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Emotion Classification by Machine Learning Algorithm using Physiological Signals

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Abstract. Recently, emotion studies have suggested emotion classification using machine learining algorithms based on physiological features. We classified three emotion (boredom, pain, and surprise) by 4 machine learning algorithms (LDA, CART, SOM, and SVM). 200 college students participated in this experiment. EDA, ECG, PPG, and SKT as physiological signals were acquired for 1 minute before emotional state as baseline and for 1-1.5 minutes during emotional state. 23 features were extracted from physiological signals. For emotion classification, the difference values of each feature substracting baseline from the emotional state were used for machine learning algorithms. The result showed that an accuracy of emotion classification by SVM was highest. This could help emotion recognition studies lead to better chance to recognize various human emotions by using physiological signals and it can be applied on human-computer interaction system for emotion detection.

Keywords: Emotion classification, Physiological signal, Machine learning algorithm

1. Introduction

Recently, emotion recognition in human-computer interaction (HCI) studies is the one of topic that researcher are most interested in. To recognize human's emotions and feelings, various physiological signals have been widely used to classify emotion [1] because signal acquisition by non-invasive sensors is relatively simple and physiological responses induced by emotion are less sensitive in social and cultural difference [2]. Previous studies have mainly reported on relation between basic emotion (e.g., happiness, sadness, anger, and fear) and physiological responses [3]. But, other emotions such as boredom, pain and surprise have been least investigated and a few studies have reported by single-channel physiological signal such as respiratory [4-5]. It is important to study physiological responses related to boredom, pain, and surprise for emotion classification of them, because they are emotions that human have often experienced in real life. Also, it is needed to study emotion classification using multi-channel physiological signals because emotion is also related to physiological signals (e.g., EDA, HR, and cortisol response). Finally, although emotion recognition was performed by various algorithms such as FP (Fisher Projection), SFFS (Sequential Floating Forward Search), KNN (k-Nearest Neighbor algorithm), and SVM (Support Vector Machines) [6], it needed to study for identification of methods and algorithm to exactly classify some emotion. The purpose of this study was to classify three different emotions, i.e., boredom, pain, and surprise (which is 'startle' response to a sudden unexpected stimulus such as a flash of light, a loud noise, etc.) by using multi-channel physiological signals. And we utilized 4 machine learning algorithms (LDA, CART, SOM, and SVM) using physiological features.

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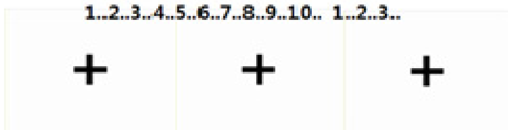
2. Methods for Emotion Classification

200 college students (mean age: 21.7years ± 2.3) participated in this experiment. They were normal persons who reported no history of medical illness due to heart disease, respiration, or central nervous system disorder. They were introduced to the experiment protocols and filled out a written consent before the beginning of experiment. Also, they were paid $30 USD per session to compensate for their participation.

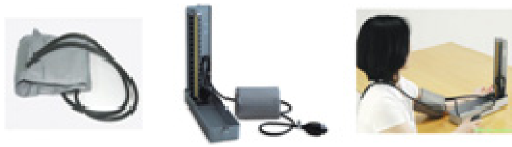
The audio-visual film clips that had been tested their appropriateness and effectiveness were used to provoke emotion (Fig. 1). The appropriateness of emotional stimuli means a consistency between the intended emotion by experimenter and the participants' experienced emotion. The effectiveness is an intensity of emotions that participants rated on a 1 to 7 point Likert-type scale (e.g.., 1 being "least boring" and 7 being "most boring"). The apporiateness and effectiveness of these stimuli were as follows; appropriateness and effectiveness of boredom were 86.0% and 5.23±1.36, in pain 97.3% appropriateness and 4.96±1.34 effectiveness and 94.1% appropriateness and 6.12±1.14 effectivess in surprise.

boredom



Repetitive sounds of number from 1 to 10 (3 min)

pain



Induction of pain using blood pressure gauge (1 min)

surprise

Sudden presentation of above images and hog-caller, sound of breaking glass, and thunder during concentration on task (1 min)

Fig. 1: The example of emotional stimuli.

EDA, ECG, PPG, and SKT were acquired by MP150 Biopac system Inc. (USA) during 1 minute prior to the presentation of emotional stimuli (baseline) and for 1 to 1.5 minutes long while participants watch stimuli as emotional state. The obtained signals were analyzed for 30 seconds from the baseline and the emotional state by AcqKnowledge (Ver. 3.8.1) software (USA). 23 parameters from these signals were extracted: SCL, NSCR, meanSCR, mean SKT, maximum SKT, sum of negative SKT, sum of positive SKT, mean PPG, mean RR interval, standard deviation RR interval, mean HR, RMSSD, NN50, percenet of NN50, SD1, SD2, CSI, CVI, LF, HF, nLF, nHF, and LF/HF ratio.

