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심근허혈검출을 위한 심박변이도의 시간과 주파수 영역에서의 특징 비교

Comparison of HRV Time and Frequency Domain Features for Myocardial Ischemia Detection

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요약

심박 변이도 (HRV) 분석은 심근허혈 (MI)를 평가하기 위한 편리한 도구이다. HRV에 대한 분석법은 시간 영역과 주파수 영역 분석으로 나눠질 수 있다. 본 논문은 단기간의 HRV 분석에 있어서 웨이블릿 변환을 주파수 영역 분석과 시간 영역 분석 비교하기 위하여 사용하였다. ST-T와 정상 에피소드는 각각 European ST-T 데이터베이스와 MIT-BIH Normal Sinus Rhythm 데이터베이스에서 각각 수집되었다. 한 에피소드는 32개 연속하는 RR 간격으로 나눠질 수 있다. 18개 HRV 특징은 시간과 주파수 영역 분석을 통하여 추출된다. 가종 퍼지소속함수 신경망 (NEWFM)은 추출된 18개의 특징을 이용하여 심근허혈을 진단하였다. 결과는 보여주는 평균 정확도로부터 시간영역과 주파수영역의 특징은 각각 75.29%와 80.93%이다.

■ 중심어 : | 심박수 변이도 | 시간 영역 | 주파수영역 | 단기 HRV 분석 | 심근허혈 |

Abstract

Heart Rate Variability (HRV) analysis is a convenient tool to assess Myocardial Ischemia (MI). The analysis methods of HRV can be divided into time domain and frequency domain analysis. This paper uses wavelet transform as frequency domain analysis in contrast to time domain analysis in short term HRV analysis. ST-T and normal episodes are collected from the European ST-T database and the MIT-BIH Normal Sinus Rhythm database, respectively. An episode can be divided into several segments, each of which is formed by 32 successive RR intervals. Eighteen HRV features are extracted from each segment by the time and frequency domain analysis. To diagnose MI, the Neural Network with Weighted Fuzzy Membership functions (NEWFM) is used with the extracted 18 features. The results show that the average accuracy from time and frequency domain features is 75.29% and 80.93%, respectively.

■ keyword : | Heart Rate Variability(HRV) | Time Domain | Frequency Domain | Short Term HRV Analysis | Myocardial Ischemia(MI) |

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I. Introduction

The method of analysis of the Heart Rate Variability (HRV) has been used for assessment of health. Alterations in the Heart Rate (HR) in various habitats are regarded as a sufficiently objective marker of adaptive reactions. Reduced HRV is a predictor of increased risk for cardiovascular mortality and morbidity [1]. HRV analysis includes long term analysis and short term analysis. Generally, the analytical data that are less than 10 minutes are considered as short term HRV analysis [18]. The time domain signals representing the HRV in the presence of an ectopic beat exhibit a sharp transient at the position of the ectopic beat, which corrupts the signal [3]. The time domain features extraction methods are the simplest to perform as they are applied straight to the series of successive RR interval (the duration of the time interval between two R waves) values [4]. The most evident measure is the mean value of the RR intervals or, correspondingly, the mean HR. In time domain analysis, the Standard Deviation of the RR intervals (SDNN) can reflect sympathetic nerve activity, whereas the Root Mean Square of Successive Differences (RMSSD), are the standard that can reflect parasympathetic nerve activity [2]. Sympathetic nerve activity and parasympathetic nerve activity interact with the digestive, cardiovascular, immune, and hormonal systems [2]. In addition, several variables that measure the variability within the RR series exist [4].

Frequency domain analysis of HRV is based on the periodicity of various biological systems, in other words, a biological signal repeats within a determined time period and thereby exhibits a certain frequency [5]. The wavelet transform specifically permits discrimination of non-stationary signals with different frequency features. A signal is stationary if it does change much over time. Fourier transform can be applied to these stationary signals [5]. However, like HRV, many signals may contain non-stationary transitory characteristics. Thus it is not ideal to directly apply Fourier transform to such signals. Frequency domain analysis may be of value in short term HRV analysis.

