function. The application of an AED improves the probability of early defibrillation [7]. In order to achieve even faster and more accurate early defibrillation, the processing and analysis of real-time electrocardiograph (ECG) signals can be used. Using ECGs improves the accuracy of defibrillation and reduces myocardial damage by allowing for prompt diagnosis and treatment. The traditional VF/VT detection algorithm uses the phase space reconstruction algorithm (PSR) to convert the time domain into a value domain [3]. PSR allows for easier and faster VF/VT detection. However, ECG signals are so complex that PSR is unable to achieve a perfect recognition rate. In this paper, we present a new algorithm, called time-delay transform (TDT). Then we extract and select six features by BSWFM [1, 8, 9] and use Neural Network with Weight Fuzzy Membership Functions (NEWFM) to improve the accuracy [2].

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2. The New VT/VF Detection

Fig. 1 shows our proposed VF/VT detection algorithm that we discuss in this paper. The algorithm contains 5 steps. In Step 1, we use the Haar wavelet transform (HWT) to filter ECG signals. In Step 2, the filtered signals are processed with the time-delay transform (TDT) to make the signal more obvious. In Step 3, we extract the initial features from the processed signal. In Step 4, the best six features are selected using bounded sum of weighted fuzzy membership functions (BSWFM) [1], based on NEWFM [2]. In the final step, Step 5, NEWFM trains the six-feature database and outputs the best performance result.

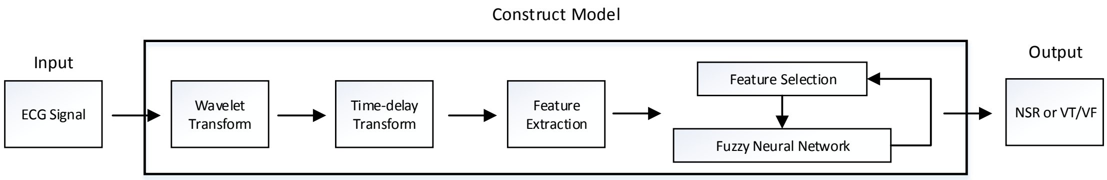

Figure 1. VT/VF Detection Flow Structure

2.1. Haar Wavelet Transform

Haar Wavelet Transform (HWT) is used to filter noisy signals and decomposes a signal into two parts [10, 11, 13]. One part is the average, or trend, sub-signal, and the other part is the fluctuation sub-signal [14, 17, 18].

$$a_m = \frac{f_{2m-1} + f_{2m}}{\sqrt{2}} \quad (1)$$

$$d_m = \frac{f_{2m-1} - f_{2m}}{\sqrt{2}} \quad (2)$$

The original signal is represented by f. The trend sub-signal, a_m, shows the running average, and the fluctuation sub-signal, d_m, shows the running difference. In our experiments, we use HWT 3-level fluctuation sub-signal as input.

2.2. Time-delay Transform

To make the ECG signal more obvious, this paper proposes a new transform, the time-delay transform. We use 0.5s as the delay time [12].

$$x'(t) = x(t) - x(t + 0.5)\,. \quad (3)$$

where x(t) is the HWT D3 signal calculated in Step 2, and x'(t) is the time delayed signal. Using this transform, the peaks of NSR and VF/VT become more distinct, as do the signal's fluctuation and variation.

The time-delay transform makes the peak values more obvious, especially in a VF signal, as shown in Fig. 2. At the same time, it can increase the number of peaks, as shown in Fig. 3, contributing to the extraction of features in the next step.

