A Novel Method to Monitor Human Stress States using Ultra-Short-Term ECG Spectral Feature

Bosun Hwang[1], Ji Woo Ryu[2], Cheolsoo Park[2], Byoung-Tak Zhang[1]
School of Computer Science and Engineering, Seoul National University[1]
Computer Engineering Department, KwangWoon University[2]

***Abstract*— Electrocardiogram (ECG) signal represents autonomous nervous system responses to human emotional states. This research demonstrates that the spectral ECG features within ultra-short-term window duration (10-sec) could be utilized to monitor the human emotional states. Experiments were conducted with five stress protocols. Experimental results showed better classification performance of ECG spectral features compared to those of HRV parameters (74%). The averaged accuracy across 13 subjects and all stress protocols was 81.16% using Naïve Bayes algorithm. In addition, the results showed arithmetic stress situation was the most separable from resting state (87.31%) compared to the other stress situations.**

I. Introduction

Human mental stress in daily life is significantly related to health condition [1], and thus continuous stress monitoring in life has become crucial for health monitoring. Among various physiological signals, ECG could be a good candidate to measure stressful states, due to its high correlation with autonomous nervous system reflecting stressful responses of the human body [2].

There have been several researches demonstrating stress monitoring systems using Heart Rate Variability (HRV) parameters [2][4]. However, HRV parameters demand relatively long time period to produce meaningful estimation of physiological status, usually 5-min long data segment [3]. However, in order to develop a practical and real-time stress monitoring system considering ambient noise and motion artifact, the current time length of ECG measurement is too long. Therefore, this study suggests a novel ECG spectral feature, extracted within ultra-short-term period [3] and representing the characteristics of ECG. The spectral features within 10-sec window could be a replacement of the HRV features, and the experimental results in this paper proved it yielded higher classification performance to detect stressful conditions compared to those of HRV.

II. Experiments

A. Subjects and Data Acquisition

Healthy 13 subjects participated in this study and each subject's data was analyzed by individually. Experiments were conducted in indoor laboratory environment. BIOPAC MP36 was used to record ECG signals. Vc+, Vc- and GND electrodes were attached on the right/left arms and right ankle respectively.

B. Experimental Protocols for Stress Conditions

We designed the five experimental protocols to elicit stressful states. The protocols consisted of Arithmetic, Stroop CWT, Interview, Visual Stimuli and Cold Pressor [5]. The detailed descriptions are shown in below Table I.

TABLE I. EXPERIMENAL PROTOCOLS

Protocols	***Description***
Arithmetic	Subtract 13 from 1022, starting from the beginning when wrong
Stroop CWT	Stress test using colored words
Interview	Short interview with various questions
Visual	Visual test using the negative videos
Cold Pressor	Press ice on skin for a short period of time

The experimental procedure for each subject was followed below Table II.

TABLE II. EXPERIMENTAL PROCEDURES

No.	***Test sessions***	***Duration(min)***
1	*Pre-test*	5
2	***Arithmetic***	5
3	*Resting*	2
4	***Stroop CWT***	5
5	*Resting*	2
6	***Interview***	10
7	*Resting*	2
8	***Visual***	5
9	*Resting*	2
10	***Cold pressor***	1
11	*Resting*	2
12	***Post-test***	5
Total		46

During the protocol number 12, Post-test, subjects talked casually without any stress as a control experiment compared to the stressful talking sessions. Since all the stress protocols could be affected by light movement artifacts due to the talks particularly during the sessions of Arithmetic, Stroop CWT and Interview. A similar situation such as the casual talking protocol without stressful conditions were prepared. In this study, this Post-test protocol was compared with the others as a resting state. In addition, the protocol number 10, Cold Pressor, was conducted only for 1 minute since the subjects could not last more than that due to the pain by the coldness of the ice water.