Myocardial ischemia (MI) is considered a major complication of cardiac function, and a prime cause for the occurrence of cardiac infarction and dangerous cardiac arrhythmias [6].The main characteristic of MI at the cellular level is manifested in the electrocardiogram (ECG) by an ST depression or elevation [7]. Several researchers have addressed the problem of automatic detection and classification of MI [5-9]. Some techniques are based on the detection of MI episodes and beat-by-beat MI detection [8-10].

A new method, which is used to detect Normal Sinus Rhythm (NSR) and MI effectively by the Neural Network with Weighted Fuzzy Membership functions (NEWFM) [11-13][20][21], is presented in this paper. The NEWFM algorithm characterizes graphs of each features using Bounded Sum of Weighted Fuzzy Membership functions (BSWFMs) [7][3]. The BSWFMs of the features trained by this method are shown visually, which makes the features explicitly interpretable.

II. MATERIALS AND PREPROCESSING

2.1 Materials

In this paper, the MI and NSR classification experiments use the European ST-T database (ST-T DB) [7] and the MIT-BIH Normal Sinus Rhythm Database (NSR DB) [14]. The ST-T DB consists of 48 data files; each file excerpts a two-channel HRV sampled at 250 Hz and 2 hours in length. This

database is intended to be used to evaluate algorithms for ischemia analysis based on ST and T wave displacement. Each file contains at least one ST or T ischemic episode. The ST episode annotations of this database provided by two independent cardiologists were analyzed to evaluate the reproducibility of the human expert opinions [7]. In this paper, only the episodes characterized by ST displacement are included, as the T-wave inversion is not generally considered a selective marker of ischemic episodes [15].

The NSR DB includes 18 long term HRV files of subjects referred to the Arrhythmia Laboratory at Boston's Beth Israel Hospital. Subjects included in this database—5 men, aged 26 to 45, and 13 women, aged 20 to 50—were found to have no significant arrhythmias. Each file excerpts a two-channel HRV sampled at 128 Hz and 24 hours in length [14].

2.2 Training Set Construction

In order to construct the dataset for neural network training HRV files from the ST-T DB and NSR DB were used. In this research 6 files from the NSR DB were selected for the normal dataset. The files in the NSR DB are too long; therefore, we only selected a 2-hour-long HRV file from each file. A segment is formed by 32 successive RR intervals [17] from each file. The definition of a segment in the MIT-BIH Normal Sinus Rhythm Database is shown in [Figure 1] We selected 2507 segments as the normal dataset from all NSR segments. In the ST-T DB there are 22 files that have ST episode. We collected 119 ST episodes from these 22 files. A segment is divided from each episode and formed by 32 successive RR intervals [17]. The definitions of ST episode and segment are shown in [Figure 2] From these episodes, we selected 2507 segments and used these segments as the MI dataset.

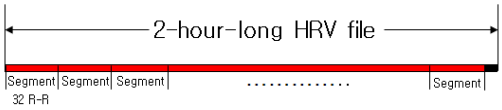

Figure 1. Definition of segment in NSR DB

Figure 2. Definition of ST episode and segment in ST-T DB

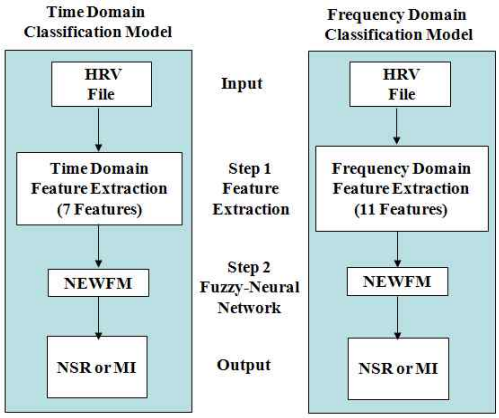

Figure 3. Time domain classification model and frequency domain classification model

III. The Classification Models Using Time and Frequency Domain Features

In this paper we use the time and frequency domain features to detect NSR and MI based on NEWFM [13][20][21]. [Figure 3] shows the time domain classification model and the frequency domain classification model. Step 1 extracts features form the input HRV file. Step 1 in the time domain classification model extracts seven features by time domain analysis. Similarly, step 1 in the frequency domain classification model extracts eleven features by frequency domain analysis. In step 2, the NEWFM

classifies the MI and NSR using the features extracted in step 1.

