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Papers:

Modeling Heart Rate Variability with a HMM-based Neural Network

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This paper proposes a method of modeling heart rate variability combining wavelet transform with a neural network based on a hidden Markov model. The proposed method has the following features: 1. The wavelet transform is used for feature extraction to extract the local change of heart rate variability in the time-frequency domain. 2. A new recurrent neural network incorporating a hidden Markov model is used to model the different patterns of heart rate variability caused by individual variations, physical conditions and so on. In experiments, five subjects were subjected to a mental workload, and the proposed method was used map subjective rating scores of their mental stress and the pattern of heart rate variability. Experiments confirmed that the proposed method achieved highly accurate modeling.

Keywords: heart rate variability, mental stress, wavelet transform, recurrent neural network, hidden Markov model

1. Introduction

Modern society is the source of physical and mental stress in many people. Cases of sudden cardiac death due to a busy life or irregular habits have also been reported, and life threatening conditions increase for patients with heart failure and cerebrovascular disease if health care is neglected in daily life. It is important to objectively evaluate physical condition based on a physiological index.

Heart rate variability (HRV) includes many frequency components, and yields information through frequency domain analysis[1,2]. For example, Delaney et al. reported that short-term psychological stress produces significant changes in sympathovagal activity[3]. They used a simple, noninvasive method based on the timing and frequency of HRV. Bernardi examined whether talking or reading (silently or aloud) could affect HRV[4]. Ishibashi et al. also used spectral analysis of HRV to estimate the changes in autonomic control in response to disparate stimuli produced by mental tasks and graded head-up tilting[5]. However, if the power spectrum of HRV is calculated using a fast Fourier transform, it expresses rough information in a fixed period of the time series signal, and the dynamic changes of the autonomic nerve activity cannot be expressed. It is difficult to analyze the nonstationary pattern of HRV using this method during exercise. The wavelet transform (WT), which extracts local features of HRV in the time-frequency domain, is used to overcome this difficulty[6,7].

When we analyze the HRV spectrum, we must take into account that the changes in the spectrum pattern differ among individuals. Most previous studies defined specified frequency ranges, such as low-frequency (LF) and high-frequency (HF) components, in the power spectrum of HRV and extracted an integrated or maximum value of the power in each range. However, this method is not always applicable because the range, scale, and speed of changes in the spectrum are affected by factors such as individual variations and physical conditions. We tried to construct an individual model of HRV. We can then examine whether the HRV pattern measured another day fits this model or not, and may detect unusual physical conditions.

Neural networks have been used to model and evaluate the ECG signal. Minami et al. combined feature extraction by Fourier transform and a back-propagation neural network (BPN)[8] and detected tachyarrhythmia in real time. Fahoum et al. combined WT and an RBF neural network (RBFN) to detect life-threatening cardiac arrhythmias[9]. However, the purpose of these reports was to detect the abnormal waveform on the ECG, and they did not state whether HRV was caused by physical and mental stress. A problem arises because BPN needs large volumes of training data and many learning iterations.

We developed a statistical neural network called a Log-Linearized Gaussian Mixture Network (LLGMN)[10,11]. This network is structured based on a Gaussian mixture model and a log-linear model, and can discriminate electroencephalograms and electromyograms[12] better than other neural networks. We also proposed a Recurrent Log-Linearized Gaussian Mixture Network (R-LLGMN)[13], which uses recurrent connections added to the units of LLGMN to discriminate a time sequence of the signals highly accurately. R-LLGMN includes a hidden Markov