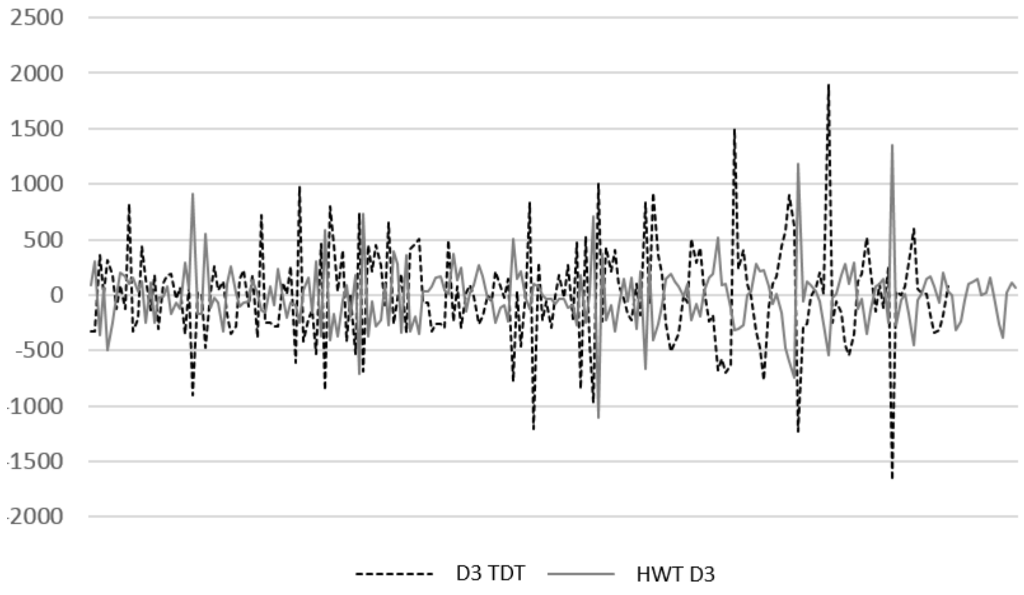

Figure 2. Comparison of D3 TDT and HWT D3 of a VF Signal

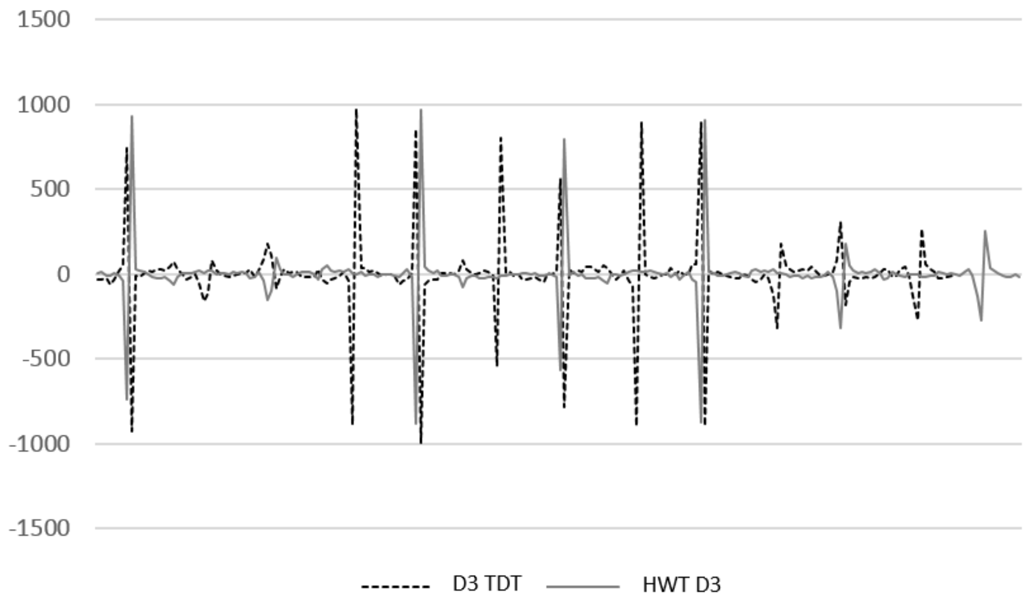

Figure 3. Comparison of D3 TDT and HWT D3 of a NSR Signal

2.3 Feature Extraction

In Step 3, the initial features are extracted from the processed ECG signal. There are 16 features extracted as initial features. Then, in Step 4, we use BSWFM, based on NEWFM, to select six features from the initial set.

