Emotion Classification Using Physiological Signals

Byoung-Jun Park[1], Eun-Hye Jang[1], Myoung Ae Chung[1], Sang-Hyeob Kim[1*], Jin Hun Sohn[2*]

[1]IT Convergence Technology Research Laboratory, Electronics and Telecommunications Research Institute, Daejeon, 305-700

[2]Department of Psychology/Brain Research Institute, Chungnam National University, Daejeon, 305-765

ABSTRACT

Objective: The aim of this study is to discriminate negative emotions, such as sadness, fear, surprise, and stress using physiological signals. **Background:** Recently, the main topic of emotion classification research is to recognize human's feeling or emotion using various physiological signals. It is one of the core processes to implement emotional intelligence in human computer interaction (HCI) research. **Method:** Electrodermal activity (EDA), electrocardiogram (ECG), skin temperature (SKT), and photoplethysmography (PPG) are recorded and analyzed as physiological signals. And emotional stimuli are audio-visual film clips which have examined for their appropriateness and effectiveness through preliminary experiment. For classification of negative emotions, five machine learning algorithms, i.e., LDF, CART, SOM, and Naïve Bayes are used. **Results:** Result of emotion classification shows that an accuracy of emotion classification by CART (84.0%) was the highest and by LDA (50.7%) was the lowest. SOM showed emotion classification accuracy of 51.2% and Naïve Bayes was 76.2%. **Conclusion:** We could identify that CART was the optimal emotion classification algorithm for classifying 4 negative emotions (sadness, fear, surprise, and stress). **Application:** This result can be helpful to provide the basis for the emotion recognition technique in HCI.

Keywords: Emotion classification, Negative emotion, Machine learning algorithm, Physiological signal

1. Introduction

Emotion classification is one of the core processes to implement emotional intelligence in HCI research (Wagner, Kim and Andre, 2005). In important HCI applications such as computer aided tutoring and learning, it is highly desirable that the response of the computer takes into account the emotional or cognitive state of the human user (Sabe, Cohen, and Huang, 2005). Emotion plays an important role in contextual understanding of messages from others in speech or visual forms. Negative emotions are primarily responsible for gradual declination or downfall of our normal thinking process, which is essential for our natural survival, even in the struggle for existence.

Recently, emotion classification has been studied using facial expression, gesture, voice, and physiological signals (Picard, Vyzas, and Healey, 2001; Cowie et al., 2001; Haag, Coronzy, Schaich, and Williams, 2004; Healey, 2000; Nasoz, Alvarez, Lisetti, and Finkelstein, 2003). Emotion classification using physiological signals have advantages which are less affected by environment than any other modalities as well as possible to observe user's state in real time. Also, they aren't caused by responses to social masking or factitious emotion expressions and measurement of emotional responses by multi-channel physiological signals offer more information for emotion recognition, because physiological responses are related to emotional state (Drummond, and Quah, 2001).

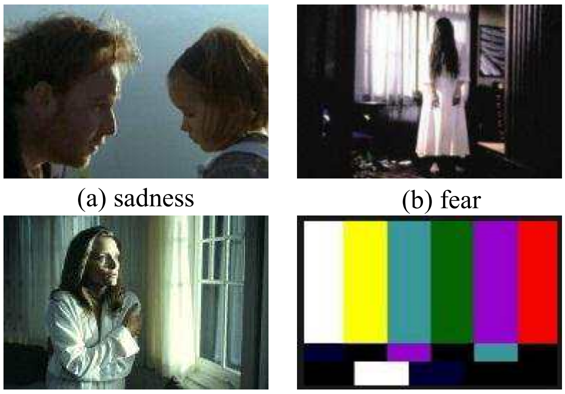
Emotion classification has been performed by various machine learning algorithms, e.g., Fisher Projection (FP), k-Nearest Neighbor algorithm (kNN), Linear Discriminant Function (LDF), and Support Vector Machine (SVM). Previous works conducted a recognition accuracy of over 80% on the average seems to be acceptable for realistic applications. For example, Haag, Goronzy, Schaich and Williams (2004) applied MLP to categorize dimensions of arousal and valence in each emotion, and then it was reported as 80% of average accuracy, and Calvo, Brown and Scheding (2009) reported 42% of accuracy by using SVM to differentiate 8 kinds of emotions (neutral, anger, grief, sadness, platonic love, romantic love, joy, & respect).

The aim of our study is to identify the best emotion classifier with feature selections based on physiology signals induced by negative emotions (sadness, fear, surprise, and stress) using several machine learning algorithms, i.e., Linear Discriminant Analysis (LDA) which is one of the linear models, Classification And Regression Tree (CART) of decision tree model, Self Organizing Map (SOM) of Neural Network, and Naïve Bayes of probability model.

2. Method

A total of 12 college students (6 males 20.8 years $\pm$ 1.26 and 6 females 21.2 years $\pm$ 2.70) participated in this study. They reported that they hadn't had any history of medical illness or psychotropic medication and any kind of medication due to heart disease, respiration disorder, or central nervous system disorder.

Forty emotional stimuli (4 emotions x 10 sets) which are the 2-4 min long audio-visual film clips captured originally from movies, documentary, and TV shows were used to successfully induce emotions (sadness, fear, surprise, and stress) in this study (Figure 1). The used audio-visual film clips were examined their appropriateness and effectiveness by preliminary study. The appropriateness of emotional stimuli means the consistency between the experimentor's intended emotion and the participanats' experienced emotion (e.g., scared, surprise, and annoying). The effectiveness was determined by the intensity of emotions reported and rated by the participants on a 1 to 11 point Likert-type scale (e.g.., 1 being "least surprising" or "not surprising" and 11 being "most surprising"). The result showed that emotional stimuli had the appropriateness of 93% and the effectiveness of 9.5 point on average (Table 1).