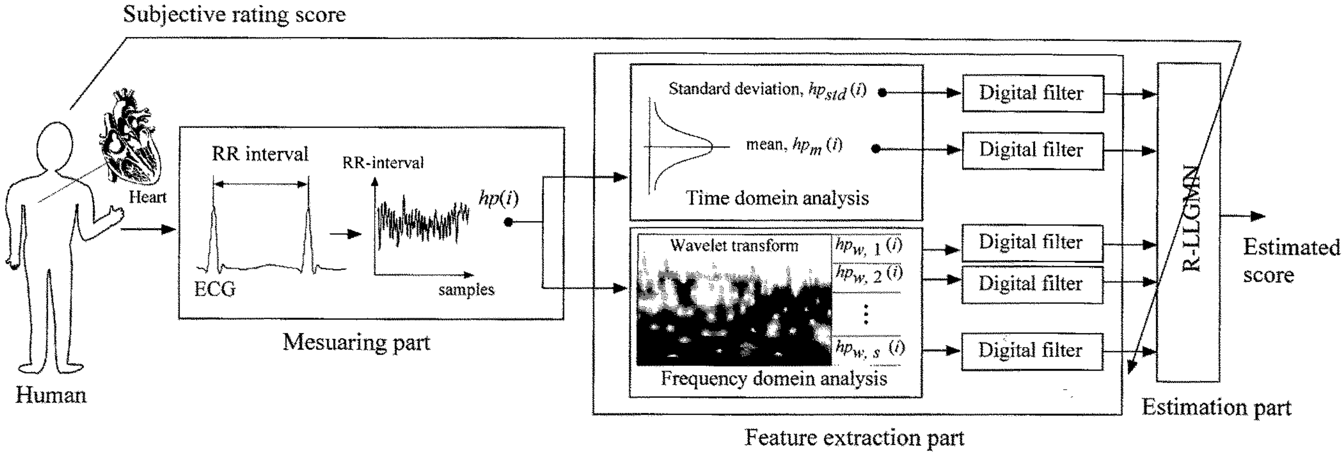


Fig. 1. Structure of the signal processing.

model (HMM)[14] in its structure and can modify the weight coefficients by the back-propagation through time (BPTT) algorithm[15]. Unlike HMM, the weight coefficients have no statistical constraints (e.g., $1 \geq$ transition probability ≥ 0, standard deviation ≥ 0), so R-LLGMN can realize a greater learning ability than HMM for even a small volume of training data.

This paper proposes a method of modeling HRV that constructs the individual model of HRV using the R-LLGMN. In the proposed method, the changes of HRV in the time-frequency domain are extracted by WT. Time histories of these changes, which correspond to many frequency components, are used for the input data of R-LLGMN because the changes of the spectrum pattern caused by physical and mental stress are complicated individually. Nonetheless, several frequency components are correlated with the autonomic nerves, respiration and so on. R-LLGMN includes the recurrent connection to cope with nonlinear and nonstationary characteristics. This network can extract the distinctive components correlated with the subject's condition, and model the complicated mapping between HRV pattern and a subject's condition through adaptation learning.

2. Modeling of HRV

Figure 1 shows the structure of the signal processing, consisting of the measuring part, the feature extraction part and the modeling part. The measuring part measures the HRV time series based on the R-R intervals, and the feature extraction part extracts the feature patterns of this time series in the time-frequency domain. The modeling part models the feature pattern using R-LLGMN. The details of each part are explained in the following subsections.

A Measuring part

The ECG is monitored with a 1.0[kHz] sampling frequency (Polygraph 360, NEC San-ei Instruments, Ltd.), and the HRV time series is sampled based on the R-R intervals. The HRV time series is then smoothed based on third-order spline curve fitting and resampled as $hp(i)$[ms] with a 2.0[Hz] sampling frequency, where i indicates the i-th sampled data.

B Feature extraction part

This part extracts the feature patterns from $hp(i)$. It first calculates the mean values $hp_m(i)(i \geq I_t)$ and standard deviations $hp_{std}(i)$ every I_t samples as time-domain information.

$$hp_m(i) = \sum_{i'=i-I_t+1}^{i} \frac{hp(i')}{I_t} \quad \ldots\ldots\ldots\ldots\ (1)$$

$$hp_{std}(i) = \sqrt{\frac{\sum_{i'=i-I_t+1}^{i} (hp(i') - hp_m(i))^2}{I_t}} \quad \ldots\ (2)$$