2.3.1 Phase Space Reconstruction: The Phase Space Reconstruction Algorithm transforms the ECG signal from a time-domain to a frequency-domain. In this method, x(t) is plotted on the x-axis and x(t +τ) is plotted on the y-axis, where τ is the delay time. Therefore, we can generate statistics regarding the number of visited boxes, or grid squares. PSR produces a 40 x 40 grid, the number of all boxes is 1600 [5].

$$d = \frac{number of\ visited\ boxes}{number of\ all boxes}, \qquad (4)$$

2.3.2 Peak Number: First, the positive values are calculated in order to obtain their average. Then, we use statistics to find the number of values greater than the average. This number is the number of peaks of NSR and VF, shown in Fig. 4 and 5, respectively.

Figure 4. Peak number of NSR

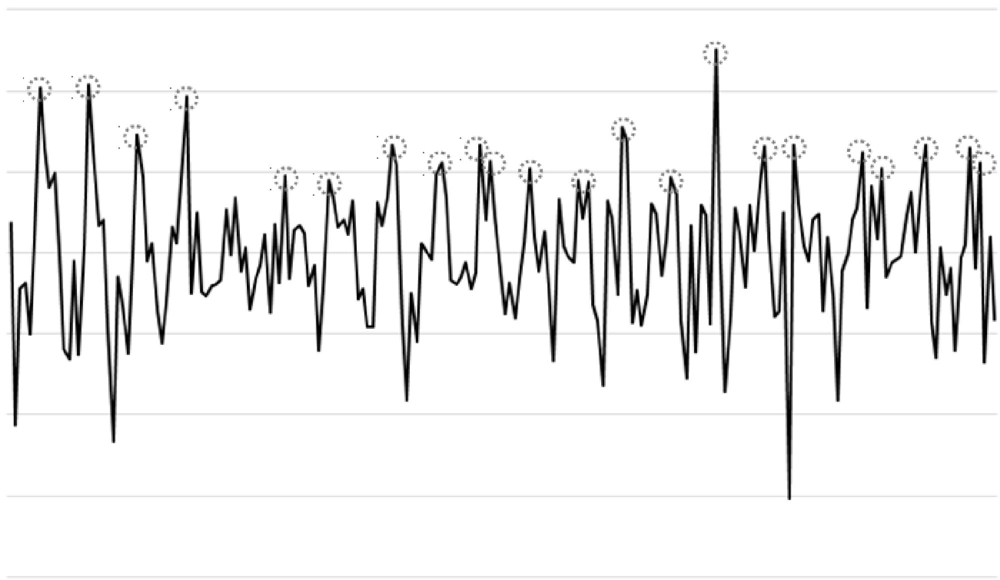

Figure 5. Peak Number of VF

2.3.3 Morphology Points: First, we obtain the maximum peak. And there are 3 previous points and 3 following points, like Fig 6. These six points contain the morphology information. Therefore, we regard these six points as six distinct features [15, 16].

