http://dx.doi.org/10.5392/JKCA.2012.12.02.001

뉴로-퍼지 신경망 기반 최적의 HRV특징을 이용한 우울증진단 알고리즘

Neuro-Fuzzy Network-based Depression Diagnosis Algorithm Using Optimal Features of HRV

장진흥, 전설위, 임준식
경원대학교 IT대학

Zhen-Xing Zhang(billzhenxing@gmail.com), Xue-Wei Tian(tian1985@ku.kyungwon.ac.kr), Joon S. Lim(jslim@kyungwon.ac.kr)

요약

본 논문은 가중 퍼지소속함수 기반 신경망 (Neural Network with Weighted Fuzzy Membership functions, NEWFM)과 심박수 변이도(Heart Rate Variability, HRV)를 이용하여 우울증 진단알고리즘을 제안하고 있다. 본 알고리즘에서 사용할 NEWFM의 입력특징을 추출하기 위해서 주파수도메인 특징추출, 시간도메인 특징추출, 웨이블릿변환 특징추출, 포인케어변환 특징추출 방법을 이용하여 22개의 초기 HRV 특징들을 추출하였다. 또한 NEWFM에서 제공하는 비중복면적 분산측정법 (Non-overlap Area Distribution Measurement, NADM)에 의해 입력특징의 중요도를 평가하여 22개의 초기특징으로부터 중요도가 가장 높은 6개 최적입력특징을 선택하였다. 이 6개 특징을 이용하여 우울증을 진단한 결과는 95.8%의 정확도를 나타내었다.

■ 중심어 : | 뉴로-퍼지신경망 | 특징추출 | 특징선택 | 심박수 변이도 | 우울증 |

Abstract

This paper presents an algorithm for depression diagnosis using the Neural Network with Weighted Fuzzy Membership functions (NEWFM) and heart rate variability (HRV). In the algorithm, 22 different features were initially extracted from the HRV signal by frequency domain, time domain, wavelet transformed, and Poincaré transformed feature extraction methods; of these 6 optimal features were selected by significance evaluation using Non-overlap Area Distribution Measurement (NADM) based on NEWFM. The proposed algorithm uses these 6 optimal features to diagnose depression with an accuracy of 95.83%.

■ keyword : | Neuro-Fuzzy Network | Feature Extraction | Feature Selection | Heart Rate Variability | Depression |

I. Introduction

Depression is defined as a state of low mood and aversion to activity, which is characterized by impairment of mood regulation and loss of interest in enjoyable activities. Due to the fluctuating nature of

* 본 연구는 2012년도 경원대학교 학술연구비 지원에 의한 결과임.
* 본 연구는 지식경제부 및 정보통신산업진흥원의 IT융합 고급인력과정 지원사업의 연구결과로 수행되었음. (NIPA-2012-C6150-1201-0001)
접수번호 : #111125-006
접수일자 : 2011년 11월 25일
심사완료일 : 2012년 02월 06일
교신저자 : 임준식, e-mail : jslim@kyungwon.ac.kr

the disease, however, it is a difficult disorder both to diagnose and to treat[1][2]. There have been many studies which used electroencephalogram (EEG) signals to distinguish depressive patients from normal healthy persons[1-4]. Recently, medical researchers use heart rate variability (HRV) to measure depression based on statistical analysis which study show that depression is associated with HRV[5-7].

However, previous studies generally used a large number of features to diagnose depression[1-4]. Hosseinifard[1] used fifteen EEG features as input features of support vector machine to diagnose depression, with 88.6% of depression diagnosis accuracy. Kalatzis[3] used eighteen EEG features to diagnose depression which based on a majority-vote engine, with 94% of depression diagnosis accuracy. But in these studies, their depression diagnosis results were not satisfactory[2-4].