To identify the difference of physiological responses among three emotional states, statistical analysis were done as paired t-test, one-way ANOVA and LSD post-hoc (SPSS 16.0). And for emotion classification, 4 machine learning algorithms were applicated by difference values substracting signals of baseline from emotional state. The used algorithms are LDA which is one of the linear models, CART of decision tree model, SOM of Neural Network, and SVM of non-linear model, which are used the well-known emotion algorithms.

3. Results of Emotion Classification

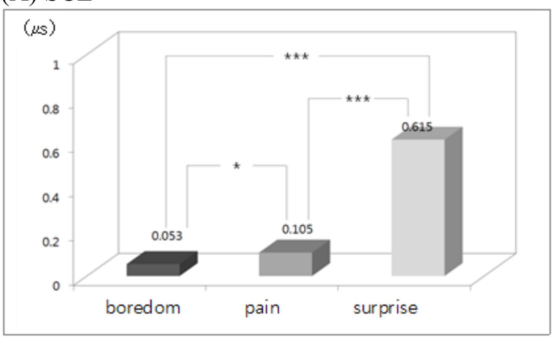
The result of difference test between baseline and each emotional state showed that physiological responses during emotional states were significantly differed compared to during baseline (Table. 1).

Table. 1: The results of difference between baseline and emotional states using paired t-test.

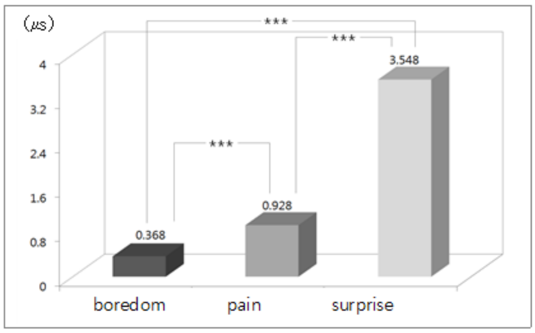
physiological parameter \ emotion	Boredom		Pain		Surprise	
	t-score	**p**	**t-score**	**p**	**t-score**	**p**
SCL	2.59	.012	5.53	.000	14.36	.000
NSCR	3.55	.001	11.64	.000	10.75	.000
meanSCR	2.68	.009	8.45	.000	7.45	.000
meanSKT	0.20	.839	-1.05	.296	2.04	.045
sum of negative SKT	-2.49	.015	-9.93	.000	-4.62	.000
sum of positive SKT	-1.75	.085	-5.86	.000	-4.84	.000
meanPPG	0.93	.355	2.66	.009	-4.64	.000
meanRRI	-3.11	.002	-0.44	.659	-4.29	.000
stdRR	2.00	.049	2.97	.004	5.43	.000
meanHR	3.00	.004	0.93	.355	3.32	.001
RMSSD	1.31	.194	3.21	.002	3.45	.001
NN50	-0.16	.875	4.19	.000	5.95	.000
pNN50	-0.42	.675	4.10	.000	4.72	.000
SD1	1.11	.270	3.09	.003	3.68	.000
SD2	2.07	.041	2.71	.008	5.73	.000
CSI	0.65	.519	-1.30	.196	5.56	.000
CVI	1.68	.097	4.10	.000	9.66	.000

In result of difference test among emotional states by one-way ANOVA, there were significant differences among three emotional states in SCL, meanSCR, meanSKT, meanHR, and meanPPG. The result of LSD post-hoc test is like Fig. 2.