III. Feature Extraction

Previously, HRV (Heart Rate Variability) parameters have been widely used as a standard ECG features [2][3][7], which demanded long-term datasets of the ECG signal, 5 minutes long in general. This has been an obstacle to develop a real-time practical ECG monitoring system in our daily life due to the difficulty to obtain a stable long-term 5 minutes ECG signal with standing still. Recently, H. Baek *et al*. investigated the meaningful length of ECG signal to yield similar performance as long-term one with shortening the time segment, and eventually proved 10 seconds duration HRV parameters were also significant.

Thus we decided to use the spectral feature of ECG in a 10 seconds window using spectrogram.

A. Signal Preprocessing

Signal preprocessing was conducted to extract low frequency components, since ECG signal has most information in relatively lower frequency band [8]. FIR band pass filter (0.1~150Hz) was preceded 60Hz notch filter, eliminating the power line noise.

B. HRV Parameters

The HRV features of ECG signal were extracted to compare with this study using the ultra-short-term (10 seconds long) spectral features. The detailed description of each parameter are explained in Figure 1.

Category	Feature	Description
Time-domain HRV Features	meanNN	Mean average NN intervals
	SDNN	Standard deviation of NN intervals
	RMSSD	Square root of the mean average of the sum of the square of NN intervals
	SDSD	Standard deviation of the difference of the NN intervals
	NNx_count	Mean number of times an hour in which the change in NN intervals exceeds x (ms)
	pNNx	Percentage of absolute differences in successive NN values > x (ms)
Frequency-domain HRV Features	TF	TF (total frequency), Power of Range 0.14-0.4Hz of the PSD of NN intervals
	VLF	VLF (very low frequency), Power of Range 0-0.04Hz
	LF	LF (low frequency), Power of Range 0.04-0.15Hz
	HF	HF (high frequency), Power of Range 0.15-0.4Hz
	LFn	Proportion of LF to LF+HF of Range 0.04-0.4Hz
	HFn	Proportion of HF to LF+HF of Range 0.04-0.4Hz
	LFHF	Proportion of LF to HF
Nonlinear HRV Features	SD1 SD2	Poincare self-similarity function using difference (SD1) and Sum (SD2)
	SD1n, SD2n	Poincare feature which uses the normalized data
	ApEn15, ApEn20	Approximate entropy. Reflects the similarity and predictability of the data, ApEn15 and ApEn20 generally use the 0.15 STD and 0.2 STD
	SampEn15, SampEn20	Sample entropy. Calculation is similar to approximate entropy, but excludes self counting so that it is more stable for variability of data lengths
	Alpha1, Alpha2	De-trended fluctuation analysis (DFA). Measures the statistical self-affinity of a signal

Figure 1: HRV feature description

C. Spectral Features (Spectrogram)

The main spectral feature was extracted using the spectrogram, the short-time Fourier transform of a time series. The power information in the frequency domain was utilized as the main feature in this study. The time window was set to 10 seconds based on the investigation by Beak *et al.* [3]. A spectral feature example corresponding to stress states is shown in Figure 2.

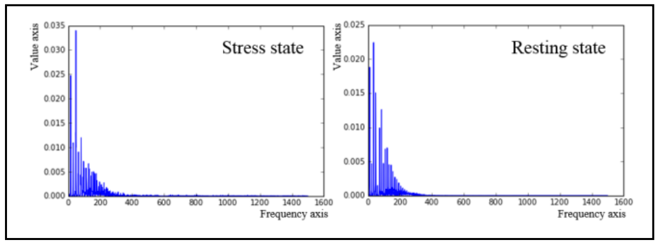

Figure 2: Spectral feature example

IV. Classification Methods

Several machine learning classification algorithms were applied to investigate the performance 10 seconds window spectral features to separate the stressful and resting conditions. The scikit-learn machine learning library and data mining software Weka were used as main analysis tools [11][12]. 5-fold cross validation was applied to measure the classification accuracies. The algorithms are listed in Table III.