Based on the above, this paper proposed a depression diagnosis algorithm which only uses six features of HRV signal to diagnose depression based on neuro-fuzzy networks. In this study, initial twenty-two different features are extracted from the HRV signal by the frequency domain feature (FDF), time domain feature (TDF), wavelet transformed feature (WTF), and Poincaré transformed feature (PTF) extraction methods. In feature selection process, six features are selected from these features by Non-overlap Area Distribution Measurement (NADM)[8-12] based on neuro-fuzzy networks: VLF, SDNN, PNN100, Power_d3, Power_d2 and SD2. The selected 6 optimal features are compared with the 22 initial features in terms of depression diagnosis accuracy, with results of 95.8% and 91.67%, respectively. This refinement not only reduces the number of the input features but also increases the classification accuracy by selecting the most discriminating features.

II. The Depression Diagnosis Model

1. Neuro-Fuzzy Network With A Weighted Fuzzy Membership Function (NEWFM)

In this study, on the basis of a neuro-fuzzy network with a weighted fuzzy membership function (NEWFM)[8-12], a new depression diagnosis algorithm was used to distinguish depressed subjects from control subjects. NEWFM is a supervised classification neuro-fuzzy system, which can obtain the bounded sum of weighted fuzzy membership functions (BSWFMs)[8-12] of input features based on training processing. In this paper, the structure of the NEWFM, illustrated in [Figure 1], comprises three layers namely the input, hyperbox, and class layer. The input layer contains 22 input nodes for 22 input features. The hyperbox layer consists of 22 hyperbox nodes. Each hyperbox node to be connected to a class node contains n BSWFMs for n input nodes. The output layer is composed of two class nodes. Each class node is connected to two hyperbox nodes[8-12].

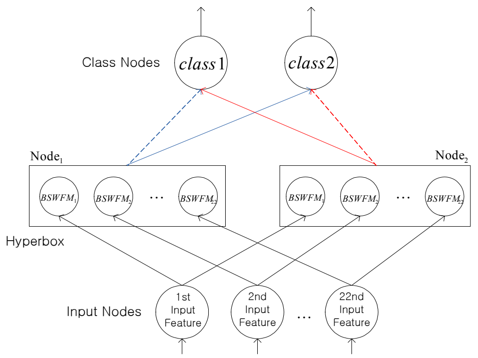

Figure 1. Structure of NEWFM.

2. Depression Diagnosis Model

The proposed depression diagnosis model includes 2 schemas, which are depression diagnosis and feature selection. In the feature selection schema, the initially 22 features included 4 FDFs, 7 TDFs, 9 WTFs, and 2 PTFs extracted from the HRV signal, from which the 6 optimal features were selected by NADM[8-12]. The depression diagnosis schema has 4 steps, as shown in [Figure 2]. In Step 1, 13 minutes of electrocardiology (ECG) signals were collected using the Holter monitor. In Step 2, the 13-minute ECG signals were transformed to HRV by a beat-to-beat interval measurement method. In Step 3, 6 features were extracted via FDF, TDF, WTF, and PTF extraction methods, which were selected in feature selection schema. In Step 4, the 6 BSWFMs, trained by NEWFM through the feature selection scheme, were shown to be able to diagnose the presence of depression in a subject.

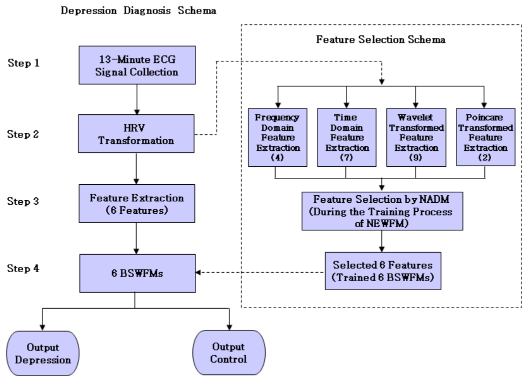

Figure 2. Proposed depression diagnosis schema and feature selection schema

III. Materials And Methods

This study designed a experiment which used for HRV signals collection. In the experiment, HRV signals were collected from 24 subjects which wore a wireless Holter monitor. Each subject underwent a 13-minute affective-contents stimulus. This section presents a self-assessment standard of the depression and control subjects, describes the affective-contents test, and explores the HRV transformation in more detail. A combination of FDFs, TDFs, WTFs, and PTFs of the HRV signal is also described in this section.