Multiple-frequency components are then extracted using WT as the frequency domain information[6,7]. Here, let us consider a continuous WT of $f(t)$. This transformation is defined as

$$(W_\psi f)(a_l,b) = \frac{1}{\sqrt{a_l}} \int f(t)\psi(\frac{t-b}{a_l})dt \quad \ldots\ldots\ (3)$$

where a_l is a scale parameter that selects the extracting frequency range, and b is a shift parameter that selects the extracting time period. $\psi(t)$ indicates a mother wavelet (Gabor function) defined as

$$\psi(t) = \frac{1}{2\sqrt{\pi\alpha}} \exp[-\frac{t^2}{4\alpha} + i\omega_0 t] \quad \ldots\ldots\ldots\ (4)$$

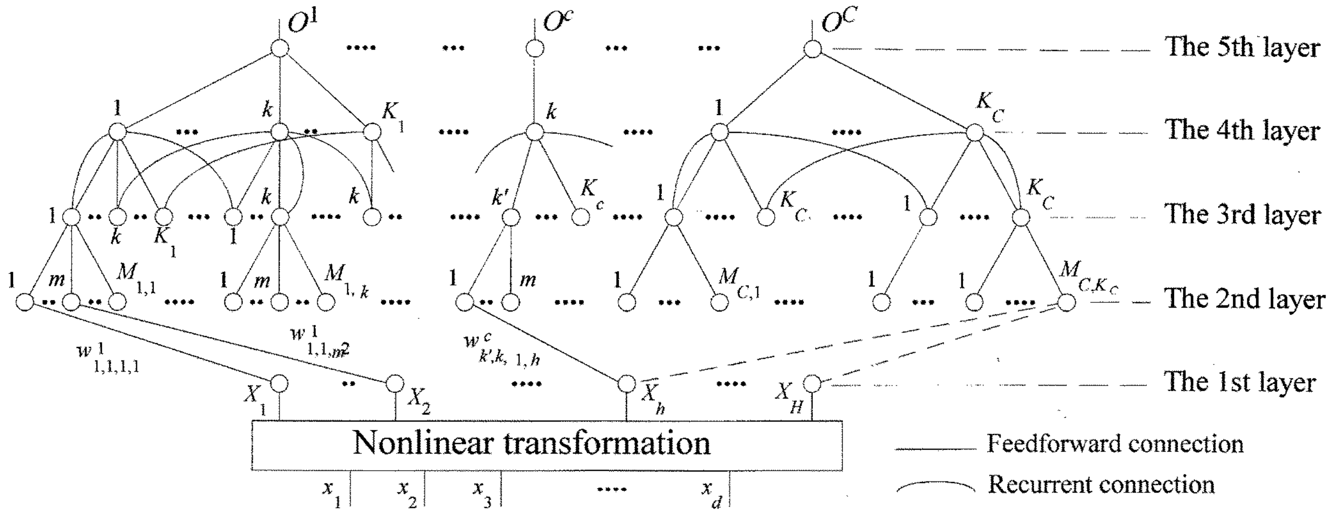


Fig. 2. Structure of R-LLGMN.

where the parameter ω_0 is set to $\omega_0 = 2\pi f_0, f_0 = 0.5$, and the parameter α, which regulates the time width of the Gabor function, is calculated as

$$\alpha = \frac{\pi^2}{\omega_0^2 \log 2} \quad \cdots\cdots\cdots (5)$$

The scale parameter a_l in (1) is calculated as $a_l = a_0^l (l = 1,2, \cdots, L-1)$. a_0 is defined as

$$a_0 = \exp\left[\frac{\log\omega_{max} - \log\omega_{min}}{L-1}\right] \quad \cdots\cdots\cdots (6)$$

where $\omega_{max} = \omega_0$, $\omega_{min} = 2\pi f_{\min}, f_{\min} = 0.01$ are the extracting maximum and minimum angular frequencies.

Using the above Eqs.(1)-(6), we calculate the power of WT $|(W_\psi f)(a_l,i)|$. The frequency components, which are calculated by the scale parameters $a_0 \sim a_{L-1}$, are divided into S equal ranges and averaged within each range. They are filtered out through the fourth order Butterworth filter (cut-off = C_f), and the smoothed signals $hp_{w,s}(i)$ ($s = 1,2, \cdots, S$) are extracted.

