THREE DIFFERENTIAL EMOTION CLASSIFICATION BY MACHINE LEARNING ALGORITHMS USING PHYSIOLOGICAL SIGNALS

Discriminantion of Emotions by Machine Learning Algorithms

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Abstract: In HCI researches, human emotion classification has done by machine learning algorithms based on physiological signals. The aim of this study is to classify three different emotional states (boredom, pain, and surprise) by 5 machine learning algorithms using features extracted from physiological signals. 200 college students participated in this experiment. The audio-visual film clips were used to provoke emotions and were tested their appropriateness and effectiveness. EDA, ECG, PPG, and SKT as physiological signals were acquired for 1 minute before each emotional state as baseline and for 1-1.5 minutes during emotional state and were analyzed for 30 seconds from the baseline and the emotional state. 23 parameters were extracted from these signals: SCL, NSCR, mean SCR, mean SKT, maximum SKT, sum of negative SKT, and sum of positive SKT, mean PPG, mean RR interval, standard deviation RR interval, mean BPM, RMSSD, NN50, percenet of NN50, SD1, SD2, CSI, CVI, LF, HF, nLF, nHF, and LF/HF ratio. For emotion classification, the difference values of each feature subtracting baseline from the emotional state were used for analysis using 5 machine learning algorithms. The result showed that an accuracy of emotion classification by SOM was lowest and SVM was highest. This could help emotion recognition studies lead to better chance to recognize various human emotions by using physiological signals. Also, it is able to be applied on human-computer interaction system for emotion detection.

1 INTRODUCTION

Emotion recognition in studies on human-computer interaction 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 (Wagner, Kim, & Andre, 2005), because signal acquisition by non-invasive sensors is relatively simple and physiological responses are less sensitive in social and cultural difference (Drummond & Quah, 2001). Also, it is known that physiological responses are significantly correlated with human emotional state.
Many studies have reported relation between emotion and physiological responses and mainly focused on physiological responses induced by basic emotions such as happiness, sadness, anger, fear, and disgust (Ax, 1953; Boiten, 1996; Kanade & Tian, 2000; Palomba, Sarlo & Angrilli, 2000). On the other hand, other emotions such as boredom, pain and surprise have been least investigated and reported by single-channel physiological signal such as respiratory (de Melo, Kenny & Gratch, 2010; Flor, Knost & Birbaumer, 2002; Jolliffe & Nicholas, 2004). But it is needed to study the emotion classification using multi-channel physiological signals because emotion is related to other signal such as GSR, EMG, HR, Cortisol response, etc.

Recently, although emotion recognition based on physiological signals 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), it needed to study for development of methods and algorithm to exactly classify some emotion.

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The purpose of this study was to classify three different emotions (boredom, pain, and surprise) by using multi-channel physiological signals. Surprise emotion may be divided into ‘wonder’ that people feel when perceiving something rare or unexpected (Collet et al., 1997), and ‘startle’ response to a sudden unexpected stimulus such as a flash of light, a loud noise, or a quick movement near the face (Nasoz et al., 2004; Verhoef et al., 2009). In this study, ‘startle’ surprise emotion was induced by emotional stimuli and 5 machine learning algorithms, linear discriminant function (LDF), classification and regression tree (CART), self organizing map (SOM), Naïve Bayes and support vector machine (SVM) for emotion classification were used.

2 METHODS FOR EMOTION CLASSIFICATION

200 college students (mean age: 21.7years ± 2.3) participated in this experiment. They reported no history of medical illness due to heart disease, respiration, or central nervous system disorder or psychotropic medication. 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 three different emotions (Figure 1). The appropriateness of emotional stimuli means the consistency between the emotion designed to provoke each emotion and the category (e.g., boring, painful, and surprising) of participants’ experienced emotion. The effectiveness was determined by the intensity of emotions that participants rated on a 1 to 7 point Likert-type scale (e.g.., 1 being “least bring” or “painful” and 7 being “most boring” or “painful”).

Figure 1: The example of emotional stimuli.

The apporiateness and effectiveness of these stimuli were as follows; boredom had appropriateness of 86.0% and effectiveness of 5.23±1.36, the results showed appropriateness of 97.3% and effectiveness of 4.96±1.34 in pain and appropriateness of 94.1% and effectivess of 6.12±1.14 in surprise.

EDA, ECG, PPG, and SKT were acquired by MP150 Biopac system Inc. (USA) during 1 minute long baseline prior to the presentation of emotional stimuli and for 1 to 1.5 min long while participants watch emotional stimuli as emotional state. The obtained signals were analyzed for 30 sec from the baseline and the emotional state by AcqKnowledge (Ver. 3.8.1) software (USA). Total 23 features were extracted from these signals (Table 1).