1. Zung Self-Rating Depression Scale (SDS)

The Zung Self-Rating Depression Scale (SDS) is a 20-item self-report questionnaire. Each item is scored on a Likert scale ranging from 1 to 4 (a little of the time, some of the time, a good part of the time, most of the time)[8]. The SDS score is the total value of all 20 items and ranges from 20 to 80. The scores fall into 4 common levels of depression: Normal Range (20~49), Mildly Depressed (50~59), Moderately Depressed (60~69), and Severely Depressed (70 and above)[13].

2. Subjects

This study involved 10 subjects who were diagnosed with depressive disorders (SDS score: greater than 60) at the Mental Health Center, Sungnam, South Korea. Another 14 participants were included as control subjects (SDS score: 20~50). They were all healthy volunteers without any history of heart disease or neurological or psychiatric illness. The 24 subjects included 9 females and 15 males, none of whom had exercised heavily in the 4 hours prior to taking part in the experiment.

3. Multimodal Affective Contents (MAC)

Many research studies have examined the influence of emotions on the ANS utilizing the analysis of HRV [5-7]. This study designed a new MAC stimulus, which can evoke various emotions, such as happiness, joy, pain, stress, irritability, and fear. While each subject underwent the MAC test, he/she ate some soft marshmallows and super-sour candies, drank sweet juice, and blew up a balloon, among other tasks. The MAC stimulus scenario is summarized in [Table 1]. The MAC test lasted for approximately 800 seconds (about 13 minutes). This included a 10-second transition time between the affective contents.

Table 1. Summary of the 13-minute Multimodal Affective-Contents Stimulus Scenario

Status	Affective Contents	Time (second)
Rest	Null	60s
Happiness, Joy,Touching	Lullaby, Perfume	30s
	Meditation, Nature Sound	30s
	Head Exercise	30s
	Funniest Video	60s
	Handsome Boy, Pretty Girl	30s
	World Cup Video	30s
	Bright Music Eating Marshmallow Drinking Sweet Juice	60s
Pain, Stress, Irritability, Fear	Blowing a Balloon	30s
	Stoop Test	30s
	Rock	30s
	Horror Movie	60s
	Noisy Sound	30s
	Ugly Men/Women	30s
	Eating Sour Candy	60s
Rest	Meditation, Nature Sound	60s

4. HRV Transformation

While the subjects were undergoing the MAC stimulus (approximately 13 minutes), their ECG signals were recorded by an Alive 2-channel wireless heart monitor. The ECG recordings were transformed into HRV values using the QRS detection algorithm[14]. [Figure 3] shows 2 HRV episodes (control and depression subjects) with fairly similar characteristics.

5. Feature Extraction

5.1 Frequency Domain Features (FDFs)

In this study, 4 FDFs were selected according to the conclusions of other studies[15][16] and HRV measurement standards[17], and these were extracted via the corresponding extraction method. The FDFs can commonly be used for short-term recordings[17]. This paper extracted 4 FDFs: very low frequency (VLF, 0.0033~0.04 Hz), low frequency (LF, 0.04~0.15), high frequency (HF, 0.15~0.4), and ratio of LF to HF (LF/HF), based on fast Fourier transform.

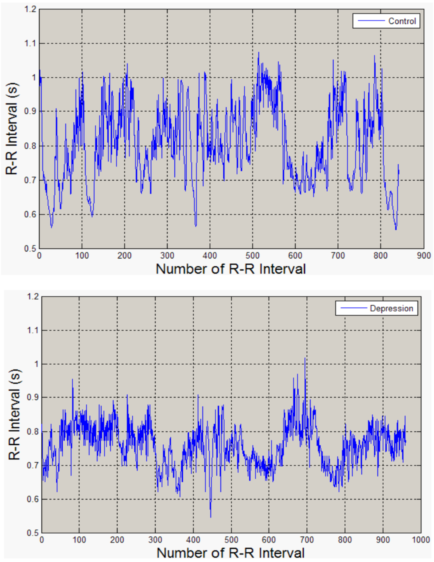

Figure 3. An HRV episode with the control and depressed subjects

5.2 Time Domain Features (TDFs)

TDFs are commonly used for long-term data recordings. This paper extracted 7 TDFs including the standard deviation of the RR intervals (SDNN), the root mean square of successive differences (RMSSD), and the standard deviation of successive RR interval differences (SDSD), which were calculated by formula:

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

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{j=1}^{N}(RR_{j+1} - RR_j)^2} \qquad (2)$$

$$SDSD = \sqrt{E\{\triangle RR_j^2\} - E\{\triangle RR_j\}^2} \quad (3)$$

$$pNN5 = \frac{NN5}{N-1} \times 100\% \quad (4)$$

where RR_j denotes the value of the jth RR interval, N is the total number of successive intervals, $\overline{RR}$ denotes the mean value of the RR intervals and ΔRR (delta-RR intervals) denotes the value difference between RR_j and RR_{j+1} [19].

Another measure calculated from successive RR interval differences is NN5, which is the number of successive intervals differing by more than 5 ms or the corresponding relative amount, which was calculated by Formula (4). Accordingly, we used the same method to obtain pNN10, pNN50, and pNN100 [19].

5.3 Wavelet and Poincar Transformed Features (WTFs & PTFs)

Fourier transform can be applied to stationary signals. However, HRV signals contain non-stationary transitory characteristics[18]. Wavelet transform is better suited to analyze non-stationary signals, as it is well localized in time and frequency. Wavelet transform analyzes HRV signals at different frequency bands with different resolutions by decomposing the signal into approximation and detailed coefficients. The following features were used to represent the frequency distribution of the HRV signals [20]:

a. Mean(abs_a3), Mean(abs_d3), Mean(abs_a2): Mean of the absolute values of the level 3 approximation coefficients, level 3 detail coefficients and level 2 approximation coefficients.

b. Power_a3, Power_d3, Power_a2: Average power values of the level 3 approximation coefficients, level 3 detail coefficients and level 2 approximation coefficients.

c. Std_a3, Std_d3, Std_a2: Standard deviation of the level 3 approximation coefficients, level 3 detail coefficients and level 2 approximation coefficients.

Another 2 nonlinear features are the standard deviation of Poincaré plot with SD1 and SD2, describing the short-term variability and long-term variability in the HRV signal, respectively. These were calculated by formulas:

$$SD1 = \frac{\sqrt{2}}{2} SDSD \quad (5)$$

$$SD2 = \sqrt{2SDNN^2 - \frac{1}{2} SDSD^2} \quad (6)$$

A total of 22 features were extracted using the FDF, TDF, WTF, and PTF extraction methods, as shown in [Table 2].

Table 2. Twenty-two Initial Features Extracted for Diagnosing Depression

Order	Feature Extraction Method	Detail Features	Selected
1	FDFs	VLF	Yes
2		LF	No
3		HF	No
4		LF/HF	No
5	TDFs	SDNN	Yes
6		RMSSD	No
7		SDSD	No
8		PNN5	No
9		PNN10	No
10		PNN50	No
11		PNN100	Yes
12	WTFs	Mean(abs_a3)	No
13		Mean(abs_d3)	No
14		Mean(abs_d2)	No
15		Power_a3	No
16		Power_d3	Yes
17		Power_d2	Yes
18		Std_a3	No
19		Std_d3	No
20		Std_d2	No
21	PTFs	SD1	No
22		SD2	Yes

IV. Feature Selection

After the feature extraction process, the 22 features of the subjects were used as NEWFM's input features to train NEWFM. During the training process, 22 BSWFMs of the input features were evaluated by NADM, which finds and counts the best input features among all the initial features using the evaluation methods [8-12]. The NEWFM was trained on the sampling data sets while the sampling data sets were tested (close test) 5,000 times; the result of the 5,000 tests appears in [Figure 4]. As [Figure 4] shows, the first, fifth, eleventh, sixteenth, seventeenth and twenty-second features were evaluated most highly among the 22 initial features, and these were selected for use in diagnosing depression; the features are numbered in [Table 2]. The highest evaluation results were for Power_d3 and Power_d2, which not only reflect significant differences in HRV between the depression and control subjects, but also reveal a close association between depression and ANS. The trained BSWFMs of the 6 optimal features are presented in [Figure 5]. The dotted and solid lines represent the control and depression characteristics, respectively, enabling the features to be interpreted explicitly.