Finally, the feature patterns in the time-frequency domain $\boldsymbol{hp}(i)=[hp_m(i), hp_{std}(i), hp_{w,1}(i), hp_{w,2}(i), \cdots, hp_{w,s}(i)]^{\mathrm{T}}$ are normalized by the mean values during the rest, and resampled as $\boldsymbol{x}(n) = [x_1(n), x_2(n), x_3(n), \cdots, x_D(n)]^{\mathrm{T}} \in \Re^D$ every I_n samples, where n indicates the n-th feature pattern.

C Modeling part

R-LLGMN[13] is used in this part to cope with nonlinear and nonstationary characteristics of the HRV patterns caused by individual variations, physical conditions and so on. R-LLGMN includes HMM[14] in its structure, and can realize greater modeling ability than HMM for even a small volume of sample data because the weight coefficients of R-LLGMN have no constraints such as the statistical properties of HMM (e. g., 1 ≥ transition probability ≥ 0, standard deviation ≥ 0).

The structure of R-LLGMN is shown in **Fig.2**. This network is a five-layer network with recurrent connections between the third and the fourth layers. First, the input pattern $\boldsymbol{x}(n) = [x_1(n), x_2(n), \cdots, x_D(n)]^{\mathrm{T}} \in \Re^D$ ($n = 1,\cdots,N$) is converted into the modified vector $\boldsymbol{X} \in \Re^H$:

$$\begin{aligned} X(n) = [&1, x(n)^{\mathrm{T}}, x_1(n)^2, x_1(n)x_2(n), \cdots, \\ &x_1(n)x_D(n), x_2(n)^2, x_2(n)x_3(n), \\ &\cdots, x_2(n)x_D(n), \cdots, x_D(n)^2]^{\mathrm{T}} \end{aligned} \quad \cdots\cdots\cdots (7)$$

The first layer consists of H units corresponding to the dimension H, ($H = 1+D(D+3)/2$), and the identity function is used to activate each unit. The input ${}^{(1)}I_h(n)$ and output ${}^{(1)}O_h(n)$ in the first layer are defined as

$${}^{(1)}I_h(n) = X_h(n) \quad \cdots\cdots\cdots (8)$$

$${}^{(1)}O_h(n) = {}^{(1)}I_h(n) \quad \cdots\cdots\cdots (9)$$

The unit c, k, k', m ($c = 1, \cdots, C$; $k, k' = 1, \cdots, K_c$; $m=1, \cdots, M_{c,k}$) in the second layer receives the output of the first layer weighted by the coefficient $w^c_{k',k,m,h}$, where C is the number of classes, K_c is the number of states, $M_{c,k}$ is the number of the components of the Gaussian mixture distribution corresponding to the class c and the state k. The relationship between the input and the output in the second layer is defined as

$${}^{(2)}I^c_{k',k,m}(n) = \sum_{h=1}^{H} {}^{(1)}O_h(n) w^c_{k',k,m,h}, \quad \cdots\cdots\cdots (10)$$

$$^{(2)}O^c_{k',k,m}(n) = \exp(^{(2)}I^c_{k',k,m}(n)). \quad \quad (11)$$

The third layer integrates the outputs in the second layer and weights them by the previous output in the fourth layer. The input and output in the third layer are defined as

$$^{(3)}I^c_{k',k}(n) = \sum_{m=1}^{M_{c,k}} {}^{(2)}O^c_{k',k,m}(n), \quad \quad (12)$$

$$^{(3)}O^c_{k',k}(n) = {}^{(4)}I^c_{k'}(n-1)\,{}^{(3)}I^c_{k',k}(n), \quad \quad (13)$$

where $^{(4)}I^c_{k'}(0) = 1.0$ for the initial state.

The fourth layer receives the integrated outputs of units in the third layer. The relationship between the input and the output in the fourth layer is defined as

$$^{(4)}I^c(n) = \sum_{k'=1}^{K_c} {}^{(3)}O^c_{k',k}(n), \quad \quad (14)$$

$$^{(4)}O_k(n) = \frac{^{(4)}I^c(n)}{\sum_{c'=1}^{C}\sum_{k'=1}^{K_{c'}} {}^{(4)}I^{c'}_{k'}(n)} \quad \quad (15)$$