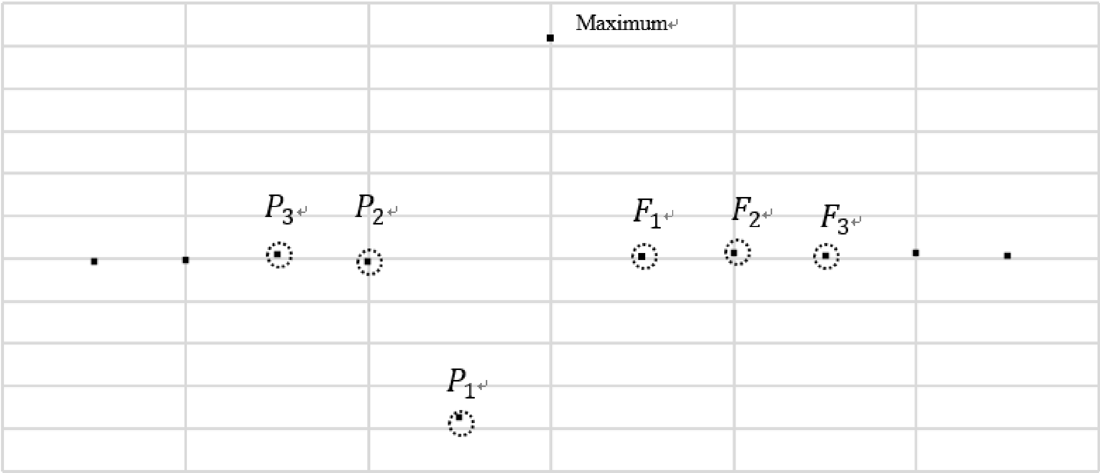

Figure 6. Morphology Points of NSR

2.3.4 Average distance: First, we obtain all the points within the thresholds contained in Table 1. Then, we calculate the distance between every pair of adjacent points, as shown in Fig. 7. Finally, we calculate the average distance using every distance to calculate the average distance, like equation 5.

$$\text{average distance} = \frac{\sum_{i=1}^{n} d_i}{n} \quad (5)$$

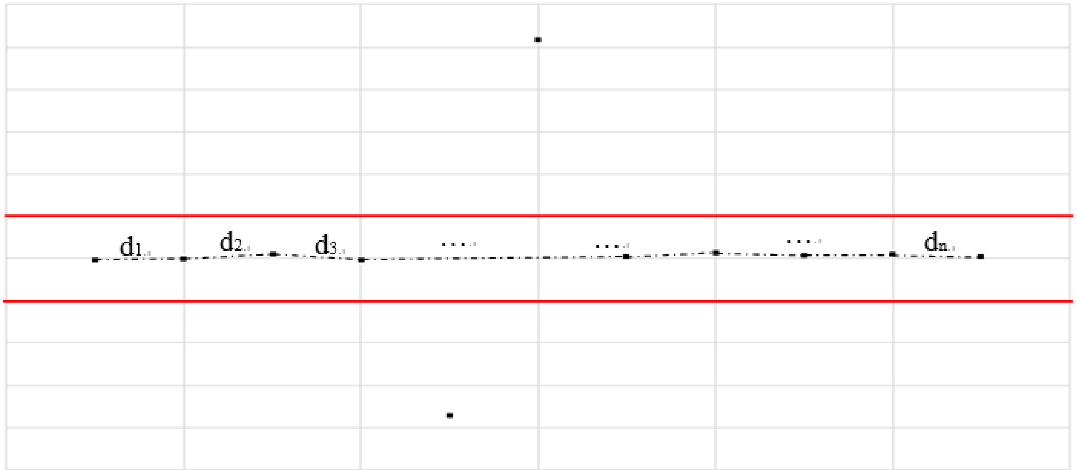

Figure 7. Average Distance of NSR

Table 1. Threshold of Average Distance and Outside Points SD

No.	Threshold
No.1	[-50, 50];
No.2	[-100, 100];
No.3	[-200, 200];
No.4	[-300, 300].

2.3.5 Outside points Standard Deviation: First, we find all of the points outside of the thresholds contained in Table 1. Then, we use these points to calculate the standard deviation, which is regarded as a feature of the signal.

