EVALUATION OF HEART RATE VARIABILITY BY USING
WAVELET TRANSFORM AND A RECURRENT NEURAL NETWORK

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Abstract- **The purpose of this paper is to evaluate the physical and mental stress based on the physiological index, and a new evaluation method of heart rate variability is proposed. This method combines the wavelet transform with a recurrent neural network. The features of the proposed method are as follows: 1. The wavelet transform is utilized for the feature extraction so that the local change of heart rate variability in the time-frequency domain can be extracted. 2. In order to learn and evaluate the different patterns of heart rate variability caused by individual variations, body conditions, circadian rhythms and so on, a new recurrent neural network which incorporates a hidden Markov Model is used. In the experiments, a mental workload was given to five subjects, and the subjective rating scores of their mental stress were evaluated using heart rate variability. It was confirmed from the experiments that the proposed method could achieve high learning/evaluating performances.**

Keywords- **Heart rate variability, Mental stress, Wavelet transform, Recurrent neural network, Hidden Markov model.**

I INTRODUCTION

An electrocardiogram (ECG) is available for a basic physiological index which evaluates the change in patient's body condition and monitors physical and mental stress in his/her daily activities. The heart rate is complicated since it is affected by various factors such as a sinus node for a pacemaker, autonomic nerves, the endocrine system and so on. It is expected that the changes of these factors can be evaluated based on the analysis of Heart Rate Variability (HRV). In this paper, we propose a new evaluation method of HRV.

HRV includes many frequency components, and various information can be obtained from them through the frequency domain analysis [1], [2]. In the report of Sayers, which is the pioneer research in this area, three peaks exist on the power spectrum of HRV. The lower frequency component $(0.02-0.06[Hz])$ is influenced by thermoregulation, and the middle frequency component $(0.07-0.14[Hz])$ is influenced by blood pressure regulation, and the high frequency component $(0.15-0.50[Hz])$ is influenced by respiration respectively. However, if the power spectrum of HRV is calculated using 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 the

exercise. To overcome this difficulty, The wavelet transform (WT), which extracts local features of HRV in the time-frequency domain, is proposed [3].

The changes in the spectrum pattern from physical and mental stress are different among individuals. The subjective feeling of the subjects is also different. These are the problems of the spectrum analysis of HRV. Most previous studies defined specified frequency ranges such as the low frequency component (LF) and the high frequency component (HF) on 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 ranges, scales and speeds of the changes in the spectrum are affected by various factors such as individual variations, body conditions, circadian rhythms and so on.

On the other hand, some approaches using a neural network have been attempted. These approaches have realized the adaptive signal processing of the ECG. Minami et al. combined the feature extraction by Fourier transform and a back-propagation neural network (BPN) [4], and detected the tachyarrhythmia in real-time. Fahoum et al. combined the WT and an RBF neural network (RBFN), in order to detect life-threatening cardiac arrhythmias [5]. The purpose of these reports was to detect the abnormal waveform on the ECG. The fact that HRV caused by physical and mental stress, etc. was not stated. Also, there is a problem in that large numbers of training data and learning iterations are needed, if the BPN is utilized for the processing of a complicated signal.

Authors have developed a new statistical neural network called Log-Linearized Gaussian Mixture Network (LLGMN) [6], [7]. This network is structured based on a Gaussian mixture model and a log-linear model, and can achieve higher performance in discriminating for electroencephalograms and electromyograms than other neural networks. The LLGMN can learn the changes of the signal patterns due to the differences among individuals, different locations of the electrodes, time variations caused by fatigue or sweat, and so on. Authors also proposed the Recurrent Log-Linearized Gaussian Mixture Network (R-LLGMN) [8]. The R-LLGMN uses the recurrent connection added to the units of the LLGMN in order to discriminate a time sequence of the signals with high accuracy. The R-LLGMN includes a hidden Markov Model (HMM) [9] in its structure and can modify the weight coefficients by the back-propagation through time (BPTT) algorithm [10]. The weight coefficients have no statistical constraints like the HMM (e. g., $1 \geq$ transition probability ≥ 0, standard deviation ≥ 0), so that the R-LLGMN can realize a higher learning ability than the HMM for even a small