The unit in the fifth layer integrates the output of units in the fourth layer. The input and the output in the fifth layer are defined as

$$^{(5)}I^c(n) = \sum_{k=1}^{K_c} {}^{(4)}O^c_k(n), \quad \quad (16)$$

$$^{(5)}O^c(n) = {}^{(5)}I^c(n). \quad \quad (17)$$

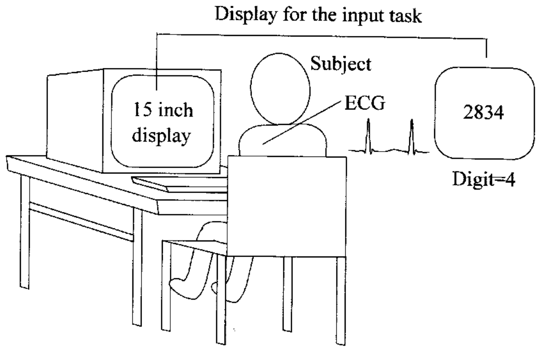
The output of R-LLGMN $^{(5)}O^c(n)$ indicates the *a posteriori* probability of the input pattern $\boldsymbol{x}(n)$ for the class c, which corresponds to the physical and mental condition. Note that, HMM is incorporated into this network through learning only the weight coefficient $w^c_{k',k,m,h}$.

As an energy function J for the network, we use

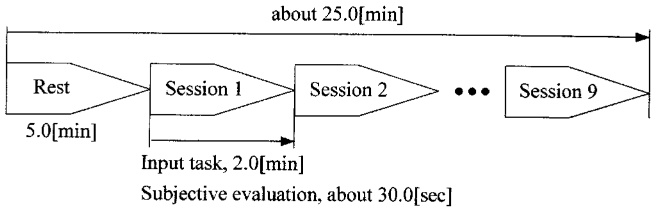
$$J = -\sum_{n=1}^{N}\sum_{c=1}^{C} T_c(n)\log{}^{(5)}O^c(n) \quad \quad (18)$$

where $T_c(n) = 1$ is the teacher signal for the particular class c and $T_c(n) = 0$ for all the other classes, and N indicates the number of learning samples. The learning is conducted to minimize this energy function, that is, to maximize the likelihood function.

We use the BPTT algorithm[15] to modify the weight coefficients $w^c_{k',k,m,h}$, because of the recurrent connections between the third layer and the fourth layer. The time history of the input pattern is considered from the previous N_s samples. Moreover the terminal attractor[10] is incorporated into BPTT to regulate the convergence time of the learning process.



(a) Experimental setup



(b) Time schedule of the experiment

Fig. 3. Experimental conditions.

3. Experiments

We conducted experiments to examine the modeling ability of the proposed method. Each subject was subjected to a mental workload as an example of mental stress, and the proposed method modeled a mapping between the subjective rating scores of their mental stress and HRV patterns. Changes of HRV patterns that were influenced by the same workload were evaluated based on this map.

A Experimental conditions

Experiments were conducted with five subjects (male/female=4/1, age = 31.6 ± 5.5). We explained the experimental protocol and obtained written consents from all subjects. The experimental setup is shown in **Fig.3(a)**. Subjects were seated at a desk, and a color display (15 inch, HMD-A101, Sony Corp.) was set at a distance of 60[cm] from their eyes. The ECG signal was measured based on the bipolar derivation method. Integer numerals were displayed for 2.0[sec] in the center of the display, and subjects were asked to input the same number after the number faded out. The font size of the displayed numbers was 54[point], and a numerical pad on the key-