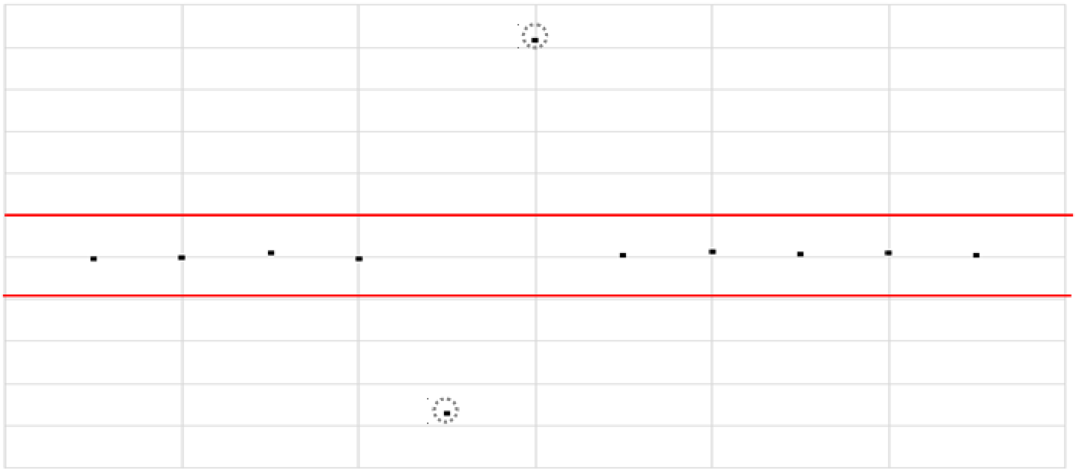

Figure 7. Outside Points Standard Deviation of NSR

2.4 Feature Selection

In the feature extraction part, we can obtain 16 initial features, like Table 2. Then, we use Bounded Sum of Weighted Fuzzy Membership Function (BSWFM) based on NEWFM to select 6 features [8, 9], like Table 3.

Table 2. Initial Features

Feature Name	Number
PSR	1;
Peak number	1;
Morphology points	6;
Average distance	4;
Outside points SD	4;
Total	16.

Table 3. Feature Description

Feature Name	Description
PSR	Phase space reconstruction
Peak number	Number of peaks;
Morphology point2	First point before second highest peak;
Average distance2	Average distance between -100 and 100;
Average distance3	Average distance between -200 and 200;
Outside points SD	The outside points standard deviation -300 and 300.

In this experiment, two hyperboxes are produced by NEWFM for VT/VF and NSR classification. Because, a hyperbox contains a set of lines (BSWFM), which is a rule for NSR signals, another rule for VT/VF signals shows in the other hyperbox graph (BSWFM). The graphs in Fig. 8 are extracted from Neural Network with Weight Fuzzy Membership Functions model (NEWFM) program. When the training part is completed, the hyperboxes and rules are produced and the NEWFM program will automatically draw the graphs and show the difference between the two signals for each input feature.