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Abstract

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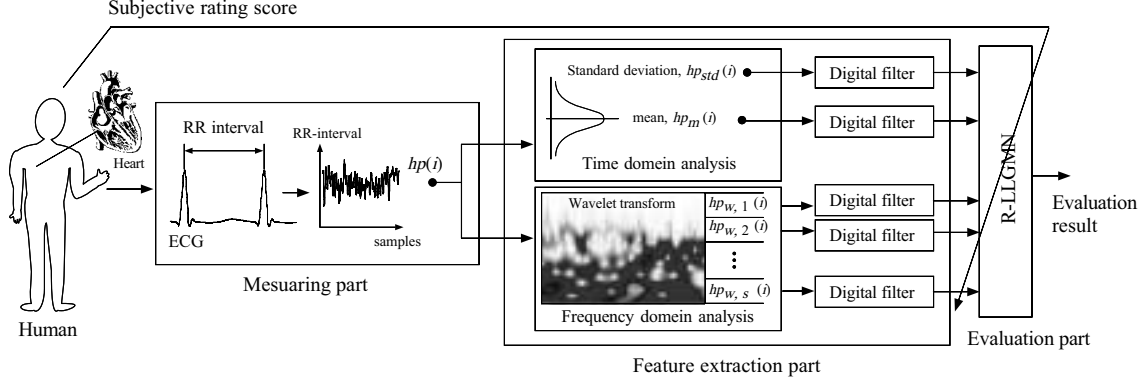| Classification of Abstract	Limitation of Abstract
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Fig.1 Structure of the signal processing.

number of training data.

This paper proposes a new evaluation method of HRV, which can evaluate the physical and mental stress based on the physiological index. In the proposed method, the local changes of HRV in the time-frequency domain are extracted by the WT, and they are used for the input data of the R-LLGMN. The R-LLGMN incorporates the HMM and can evaluate HRV patterns, which are affected by various factors such as individual variations, body conditions, circadian rhythms and so on.

II   EVALUATION METHOD OF HRV

Figure 1 shows the structure of the signal processing, which consists of the measuring part, the feature extraction part and the evaluation 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 evaluation part learns and evaluates the feature pattern using the R-LLGMN. The details of each part are explained in the following sections.

A   Measuring part

The ECG is monitored with 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. Then, it is smoothed according to the 3rd order spline curve fitting and re-sampled as $hp(i)$[msec] with 2.0[Hz] sampling frequency, where i indicates the i-th sampled data.

B   Feature extraction part

This part extracts the feature patterns from $hp(i)$. First, the mean values $hp_m(i)$ $(i \geq I_t)$ and standard deviations $hp_{std}(i)$ are calculated every I_t [sec] as the time domain information. Then, multiple frequency components are extracted using the WT as the frequency domain information [3]. Here, let us consider a continuous WT of $f(t)$. This transformation is defined as

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

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

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

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

$$\alpha = \frac{\pi^2}{\omega_0^2 \log 2}. \qquad (3)$$

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

$$a_0 = \exp[\frac{\log \omega_{max} - \log \omega_{min}}{L-1}], \qquad (4)$$

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 equations (1) $\sim$ (4), the power of WT $|(W_\psi f)(a_l, i)|$ is calculated. 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 4th 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 $\boldsymbol{hp}(i) = [hp_m(i), hp_{std}(i), hp_{w,1}(i), hp_{w,2}(i), \cdots, hp_{w,S}(n)]^T$ are normalized by the mean values during the rest, and re-sampled as $\boldsymbol{x}(n) = [x_1(n), x_2(n), x_3(n), \cdots, x_D(n)]^T \in \Re^D$ every I_n [sec], where n indicates the n-th feature pattern.

C   Evaluation part

The R-LLGMN [8] is used in this part in order to cope with non-linear and non-stationary characteristics of the HRV patterns caused by individual variations, body conditions, circadian rhythms and so on. The R-LLGMN includes the HMM [9] in its structure, and can realize higher learning ability than the HMM for even a small number

of training data because the weight coefficients of the R-LLGMN have no constraints such as the statistical properties of the HMM (e. g., $1 \geq$ transition probability ≥ 0, standard deviation ≥ 0). The R-LLGMN receives the feature patterns $x(n)$ and outputs the *a posteriori* probability for the class, which corresponds to the state of physical and mental stress.

Before evaluation of the input patterns, the R-LLGMN must be learned. The BPTT algorithm [10] is used because of the recurrent connections. The time history of the input pattern is considered from the previous N_s samples. Moreover the terminal attractor [6] is incorporated with the BPTT in order to regulate the convergence time of the learning process.

III EXPERIMENTS

The experiments were carried out in order to examine the ability of the proposed method. The mental workload, as an example of the physical and mental stress, was given to the subjects, and the subjective rating scores of the mental stress were estimated using the HRV patterns.

A Experimental conditions

The experiments were performed for five subjects (male/female=4/1, age = 31.6 ± 5.5). They were seated at a desk, and a color display (15 inch, HMD-A101, Sony Corp.) was set at a distance of 60[cm] apart from their eyes. Integer numerals were displayed for 2.0[sec] in the center of the display, and the subjects were asked to input the same number after fading out the number. The font size of the displayed numbers was 54[point], and a ten-key pad of the keyboard was used for the input. During the experiments, the ECG signal was measured based on the bipolar derivation method, and there was no indication of the subject's respiration.