Table 1: Features extracted from physiological signals.

signal		feature
EDA		SCL, NSCR, mean SCR
SKT		mean SKT, maximum SKT, sum of negative SKT, sum of positive SKT
PPG		Mean PPG
ECG	time domain	mean RRI, std RRI, mean HR, RMSSD, NN50, pNN50, SD1, SD2,
	frequency domain	LF, HF, nLF, nHF, LF/HF ratio

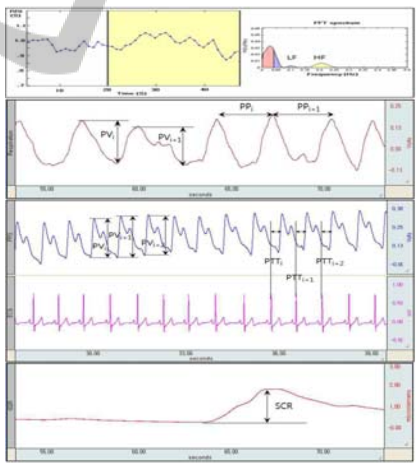

Figure 2: The example of feature extraction.

To identify the difference of physiological signals between baseline and emotional state, statistical analysis were done as paired t-test (SPSS 16.0). And for emotion classification, five different machine learning algorithms were applicated by difference values substracting signals of baseline from emotional state. The used algorithms are as follows; LDA which is one of the linear models, CART of decision tree model, SOM of Neural Network, Naïve Bayes of probability model, and SVM of non-linear model, which are used the wellknown emotion algorithms.

3 RESULTS OF EMOTION CLASSIFICATION

The result of difference between baseline and each emotional state showed that physiological responses during emotional states were significantly differed from baseline (Table 2). Boredom significantly differed from baseline in SCL, NSCR, meanSCR, s_n SKT, meanRRI, stdRR, meanHR, and SD2. The features of SCL, NSCR, mean SCR, s_n SKT, s_p SKT, meanPPG, stdRR, RMSSD, NN50, pNN50, SD1, SD2, CVI, and LF during painful state showed significant difference from baseline. In surprise, there were significant differences between baseline and emotional state at all parameters except for max SKT and LF, HF, nLF, nHF, and LF/HF ratio.

Table 2: The result of difference between baseline and emotional states.

parameter / emotion	boredom	pain	surprise
SCL	2.59*	5.53***	14.36***
NSCR	3.55***	11.64***	10.75***
meanSCR	2.68**	8.45***	7.45***
meanSKT	0.20	-1.05	2.04*
s_n SKT	-2.49*	-9.93***	-4.62***
s_p SKT	-1.75	-5.86***	-4.84***
meanPPG	0.93	2.66**	-4.64***
meanRRI	-3.11**	-0.44	-4.29***
stdRR	2.00*	2.97**	5.43***
meanHR	3.00**	0.93	3.32**
RMSSD	1.31	3.21**	3.45**
NN50	-0.16	4.19***	5.95***
pNN50	-0.42	4.10***	4.72***
SD1	1.11	3.09**	3.68***
SD2	2.07*	2.71**	5.73***
CSI	0.65	-1.30	5.56***
CVI	1.68	4.10***	9.66***
LF	1.48	2.78**	1.49

* $p < .05$, ** $p < .01$, *** $p < .001$

23 features extracted from physiological signals were applied to emotion classification algorithms for emotion classification of 3 emotions. Table 3 shows the result of emotion classification by 5 algorithms.

Table 3: Result of emotion classification.

algorithm	accuracy (%)	features (N)
LDA	78.6	23
CART	93.3	23
SOM	70.4	23
Naïve Bayes	83.4	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 4). 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 5). 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 6).

Table 4: 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

Table 5: 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

Table 6: 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

The accuracy of Naïve Bayes algorithm to classify all emotion was 83.4%. And each emotion was recognized by Naïve Bayes with 84.7% of boredom, 82.8% of pain, and 84.4% of surprise (Table 7). Finally, accuracy of SVM was 100.0% and classifications of each emotion were 100.0% in all emotions (Table 8).

Table 7: Result of emotion classification by NAÏVE BAYES.

	boredom	pain	surprise	total
boredom	84.7	0.6	14.8	100.0
pain	1.2	82.8	16.0	100.0
surprise	5.2	10.4	84.4	100.0

Table 8: 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

This study was to classify three different emotional states (boredom, pain, and surprise) by machine learning algorithms using physiological features. Our results showed that physiological responses of three emotions were differed and SVM were the best algorithm for classification of three emotions. This result could help emotion recognition studies lead to better chance to recognize human emotions by using physiological signals. Also, it can be useful in profiling various emotion-specific physiological responses or establishing the basis for emotion recognition system in human-computer interaction.

However, this result was 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. Therefore, we will perform the average classification in further analysis. Also, although it is known that 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 (Arroyo-Palacios & Romano, 2008).

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