3.1 Time Domain Feature Extraction

The time domain analysis [3] is applied directly to the series of successive RR interval values. The most evident measure is the mean value of the RR intervals ($\overline{RR}$) or, correspondingly, the mean HR ($\overline{RR}$). In addition, several variables that measure the variability within the RR series exist. The standard deviation of the RR intervals (SDNN) is defined as

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_j - \overline{RR})^2} \quad (1)$$

where RR_j denotes the value of the jth RR interval and N is the total number of successive intervals. The SDNN reflects the overall (both short term and long term) variation within the RR interval series, whereas the Standard Deviation of Successive RR interval Differences (SDSD) given by

$$SDSD = \sqrt{E\{\triangle RR_j^2\} - E\{\triangle RR_j\}^2} \quad (2)$$

can be used as a measure of the short term variability. For stationary RR series,

$$E\{\triangle RR_j\} = E\{RR_{j+1}\} - E\{RR_j\} \quad (3)$$

and equals the Root Mean Square of Successive Differences (RMSSD) given by

$$rMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_{j+1} - RR_j)^2} \quad (4)$$

Another measure calculated from successive RR interval differences is the NN50, which is the number of successive intervals differing by more than 50 ms or the corresponding relative amount:

$$pNN50 = \frac{NN50}{N-1} \times 100\% \quad (5)$$

Accordingly we use the same method above to obtain pNN5, pNN10, and pNN100. This paper used SDNN, SDSD, RMSSD, pNN50, pNN5, pNN10, and pNN100 as time domain input features of NEWFM.

3.2 Frequency Domain Feature Extraction

Two different procedures are studied by which a frequency analysis of a time-dependent signal can be carried out, locally in time [5]. The first procedure is the short-time or windowed Fourier transform, and the second is the "wavelet transform," in which high frequency components are studied with sharper time resolution than low frequency components.

The wavelet transform specifically permits the discrimination of non-stationary signals with different frequency features. A signal is stationary if it does change much over time. Fourier transform can be applied to the stationary signals. However, like HRV, many signals may contain non-stationary of transitory characteristics [5]. Thus directly applying Fourier transform to such signals is not ideal.

Wavelet transform decomposes a discrete signal into two sub-signals of half its length. One sub-signal is a running average or trend; the other sub-signal is a running difference or fluctuation. The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the HRV signal in time and frequency. The following statistical features were used to represent the frequency distribution of the HRV signals [19]:

(1) Mean of the absolute values of the coefficients in each sub-band.
(2) Average power of the wavelet coefficients in each sub-band.
(3) Standard deviation of the coefficients in each sub-band.
(4) Ratio of the absolute mean values of adjacent sub-bands.

Features 1 and 2 represent the frequency distribution of the signal, and features 3 and 4 represent the amount of changes in frequency distribution. In this paper, we selected level 3 from wavelet transform for the frequency features

collection. These feature vectors, calculated for the frequency bands A3 and D2 - D3, are used for classification of the HRV signals.

IV. Experimental Results

This section presents the experimental materials dataset and feature extraction, compares the features process for both feature extraction methods which are time domain and frequency domain based on NEWFM, and evaluates the experimental accuracy for time domain and frequency domain. To evaluate the proposed feature extraction methods, 5014 segments were obtained from the ST-T DB and NSR DB.

Table 1. MIT-BIH Normal Sinus Rhythm Database (NSR DB)

File Name	Number of Episodes	Number of Segments	File Name	Number of Episodes	Number of Segments
16265	1	246	16539	1	219
16272	1	233	16786	1	219
16273	1	212	17453	1	231
16773	1	238	19093	1	223
16420	1	227	19140	1	210
16483	1	249			
			Total:	11	2507

Table 2. European ST-T Database (ST-T DB)