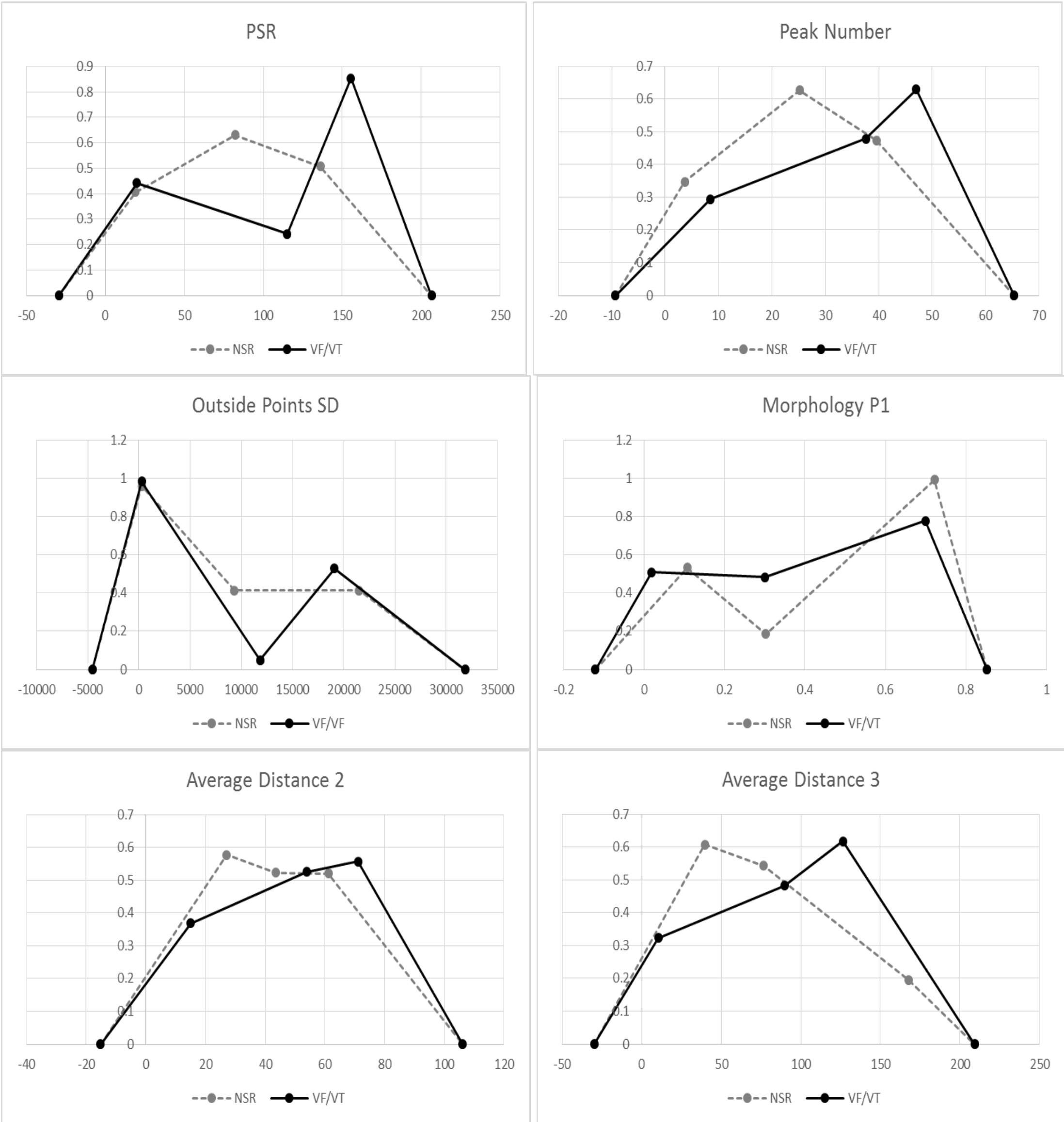

Figure 8. NEWFM Hyperboxes of 6 Features

3. Experiment and Result

The Creighton University Ventricular Tachyarrhythmia Database (CUDB) is downloaded from the physioNet website [4]. CUDB consists of 35 files, each of them 508s long and using a frequency of 250Hz. We use the complete CUDB for our experiment. All signals are detected under equal conditions. 7 s without any pre-selection continuous samples are simulated in the analysis. Table 4 shows some sample numbers and numbers indicating whether the result is a true positive (TP), false negative (FN), false positive (FP), or true negative (TN).

Table 4. Sample Numbers

Classification	Result	
VT/VF	TP	FP
(489)	400	89
NSR	FN	TN
(1952)	130	1822

Table 5 shows the performance of proposed new algorithm and Amann algorithm [5]. The results contain Sensitivity rates (Se), Specificity rates (Sp), Positive productivity rates (Pp) and Accuracy rates (Ac).

Table 5. Experiment Results

Algorithm	Se	Sp	Pp	Ac
Amann	70.2	89.3	65	85
TDT	75.5	93.5	81.8%	91

From Table 5, the Sensitivity rates (Se), Specificity rates (Sp), Positive productivity rates (Pp) and Accuracy rates (Ac), we can see that the results of our TDT-NEWFM model are better than those of Amann's algorithm, which means our proposed algorithm more accurately classifies cases of VT/VF and NSR.

4. Conclusion

This paper proposes a new transform, the time-delay transform, and three new features, such as average distance 2, average distance 3 and so on. A minimum of six features are selected by BSWFM, which is based on NEWFM. The performance results are better than those of Amann's algorithm. In addition, the analysis time required is decreased from 8 s to 7 s. Therefore, our proposed algorithm has two advantages. First, it has a high accuracy rate, and, second, it performs more quickly than the previous approach. The six-feature model can be used in to detect when shock is required for patient treatment.

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