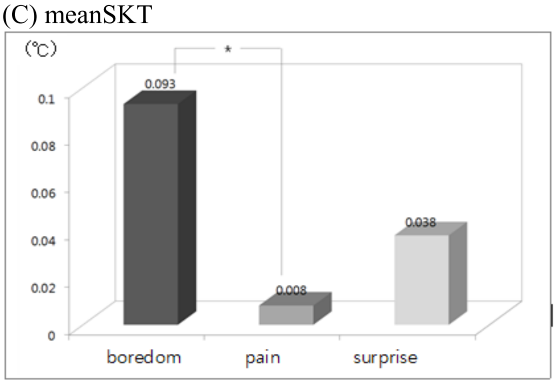
(A) SCL



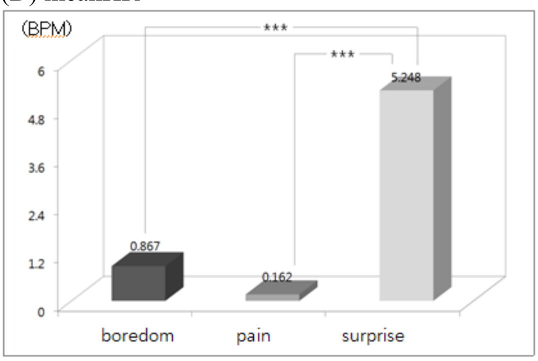
(B) mean SCR



(C) meanSKT



(D) meanHR



(E) meanPPG

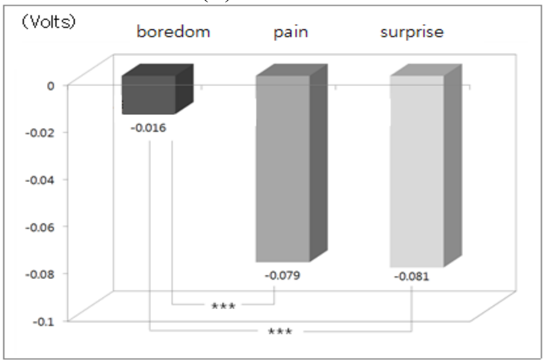


Fig. 2. The results of difference test among three emotions by LSD post-hoc.

23 features extracted from physiological signals were applied to 4 different emotion classification algorithms for emotion classification (Table. 2).

Table. 2: The result of emotion classification by machine learning algorithms.

Algorithm	Accuracy (%)	Features (N)
LDA	78.6	23
CART	93.3	23
SOM	70.4	23
SVM	100.0	23

In analysis of LDA, accuracy of all emotions was 78.6% and in each emotion, boredom was recognized by LDA with 77.3%, pain 80.0%, and surprise 78.6% (Table. 3).

Table. 3: The result of emotion classification by LDA.

	Boredom	Pain	Surprise	Total
boredom	77.3	4.5	18.2	100.0
pain	1.2	79.9	18.9	100.0
surprise	4.2	17.2	78.6	100.0

CART provided accuracy of 93.3% when it classified all emotions. In boredom, accuracy of 94.3% was achieved with CART, 95.9% in pain, and 90.1% in surprise (Table. 4).

Table. 4: The result of emotion classification by CART.

	Boredom	Pain	Surprise	Total
boredom	94.3	1.1	4.5	100.0
pain	1.2	95.9	3.0	100.0
surprise	5.7	4.2	90.1	100.0

The result of emotion classification using SOM showed that according to orders of boredom, pain, and surprise, recognition accuracy of 80.1%, 65.1%, and 66.2% were obtained by SOM (Table. 5).

Table. 5: The result of emotion classification by SOM.

	Boredom	Pain	Surprise	Total
boredom	80.1	5.1	14.8	100.0
pain	7.7	65.1	27.2	100.0
surprise	13.0	20.8	66.2	100.0

Finally, accuracy of SVM was 100.0% and classifications of each emotion were 100.0% in all emotions (Table. 6).

Table. 6: The result of emotion classification by SVM.

	Boredom	Pain	Surprise	Total
boredom	100.0	0.0	0.0	100.0
pain	0.0	100.0	0.0	100.0
surprise	0.0	0.0	100.0	100.0

4. Conclusions

We identified that three different emotions (boredom, pain, and surprise) were classified by machine learning algorithms using various physiological features. Our result showed that SVM is the best algorithm being able to classify these emotions. The SVM is designed for two class classification by finding the optimal hyperplane where the expected classification error of test samples is minimized and it shows an accuracy much higher chance probability when applied to physiological signal databases. Also, this has utilized as a pattern classifier to overcome the difficulty in pattern classification due to the large amount of within-class variation of features and the overlap between classes, although the features are carefully extracted [7]. However, our result is the classification accuracy using only training set which didn't divide training and test sets. An average accuracy of classification is necessary for repeated sub-sampling validation using training and test sets as the choice of training and test sets can affect the results. To overcome this, we will perform the average classification in further analysis. Our result could help emotion recognition studies lead to better chance to recognize various human emotions by physiological signals. Also, this result can be useful in establishing the basis for emotion recognition system in human-computer interaction. But, although physiological signals offer a great potential for the recognition of emotions in computer systems, in order to fully exploit the advantages of physiological measures, standardization needs to be established on the emotional model, stimulus used for the identification of physiological patterns, physiological measures, parameters for analysis, and model for pattern recognition and classification [8].

5. Acknowledgements

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