File Name	Number of Episodes	Number of Segments	File Name	Number of Episodes	Number of Segments
e0103	5	22	e0139	1	69
e0105	7	67	e0159	1	34
e0107	2	21	e0161	1	56
e0111	1	6	e0163	1	1
e0113	7	16	e0205	1	58
e0121	1	21	e0207	5	53
e0405	5	109	e0211	2	84
e0123	3	44	e0213	2	114
e0125	4	13	e0403	3	16
e0127	4	16	e0409	1	383
e0147	4	21	e0603	4	49
e0151	2	11	e0605	1	77
e0203	2	86	e0607	3	203
e0303	1	39	e0609	2	75
e0305	1	112	e0613	7	54
e0411	1	26	e0615	1	2
e0413	1	25	e0801	2	29
e0415	3	184	e0807	2	21
e0417	6	43	e1301	2	36
e0501	3	74	e0115	1	28
e0515	2	17	e0119	5	27
e0601	2	2	e0129	4	27
			Total:	118	2507

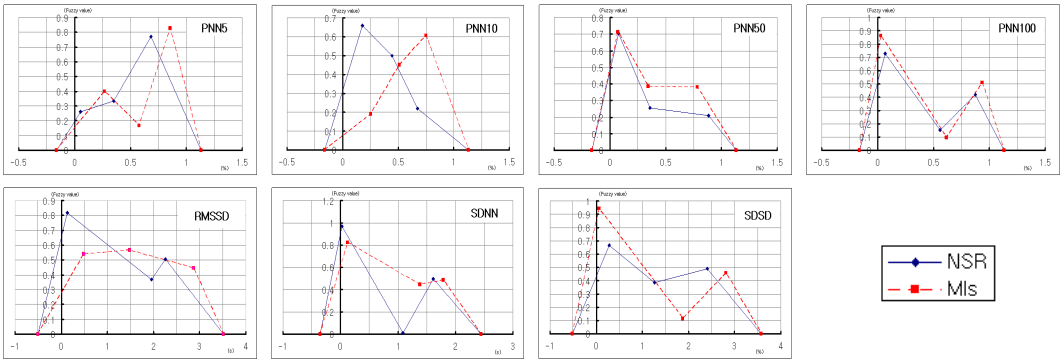

Figure 4. BSWFMs of the input time domain features

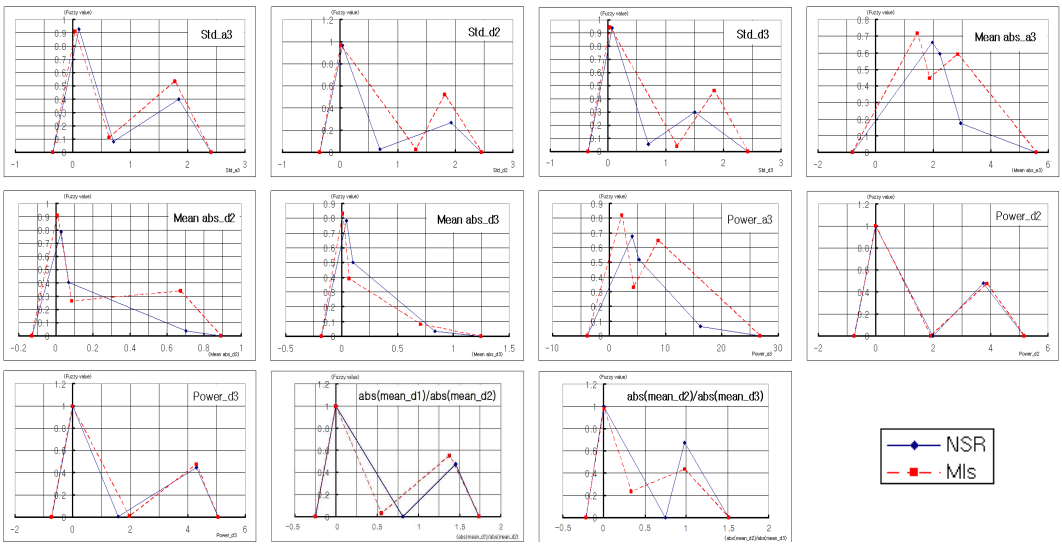

Figure 5. BSWFMs of the input frequency domain features

$$Se = \frac{TP}{TP+FN} = \frac{\text{detected case of } MI}{\text{all case of } MI} \tag{5}$$

$$Sp = \frac{TN}{TN+FP} = \frac{\text{detected case of 'no } MI'}{\text{all case of 'no } MI'} \tag{6}$$

$$Pp = \frac{TP}{TP+FP} = \frac{\text{detected case of } MI}{\text{all case classified by the algorithm } MI} \tag{7}$$

$$Ac = \frac{TP+TN}{TP+FP+TN+FN} = \frac{\text{all true decisions}}{\text{all decisions}} \tag{8}$$