TABLE III. Applied Classification Algotirhms

Software tools	***Classification algorithms***
Python scikit-learn library	KNeighbors
	Linear SVM
	RBF SVM
	Gaussian Process
	Decision Tree
	Random Forest
	Neural Network
	AdaBoost
	Naïve Bayes
	Quadratic Discriminant Analysis
Weka	DTNB
	Hoeffding Tree
	NBTree

V. Experimental Results

This study investigated the binary classification problem between the stressful and resting states using the aforementioned spectral features. At first, the experiment using HRV parameters with varying the length of window was conducted for the benchmark test with this study. Figure 3 shows the classification accuracy corresponding to the various time window size from 30 seconds to 4 minutes. The accuracy was achieved using 5-fold cross validation. As can be seen in Figure 3, one minute time window shows the best accuracy, 74%.

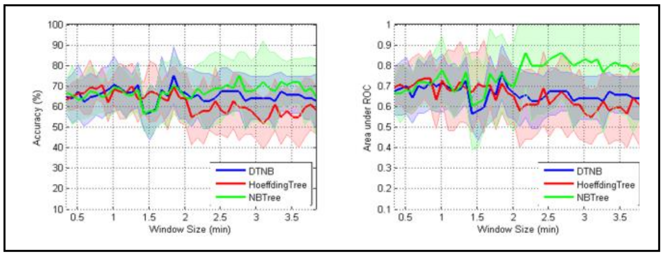

Figure 3: Classification result using HRV parameters

Secondly, the target experiment was taken using the ultra-short-term spectral feature. 5-fold cross validation was also conducted corresponding to the experimental protocols. The performances of the various machine learning classifiers were shown in Table IV, which demonstrates Naïve Bayes and ensemble machines (AdaBoost) yielded higher performances on emotional stress state classification problem using the ultra-short-term spectral feature than the others.

TABLE IV. PERFORMANCE COMPARISONS OF CLASSIFICATION ALGORITHMS ON EXPERIMENTAL PROTOCOLS

Accuracy (%)	Arith-metic	Stroop CWT	Inter-view	Visual	Cold Pressor	Algorithm Mean
KNeighbors	72.31	63.44	66.62	77.69	74.23	70.86
Linear SVM	76.13	66.54	68.03	78.41	75.00	72.82
RBF SVM	69.51	65.03	66.21	70.23	67.69	67.73
Gaussian Process	77.92	69.26	69.31	80.46	77.69	74.93
Decision Tree	78.38	76.97	68.31	77.54	86.92	77.62
Random Forest	79.67	71.64	68.74	66.59	85.77	74.48
Neural Network	78.23	71.31	70.49	81.28	82.69	76.80
AdaBoost	82.15	80.08	73.59	81.85	82.69	80.07
Naïve Bayes	87.31	81.10	75.87	79.97	81.54	81.16
Quadratic Discriminant Analysis	58.31	58.82	58.62	65.90	61.54	60.64
Protocol Mean	75.99	70.42	68.58	75.99	77.58	73.71
Protocol Max	87.31	81.10	75.87	81.85	86.92	82.61

Interestingly, the Arithmetic protocol showed the best classification performance, which might infer the mental burden could make stressful state in human body.