The subjects were asked to take a rest for 5.0[min]. Then, the sessions $1 \sim 9$ were executed. Each session consisted of the input task (2.0[min]) and the subjective evaluation (about 30.0[sec]). The digit of 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 carried out two sets of this time schedule. The pattern which was extracted in the first set was used as the learning data, and one pattern in the second set was used as the evaluation data.

The parameters in the feature extraction part were settled as $I_t = 5.0[\text{sec}]$, $I_n = 5.0[\text{sec}]$, $C_f = 0.005[\text{Hz}]$, $S = 8$, $D = 10$. The scale parameter of the WT, which selects the extracting frequency range, was $L = 160$, where $l = 159$, $l = 131$, $l = 0$ corresponded to 0.01[Hz], 0.25[Hz], 0.5[Hz] respectively. In the evaluation part, the number of output units corresponded to the one of the stress levels. The number of learning samples was $N = 180$(20 in each session). The time history of the input pattern was considered from the previous $N_s = 5$ samples in the BPTT.
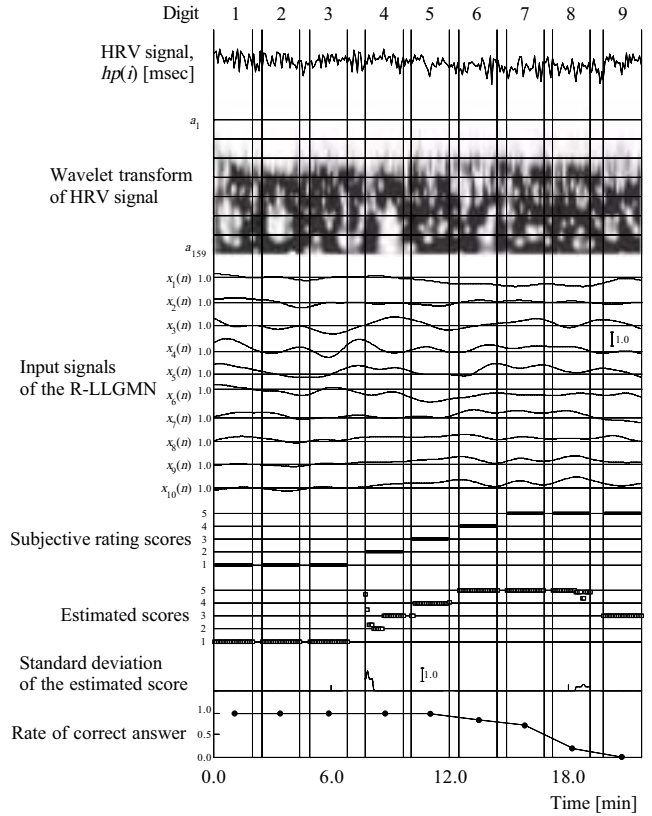
B Experimental results

Fig.2 An example of the evaluation results

Figure 2 shows an example of the experimental result, which shows: digits of the displayed numbers (session numbers), the HRV signal, the WT of the HRV signal, input signals of the R-LLGMN, subjective rating scores, mean values of the estimated scores, standard deviations of the estimated scores and rates of correct answer. The 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 kinds of initial weight coefficients, which are randomly chosen.

It can be seen that the R-LLGMN estimated the gradual increase of the mental stress successfully, though the estimated scores of the R-LLGMN increased earlier than the subjective rating scores. The standard deviations of the estimated scores were considerably small. The correlation coefficient between subjective rating scores and the estimated scores was 0.89. The estimation accuracy of the R-LLGMN remarkably decreased when digits of the displayed number was 9. In this case, the difficulty of the task seemed to saturate the ability of the subject.

Next, the evaluation results for five subjects are shown in Table 1. The results of Subject E corresponds to the Fig. 2. The table shows the subjective rating scores, estimated scores and the rates of correct answers for the sessions $1 \sim 9$. The mean values and the standard deviations of the estimated scores were calculated for 10 kinds of initial weight coefficients.

Subjects	Digits	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 1 Experimental results for five subjects.

We see from the table that the changes in the subjective rating score and the rate of correct answer were different among individuals. Under such situations, the R-LLGMN estimated the gradual increase of the mental stress successfully. The correlation coefficients between subjective rating scores and the estimated scores were 0.92 ~ 0.89. The evaluation performance of Subject D decreased like Fig. 2 (Subject E) during Session 9.

IV CONCLUSION

This paper proposed a new evaluation method of heart rate variability in order to evaluate the physical and mental stress based on the physiological index. In this method, the feature patterns of HRV were extracted by using the WT, and the R-LLGMN learned and evaluated these patterns. In the experiments, the subjective rating scores of the subject's mental stress were evaluated with high accuracy.

In the future, we would like to develop a monitoring system, which incorporates the proposed method, in order to evaluate HRV patterns in daily life.

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