The total number of ischemic segments is 2507. Other segments are considered normal. The segments selection is shown in [Table 1] and [Table 2]. Episodes from the ST-T DB are characterized by ST displacement in each data file. In the NSR DB, one 2-hour-long file from each data file is selected as one episode. A segment is divided from each episode and formed by 32 successive RR intervals.

After the segments were selected, the HRV features were then selected from each segment, using the time and frequency domain feature extraction methods. This paper used these features as NEWFM input data. The graphs in [Figure 4] are the BSWFMs of the input time domain features. There are pNN5, pNN10, pNN100, pNN50, RMSSD, SDNN, and SDSD.

The graphs in [Figure 5] are the BSWFMs of the input frequency domain features. Std_a3, std_d2, std_d3 are the standard deviation of a3, d2, d3, respectively, mean(abs_a3); mean(abs_d2), and mean(abs_d3) are the mean of the absolute values of a3, d2, and d3, respectively; power_a3 is the average power of a3, accordingly power_d2 and power_d3 are the average power of d2 and d3, respectively; abs(mean_d1)/abs(mean_d2) and abs(mean_d2)/abs(mean_d3) are the ratios of the absolute mean values of adjacent sub-bands, respectively. The solid lines and dotted lines visually represent the NSR and MI characteristics of HRV features visually, which allows the features to be interpreted explicitly.

[Table 3] shows the sampling sets of NSR segments (2507) and MI segments (2507), and the number of true positives (TP), false negatives (FN), false positives (FP), and true negatives (TN). Sensitivity (Se) is the probability to detect ventricular fibrillation. It is given by the formula (6) with TP being the number of true positive decisions, FN the number of false negative decisions. Specificity (Sp) is the probability to identify "no MI" correctly. It is given by the formula (7) where TN is the number of true negative decisions, and FP is the number of false positive decisions. Positive predictivity (Pp) is the probability, that classified MI is truly MI, as formula (8). Accuracy (Ac) is the probability to obtain a correct decision, as formula (9). Table 4 shows that the sensitivity, specificity, positive productivity, and accuracy rates from time domain features are 66.45%, 84.12%, 80.72%, and 75.29%, respectively; and from frequency domain features are 81.9%, 79.18%, 79.73%, and 80.93%, respectively.

Table 3. The NSR, MI, Detection Algorithm Evaluation Results: Sensitivity (Se), Specificity (Sp), Positive predictivity (Pp), Accuracy (Ac)

Algorithm	Se	Sp	Pp	Ac
Time Domain	66.45%	84.12%	80.72%	75.29%
Frequency Domain	81.9%	79.18%	79.73%	80.93%

IV. Concluding Remarks

This paper proposes a new MI detection methodology using the time and frequency domain features of HRV based on NEWFM. Measuring the HRV provides information not only about the central control mechanisms but also the organ situation. The time and frequency domain feature extractions are applied directly to the series of successive RR interval values. This paper uses 32 RR intervals as one segment for HRV analysis. Short term HRV analysis does a noticeable job of acute heart disease detection. The accuracy of the time domain features is 75.29%, and the accuracy of the frequency domain features is 80.93%. The frequency domain features enhance the average accuracy of MI detection. Frequency domain

analysis does a noticeable job of short term HRV analysis. This research can be used in real time MI detection, and can give MI patient alarm in good time.

In this paper, a set of results by several effective methods are chosen as characteristic features. There are totally 32 features which will distinguish between NSR and MI of class node as NEWFM common input features. The BSWFM of 22 features trained by NEWFM are shown visually. Since each BSWFM combines multiple weighted fuzzy membership functions into one using bounded sum, the 22 small-sized BSWFM can realize real-time NSR, MI detection in mobile environment.

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