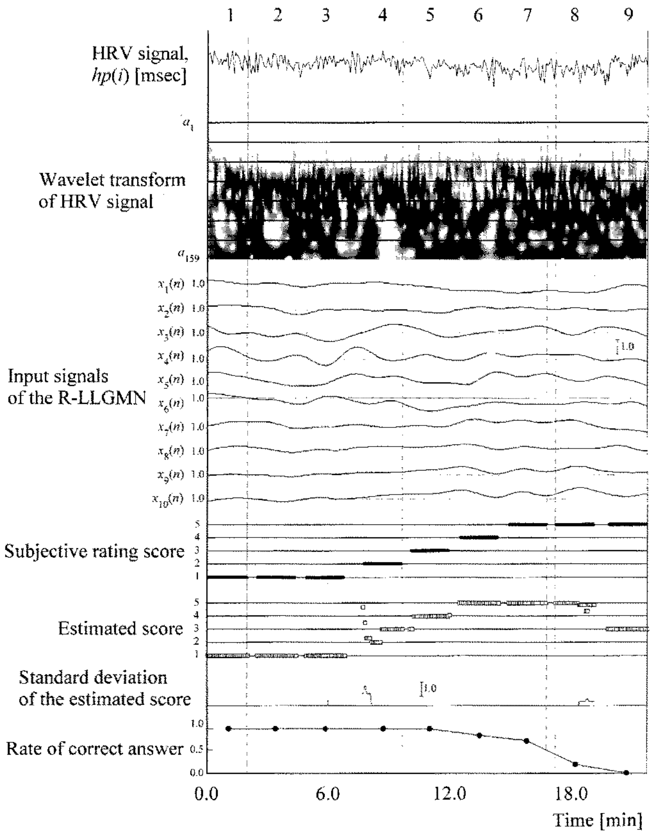


Fig. 4. An example of the evaluation results.

board was used for the input. During experiments, there was no indication of the subject's respiration, and changes of HRV pattern, which were influenced by the respiration, were regarded as the individual features and used for modeling. This method is suitable for a monitoring system in the home environment because we do not have to be concerned about respiration.

The time schedule is shown in **Fig.3(b)**. Subjects were asked to take a rest for 5.0[min], after which sessions 1~9 were executed. Each session consisted of the input task (2.0[min]) and the subjective evaluation (about 30.0[sec]). The digit of the displayed numbers was equal to the session number, and the number was displayed for 2.0[sec]. The subjective evaluation of the mental stress was expressed in five levels, where Level 5 indicated the most stressful conditions. Each subject executed two sets of this time schedule. The pattern extracted in the first set was used as the modeling data, and one pattern in the second set was used as the evaluation data.

The parameters in the feature extraction part were set to I_t=5.0[sec], I_n=5.0[sec], C_f=0.005[Hz], S=8, D=10. The scale parameter of WT, which selects the extracting frequency range, was L=160, where l=159, l=131, and l=0 corresponded to 0.01[Hz], 0.25[Hz], and 0.5[Hz]. In the modeling part, the number of output units corresponded to one of the stress levels. There were N=180(20 in each session) samples for modeling. The time history of the input pattern was considered from the previous N_s=5 samples in BPTT.

B Experimental results

Figure 4 shows an example of the experimental result, showing digits of the displayed numbers (session numbers), the HRV signal, WT of the HRV signal, input signals of R-LLGMN, subjective rating scores, mean values of the estimated scores, standard deviations of the estimated scores, and rates of correct answer. WT of the HRV signal is darkened as its power increases. The mean values and the standard deviations of the estimated scores are calculated for 10 randomly chosen initial weight coefficients.

Our proposed method estimated the gradual increase of the mental stress successfully, though the estimated scores increased earlier than the subjective rating scores. The standard deviations of the estimated scores were quite small. The correlation coefficient between subjective rating scores and the estimated scores was 0.89. The estimation accuracy decreased remarkably when "9" was displayed. In this case, the task difficulty seemed to saturate the subject's ability.

Next, the same experiment was conducted for five subjects. The results of Subject E correspond to **Fig.4**. To compare our method with previous methods, we examined $CV_{R\text{-}R}$, LF/HF that were frequently used in a clinic and the previous research. **Table 1** shows the results. We calculated these values every period where the subjective rating score was the same level. The mean values and the standard deviations are shown for LF/HF.

In this experiment, we cannot see a correlation between the HRV patterns and $CV_{R\text{-}R}$, LF/HF, so it is difficult to find the mapping between these values.

The results evaluated by the proposed method are shown in **Table 2**. The results of Subject E correspond to **Fig.4**. The table shows the subjective rating scores, estimated scores, and the rates of correct answers for sessions 1~9. We calculated the mean values and the standard deviations of the estimated scores for 10 initial weight coefficients.