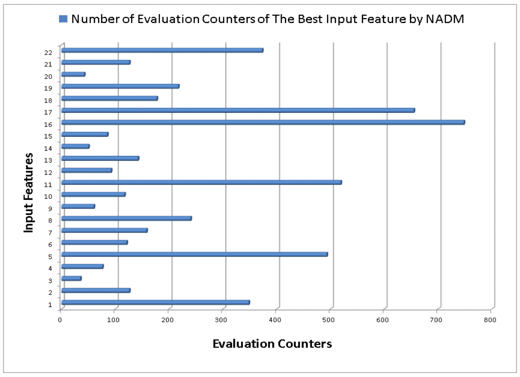

Figure 4. Twenty-two HRV feature evaluations by NADM.

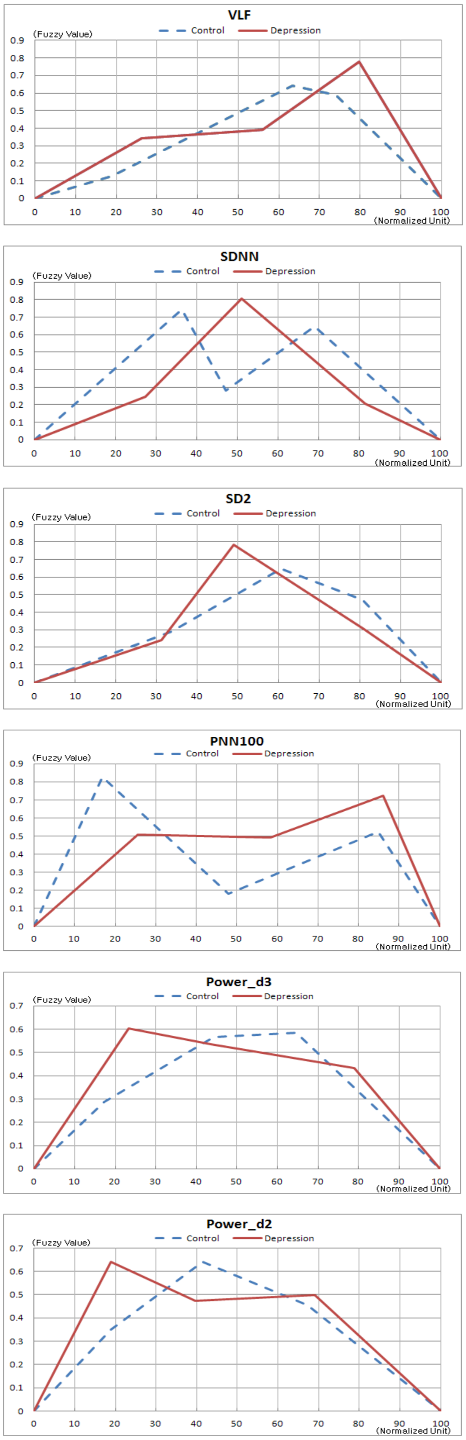

Figure 5. Trained BSWFMs of the 6 optimal features for depression diagnosis.

V. Performance Results

This paper uses 4 types of feature sets, which are 22 initial features and 6 optimal features for diagnosing depression. [Table 3] presents a comparison between the performance of the 22 initial features and the performance of the 6 optimal features on the 24 subjects' HRV signal sets. The performance results of the initial features were 100% for sensitivity, 85.7% for specificity, 83.3% for productivity, and 91.67% for accuracy rate. The performance results for the optimal features were 100% for sensitivity, 92.8% for specificity, 90.9% for productivity, and 95.8% for accuracy rate. A summary of different methods together with their reported results in terms of the accuracy and the number of features is summarized in [Table 4]. Hosseinifard[1] used fifteen EEG features as input features of support vector machine to diagnose depression, with 88.6% of depression diagnosis accuracy. Li[2] used eighteen EEG features as input features of artificial neural networks to diagnose depression, with 60% of depression diagnosis accuracy. Kalatzis[3] used eighteen EEG features to diagnose depression based on a majority-vote engine, with 94% of depression diagnosis accuracy. The proposed depression diagnosis algorithm uses least features while obtaining the highest accuracy results.