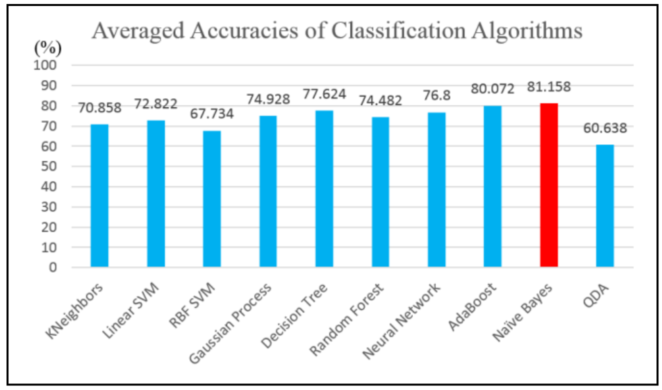

Figure 4: Summary of Algorithm Performance Comparison

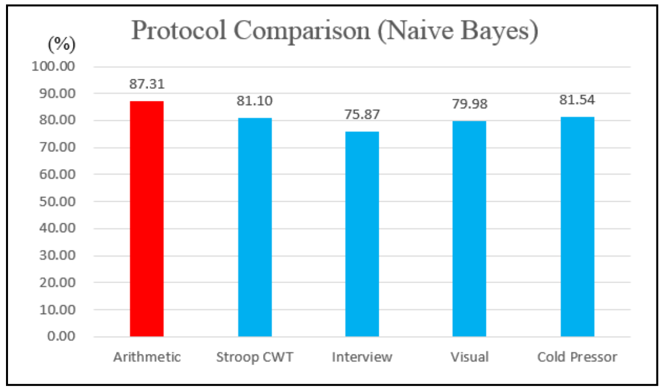

Figure 5: Protocol Comparison Result (Naïve Bayes)

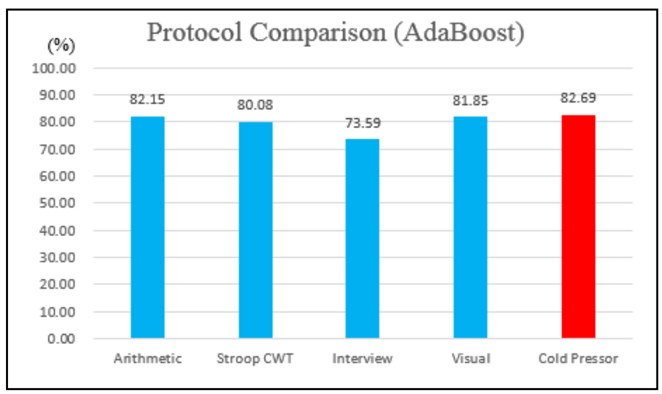

Figure 6: Protocol Comparison Result (AdaBoost)

The classification accuracies corresponding to the subjects are shown in Table V and VI. The listed algorithms are Naïve Bayes and AdaBoost respectively.

TABLE V. PERFORMANCE COMPARISONS OF SUBJECTS ON EXPERIMENTAL PROTOCOLS (NAÏVE BAYES)

Accuracy (%)	**Arith-metic**	**Stroop CWT**	**Inter-view**	**Visual**	**Cold Pressor**	**Subject Mean**
Sub 1	100.00	92.33	73.67	76.67	80.00	84.53
Sub 2	98.33	94.33	98.00	88.67	70.00	89.87
Sub 3	100.00	96.67	70.33	65.00	75.00	81.40
Sub 4	100.00	100.00	100.00	100.00	95.00	99.00
Sub 5	76.67	60.67	61.67	94.00	100.00	78.60
Sub 6	87.33	92.67	89.33	90.67	80.00	88.00
Sub 7	54.00	64.33	51.00	70.33	80.00	63.93
Sub 8	94.00	62.67	77.33	63.33	100.00	79.47
Sub 9	85.00	61.00	74.00	64.67	75.00	71.93
Sub 10	96.33	73.67	72.00	65.67	80.00	77.53
Sub 11	85.00	93.00	67.33	90.67	90.00	85.20
Sub 12	89.00	96.00	95.00	98.00	85.00	92.60
Sub 13	69.33	67.00	56.67	72.00	50.00	63.00
Protocol Mean	87.31	81.10	75.87	79.98	81.54	81.16
Protocol Max	100.00	100.00	100.00	100.00	100.00	99.00

TABLE VI. PERFORMANCE COMPARISONS OF SUBJECTS ON EXPERIMENTAL PROTOCOLS (ADABOOST)

Accuracy (%)	**Arith-metic**	**Stroop CWT**	**Inter-view**	**Visual**	**Cold Pressor**	**Subject Mean**
Sub 1	92.67	96.33	58.67	74.33	95	83.40
Sub 2	94.67	95	95	91.33	85	92.20
Sub 3	81	84	72.67	83	80	80.13
Sub 4	94.67	98.33	96.33	98	85	94.47
Sub 5	77.33	70.33	51	89	60	69.53
Sub 6	96.33	98.33	100	98.33	60	90.60
Sub 7	33	59.67	58.67	83.67	90	65.00
Sub 8	84.33	66.33	71.67	68.67	90	76.20
Sub 9	90	72.33	79.33	60.33	85	77.40
Sub 10	83.67	77.33	63.33	65.33	100	77.93
Sub 11	77.33	64	57.67	86.67	90	75.13
Sub 12	89	83.33	86	85.67	70	82.80
Sub 13	74	75.67	66.33	79.67	85	76.13
Protocol Mean	82.15	80.08	73.59	81.85	82.69	80.07
Protocol Max	96.33	98.33	100.00	98.33	100.00	94.47