We see from **Table 2** that the changes in the subjective rating score and the rate of correct answers differed among individuals. Under such situations, the proposed method successfully estimated a gradual increase of the mental stress. The correlation coefficients between subjective rating scores and the estimated scores were 0.92 ~0.89. The evaluation performance of Subject D decreased as shown in **Fig.4** (Subject E) during Session 9.

4. Conclusion

We have proposed a method of modeling heart rate variability. This method extracts the feature patterns of HRV using WT; R-LLGMN modeled and evaluated these patterns. In experiments, the subjective rating scores of the subject's mental stress were evaluated highly accurately.

Table 1. Changes of the HRV indices during the experiments.

Subjects	Digit	1	2	3	4	5	6	7	8	9	
A	Subjective rating score	1	1	1	1	2	3	4	5	5	
	ES_m	1.27	1.09	1.00	1.16	2.73	3.12	2.95	4.57	5.00	$Cor = 0.921$
	ES_{std}	0.44	0.41	0.00	0.53	0.64	0.33	0.32	1.24	0.00	
	Rate of correct answer	1.00	1.00	1.00	1.00	0.95	0.89	0.67	0.40	0.00	
B	Subjective rating score	1	2	3	3	3	4	4	5	5	
	ES_m	1.23	1.65	2.95	3.00	2.25	3.79	4.28	5.00	5.00	$Cor = 0.920$
	ES_{std}	0.51	0.48	0.21	0.00	1.79	0.72	0.57	0.00	0.00	
	Rate of correct answer	1.00	1.00	1.00	1.00	0.96	0.84	0.78	0.86	0.26	
C	Subjective rating score	1	2	2	2	3	4	5	5	5	
	ES_m	1.00	2.00	2.00	2.00	3.53	3.00	4.73	5.00	5.00	$Cor = 0.890$
	ES_{std}	0.00	0.00	0.00	0.00	0.89	1.42	0.68	0.00	0.00	
	Rate of correct answer	1.00	1.00	1.00	1.00	0.96	0.82	0.45	0.29	0.04	
D	Subjective rating score	1	1	2	3	4	5	5	5	5	
	ES_m	1.55	1.01	1.00	3.49	4.38	5.00	5.00	5.00	3.41	$Cor = 0.855$
	ES_{std}	0.89	0.12	0.00	0.49	0.49	0.00	0.00	0.00	0.81	
	Rate of correct answer	1.00	1.00	1.00	0.93	0.78	0.40	0.19	0.07	0.00	
E	Subjective rating score	1	1	1	2	3	4	5	5	5	
	ES_m	1.00	1.00	1.00	2.74	3.93	5.00	5.00	4.97	3.00	$Cor = 0.888$
	ES_{std}	0.00	0.00	0.00	1.12	0.25	0.00	0.00	0.16	0.00	
	Rate of correct answer	1.00	1.00	1.00	1.00	1.00	0.86	0.74	0.19	0.00	

ES_m : Mean values of the estimated score
ES_{std} : Standard deviations of the estimated score
Cor : Correlation coefficient between subjective rating score and estimated score

Table 2. Evaluation results by the proposed method.

Subjects	Subjective rating score	1	2	3	4	5
A	CV_{RR}	4.6	4.4	5.2	5.0	4.0
	LF/HF	11.5 ± 3.3	16.1 ± 5.6	11.3 ± 1.0	15.4 ± 2.4	11.5 ± 2.6
B	CV_{RR}	4.2	4.9	4.7	5.0	4.6
	LF/HF	6.5 ± 1.5	3.2 ± 0.8	6.4 ± 2.6	4.5 ± 2.0	4.6 ± 1.7
C	CV_{RR}	6.9	8.3	6.1	6.2	6.6
	LF/HF	36.3 ± 4.3	80.4 ±13.7	23.4 ±13.2	22.4 ± 1.1	41.1 ±10.1
D	CV_{RR}	4.1	4.5	3.8	3.6	4.7
	LF/HF	33.4 ± 8.4	33.8 ± 4.2	22.5 ± 4.7	20.7 ± 4.3	30.0 ± 3.7
E	CV_{RR}	5.3	5.1	4.3	3.9	5.5
	LF/HF	9.5 ± 2.8	4.3 ± 1.7	8.9 ± 0.3	8.7 ± 2.3	19.0 ± 6.1
Total	CV_{RR}	5.0 ± 1.2	5.4 ± 1.6	4.8 ± 0.9	4.7 ± 1.0	5.1 ± 1.0
	LF/HF	19.4 ± 4.0	27.5 ± 5.2	14.5 ± 4.3	14.3 ± 2.4	21.2 ± 4.8

$$CV_{RR} = \frac{\text{Standard deviation of the R-R Intervals}}{\text{Mean value of the R-R Intervals}} \times 100\%$$