Table 3. Results of The Proposed Algorithm Evaluation in Terms of Sensitivity (Se), Specificity (Sp), Positive productivity (Pp), Accuracy (Ac)

Algorithm	Number of Features	Se	Sp	Pp	Ac
Proposed Algorithm	22	100%	85.7%	83.3%	91.7%
	6	100%	92.8%	90.9%	95.8%

Table 4. Comparison of The Proposed Algorithm with Other Algorithms in Depression Diagnosis

Paper	Signal	Number of Features	Accuracy
Hosseinifard[1]	EEG	15	88.6%
Li[2]	EEG	18	60%
Kalatzis[3]	EEG	18	94%
Proposed Algorithm	HRV	6	95.8%

VI. Concluding Remarks

Medical studies show a significant relationship between depression and HRV features[7]. This paper proposes a new depression diagnosis algorithm based on NEWFM. Six optimal features - VLF, SDNN, PNN100, Power_d3, Power_d2, and SD2 - were selected by NADM as input features of NEWFM to diagnose depression. Power_d3 and Power_d2 in particular, having the highest evaluation of the accumulated counters among the 22 initial features, are the most distinguishable between depression and control subjects, which may aid in diagnosing depression and understanding the relationship between HRV and depression. The performance of the 6 optimal features has been compared with other depression diagnosis algorithm. A 95.8% accuracy rate in the diagnosis result is satisfactory, outperforming the Kalatzis's[3] algorithm by 1.8%.

참 고 문 헌

[1] B. Hosseinifard, M. H. Moradi, and R. Rostami, "Classifying Depression Patients and Normal Subjects Using Machine Learning Techniques," Proceeding of Iranian Conference Electrical Engineering, pp.131-134, 2011.

[2] Y. J. Li and F. Y. Fan, "Classification of

Schizophrenia and Depression by EEG with ANNs," Proceeding of IEEE Engineering in Medicine and Biology Society, pp.2679-2682, 2005.

[3] I. Kalatzis, N. Piliourasa, E. Ventourasa, C. C. Papageorgioub, A. D. Rabavilas, and D. Cavourasa, "Design and Implementation of an SVM-based Computer Classification System for Discriminating Depressive Patients from Healthy Controls Using the P600 Component of ERP Signals," Computer Methods and Programs in Biomedicine, Vol.75, No.1, pp.11-22, 2004.

[4] A. K. Rostamabad, J. P. Reilly, G. Hasey, H. Bruin, and D. MacCrimmon, "Diagnosis of Psychiatric Disorders Using EEG Data and Employing a Statistical Decision Model," Proceeding of IEEE Engineering in Medicine and Biology Society, pp.4006-4009, 2010.

[5] G. Licht, E. Geus, F. Zitman, W. Hoogendijk, R. Dyck, and B. Penninx, "Association Between Major Depressive Disorder and Heart Rate Variability in the Netherlands Study of Depression and Anxiety," Archives of General Psychiatry, Vol.65, No.12, pp.1358-1367, 2008.

[6] M. Karavidas, "Heart Rate Variability Biofeedback for Major Depression," Applied Psychophysiology and Biofeedback, Vol.36, No.1, pp.18-21, 2008.

[7] M. W. Agelink, C. Boz, H. Ullrich, and J. Andrich, "Relationship between Major Depression and Heart Rate Variability," Clinical Consequences and Implications for Antidepressive Treatment. Vol.113, No.2, pp.139-149, 2002.

[8] J. S. Lim, "Finding Features for Real-Time Premature Ventricular Contraction Detection Using a Fuzzy Neural Network System," IEEE Trans. on Neural, Vol.20, No.3, pp.522-527, 2009.