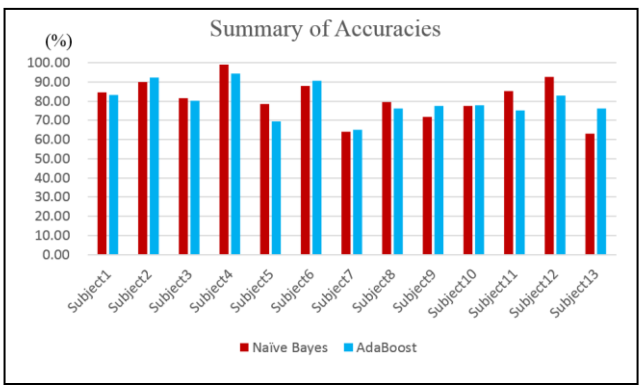

Figure 7: Experimental Results on All Subjects

VI. CONCLUSION

Our research works proved the effectiveness of the ultra-short-term spectral feature of ECG for emotional stress state classification problem. We also demonstrated which classification algorithms were optimal for the proposed feature, and which stress situation was the most stressful among various stressful conditions.

This proposed approach could be adopted to wearable system in a real-time manner, and also implemented into various areas in easy way without domain specific feature engineering.

For future works, we have a plan to develop a system which is able to handle with multi-modal bio sensor data using ultra-short-term biological signal features.

REFERENCES

[1] Thorn, B.E et al., "A randomized clinical trial of targeted cognitive behavioral treatment to reduce catastrophizing in chronic headache sufferers", Journal of Pain 8, 938-949, 2007

[2] S.G. Ponnambalam et al., "Analysis of Electrocardiogram (ECG) Signals for Human Emotional Stress Classification, IRAM 2012, CCIS 330, pp. 198–205.

[3] Hyun Jae Baek et al., "Reliability of Ultra-Short-Term Analysis of a Surrogate of Standard 5-Min Analysis of Heart Rate Variability", Telemedicine and e-Health, May 2015.

[4] K. H. Kim et al., "Emotion recognition system using short-term monitoring of physiological signals", Medical & Biological Engineering & Computing 2004, Vol. 42.

[5] Ulf Lundberg et al., "Psychophysiological Stress and EMG Activity of the Trapezius Muscle", *International Journal of Behavioral Medicine, l(4), 354-370. 1994.* .

[6] Pouya Bashivan et al., "Learning Representaions from EEG with Deep Recurrent-Convolutional Neural Networks", ICLR 2016.

[7] Jerritta Selvaraj et al., "Classification of emotional states from electrocardiogram signals: a non-linear approach based on hurst", BioMedical Engineering OnLine 2013, 12:44

[8] Murugappan MurugaPPan et al., "Frequency Band Analysis of Electrocardiogram (ECG) Signals for Human Emotional State Classification Using Discrete Wavelet Transform (DWT)", J. Phys. Ther. Sci. 25: 753-759, 2013.

[9] Serkan Kiranyaz et al., "Convolutional Neural Networks for Patient-Specific ECG Classification", Engineering in Medicine and Biology Society (EMBC) 2015..

[10] Bong Siao Zheng et al., "Human Emotional Stress Assessment through Heart Rate Detection in a Customized Protocol Experiment", IEEE Symposium on Industrial Electronics and Applications (ISIEA2012), Sep. 23-26 , 2012.

[11] https://docs.scipy.org/doc/scipy/reference/index.html

[12] http://www.cs.waikato.ac.nz/ml/weka/