LF/HF LF: Power of low band frequency calculated by the wavelet transform
HF: Power of high band frequency calculated by the wavelet transform

We hope to evaluate changes in HRV patterns for a long period based on the proposed method. We will try to measure the HRV pattern every month and determine whether the HRV pattern fits the model constructed the previous month. We may detect unusual physical conditions in this way. The results of the short-period experiments in this paper will be useful for later long-period experiments. Also, we would like to develop a healthcare system incorporating the proposed method to help people lead healthy lives.

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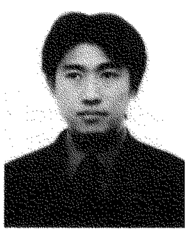

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Research Scientist Assistive Device Technology Group, Institute for Human Science and Biomedical Engineering, National Institute of Advanced Industrial Science and Technology (AIST)

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Brief Biographical History:
2000- Received the Ph. D. from Hiroshima University
2000- Mechanical Engineering Laboratory
2001- National Institute of Advanced Industrial Science and Technology

Main Works:
- Neural networks
- Pattern discrimination of the bioelectric signals
- Assistive devices for the handicapped

Membership in Learned Societies:
- The Japan Society of Mechanical Engineers (JSME)
- The Robotics Society of Japan (RSJ)
- The Institute of Electronics, Information and Communication Engineers (IEICE)
- Japan Ergonomics Society (JES)

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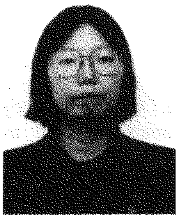
Brief Biographical History:
1986- Joined Mechanical Engineering Laboratory, AIST, MITI Assigned to Advanced Technology Division
1994- Assigned to Human Support Technology
2001- Joined National Institute of Advanced Industrial Science and Technology

Main Works:
- "The Influence of the Motion of Powered Ceiling Hoists on the Subjective Sense of Safety," The Japanese Journal of Ergonomics, Vol.36, No.4, 5-8, 2000.

Membership in Learned Societies:
- Japan Ergonomics Society
- The Japan Society for Precision Engineering



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Brief Biographical History:

1989- Joined Mechanical Engineering Laboratory

1995-1996 Visiting Researcher, Helsinki University of Technology (Finland)

2001- Senior Research Scientist, National Institute of Advanced Industrial Science and Technology

Main Works:

- "Study of a Wire-driven Leg Rehabilitation System," Proceedings of IEEE/RSJ Conference on Intelligent Robots and Systems 2002 (To be presented).

Membership in Learned Societies:

- The Robotics Society of Japan (RSJ)
- The Society of Instrument and Control Engineers (SICE)
- The Society of Life Support Technology
- Society of Biomechanisms Japan
- The Japan Society for Precision Engineering (JSPE)
- The Japanese Society for Wellbeing Science and Assistive Technology

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Brief Biographical History:

1985-1994 Research Associate in Faculty of Engineering at Hiroshima University

1994-2001 Associate Professor of Department of Industrial and Systems Engineering at Hiroshma University

2002- Full Professor of Department of Artificial Complex Systems Engineering at Hiroshima University

1992-1993 Visiting Professor of University of (Genova, Italy)

Main Works:

- Biological motor control
- Computational neural sciences
- Human-machine interface

Membership in Learned Societies:

- The Institute of Electrical and Electronics Engineers (IEEE)
- The Japan Society of Mechanical Engineers (JSME)
- The Robotics Society of Japan (RSJ)
- The Institute of Electronics, Information and Communication Engineers (IEICE)
- Japan Ergonomics Society (JES)