[9] 신동근, 장진홍, 이상홍, 임준식, 이정현, "가중 퍼지소속함수 기반 신경망과 웨이블릿 변환을 이용한 심실빈맥/세동 검출", 한국콘텐츠학회논문지, 제9권, 제7호, pp.19-26, 2009.

[10] 이상홍, 신동근, 임준식, "운동 형상 분류를 위한 웨이블릿 기반 최소의 특징 선택", 한국콘텐츠학회논문지, 제10권, 제6호, pp.27-34, 2010.

[11] 신동근, 정경용, "웨이블릿 변환과 퍼지 신경망을 이용한 단기 KOSPI 예측", 한국콘텐츠학회논문지, 제11권, 제6호, pp.1-7, 2011.

[12] 신동근, "주성분 분석과 수면 2기를 이용한 수면장애 분류", 한국콘텐츠학회논문지, 제11권, 제4호, pp.27-32, 2011.

[13] W. W. Zung, "A Self-rating Depression Scale," Archives of General Psychiatry, Vol.12, No.1, pp.63-70, 1965.

[14] P. S. Hamilton and W. J. Tompkins, "Quantitative Investigation of QRS Detection Rules Using the MIT/BIH Arrhythmia Database," IEEE Trans. on Biomedical Engineering, Vol.33, No.12, pp.1157-1165, 1986.

[15] E. Nahshont, D. Aravot, D. Aizenberg, M. Sigler, G. Zalsman, B. Strasberg, S. Imbra, E. Adler, and A. Weizman, "Heart Rate Variability in Patients With Major Depression," Psychosomatics, Vol.45, No.2, pp.129-134, 2004.

[16] C. K. Lee, S. K. Yoo, Y. J. Park, K. NamHyun, K. S. Jeong, and B. Lee, "Using Neural Network to Recognize Human Emotions from Heart Rate Variability and Skin Resistance," Proceeding of Engineering in Medicine and Biology Society, pp.5523-5525, 2005.

[17] M. Malik, "Heart Rate Variability Standards of Measurement, Physiological Interpretation, and Clinical Use," European Heart Journal, Vol.17, No.3, pp.354-381, 1996.

[18] A. Subasi, "Automatic Recognition of Alertness Level from EEG by Using Neural Network and

Wavelet Coefficients," Expert Systems with Applications, Vol.28, No.4, pp.701 - 711, 2005.

[19] M. Brennan, M. Palaniswami, and P. Kamen "Do Existing Measures of Poincare Plot Geometry Reflect Nonlinear Features of Heart Rate Variability?" IEEE Trans. on Biomedical Engineering, Vol.48, No.11, pp.1342-1347, 2001.

[20] A. Kandaswamy, C. S. Kumar, R. P. Ramanathan, S. Jayaraman, N. Malmurugan, "Neural Classification of Lung Sounds Using Wavelet Coefficients," Computers in Biology and Medicine, Vol.34, No.6, pp.523-537, 2004.

저 자 소 개

장 진 홍(Zhen-Xing Zhang) 정회원

- 2005년 : 중국 산동이공대학교 전자계산학과 졸업(공학사)
- 2008년 : 경원대학교 전자계산학과 졸업(공학 석사)
- 2011년 : 경원대학교 전자계산학과 박사수료

<관심분야> : signal processing, neuro-fuzzy system, ubiquitous healthcare system

전 설 위(Xue-Wei Tian) 정회원

- 2008년 : 중국 산동이공대학교 전자계산학과 졸업(공학사)
- 2010년 : 경원대학교 전자계산학과 졸업(공학 석사)
- 2011년 3월 ~ 현재 : 경원대학교 전자계산학과 박사과정

<관심분야> : neuro-fuzzy system, biomedical systems

임 준 식(Joon S. Lim) 정회원

- 1986년 : 인하대학교 전자계산학과(학사)
- 1989년 : University of Alabama at Birmingham, Dept. of Computer Science (M.S.)
- 1994년 : Louisiana State University, Dept. of Computer Science(Ph.D.)
- 1995년 ~ 현재 : 경원대학교 IT 대학 교수(현)

<관심분야> : neuro-fuzzy systems, biomedical systems