(a) sadness (b) fear (c) surprise (d) stress

Figure 1. The example of emotional stimuli

Prior to the experiment, participants were introduced to detail experiment procedure and had an adaptation time to feel comfortable in the laboratory's environment. Then an experimentor attached electrodes on the participants' wrist, finger, and ankle for measurement of physiological signals. Physiological signals were measured for 60 sec prior to the presentation of emotional stimulus (baseline) and for 2 to 4 min during the presentation of the stimulus (emotional state) then for 60 sec after presentation of the stimulus as recovery term (Figure 2). Participants rated the emotion that they experienced during presentation of the film clip on the

Table 1. Appropriateness and effectiveness of evoked emotions

Set	1	2	3	4	5	6	7	8	9	10	M
Sadness	92% (9.5)	100% (9.1)	100% (8.7)	100% (9.7)	100% (9.3)	100% (9.3)	75% (8.9)	100% (9.0)	100% (9.2)	100% (9.3)	96% (9.2)
Fear	75% (10)	100% (9.9)	83% (9.8)	92% (9.6)	92% (9.7)	92% (9.7)	83% (9.6)	100% (9.3)	100% (9.3)	75% (8.7)	89% (9.6)
Surprise	75% (9.3)	92% (9.7)	100% (9.7)	100% (9.9)	83% (9.6)	83% (9.6)	100% (9.5)	83% (9.4)	83% (8.6)	75% (10.3)	89% (9.5)
Stress	92% (9.3)	100% (9.1)	100% (8.8)	100% (8.9)	100% (9.3)	100% (8.8)	92% (9.3)	100% (9.3)	100% (9.1)	100% (9.3)	98% (9.1)
M	83% (9.5)	94% (9.6)	93% (9.3)	95% (9.7)	94% (9.6)	95% (9.5)	92% (9.3)	92% (9.2)	96% (9.4)	91% (9.5)	93% (9.5)

above: appropriateness (%), below ( ): effectiveness (point) emotion assessment scale. This procedure was repeated 4 times for elicitation of 4 emotions during one session. Presentation of each film clip was count-balanced across each emotional stimulus to exclude order effect. This experiment was progressed by the same procedures over 10 times.

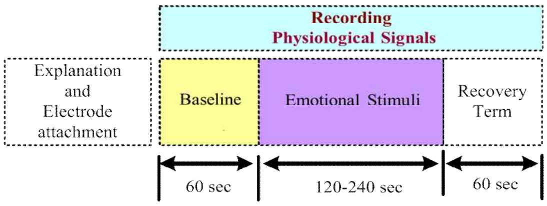


Figure 2. Experiment procedures

The physiological signals were acquired by the MP100 system (Biopac system Inc., USA). The sampling rate of signals was fixed at 256 samples for all the channels. Signals were acquired for 1minute long baseline state prior to presentation of emotional stimuli and 2-4 minutes long emotional states during presentation of the stimuli. The obtained signals were analyzed for 30 seconds from the baseline and the emotional state by AcqKnowledge (Ver. 3.8.1) software (USA). The emotional states were determined by the result of participant's self-report. Features extracted from the physiological signals and were used to analysis are as follows: SCL, meanSCR, NSCR, meanSKT, max SKT, meanPPG, meanRR(s), STD(s), meanHR(1/min), RMSSD(ms), NN50(count), pNN50(%), SD1(ms), SD2 (ms), CSI, CVI, RR tri index, TINN(ms), FFTap_LF, FFTap_HF, ARap_LF, ARap_HF, FFTnLF, FFTnHF, FFTL/Hratio, ARnLF, ARnHF, and AR LF/HF ratio. 360 data except for severe artifact by movements and noises were used for analysis. Features differences between emotional states and baseline extracted from signals were used to apply emotion classification algorithms. Also, 4 machine learning algorithms, i.e., LDA, CART, SOM, and Naïve Bayes classifier based on density, were used to identify the optimal algorithm being able to classify 4 negative emotions.

3. Results

28 features extracted from physiological signals were applied to 4 algorithms for emotion classification of sadness, fear, surprise and stress. LDA, CART, SOM, and Naïve Bayes were tested to confirm emotion classification rate. The result of emotion classification is like Table 2. 50.7% of originally grouped cases were correctly classified by LDA, 84.0% by CART, 51.2% by SOM, and 76.2% by Naïve Bayes. 4 emotions, i.e., sadness, fear, surprise and stress were classified by CART optimally.

Table 2. The results of emotion classification

Algorithm	Accuracy (%)	Features (N)
LDA	46.8	28
CART	84.0	28
SOM	51.2	28
Naïve Bayes	76.2	28

The more detail results of emotion classification accuracy by each algorithm are like from Table 3 to 6. In analysis of LDA, accuracy of each emotion had range of 42.7% to 57.4%. Sadness was recognized by LDA with 46.2%, fear 57.4%, surprise 42.7%, and stress 57.0% (Table 3).

Table 3. The results of emotion classification by LDA

	SAD	FEA	SUR	STR	Total
SAD	46.2	22.1	8.7	23.1	100.0
FEA	11.9	57.4	14.9	15.8	100.0
SUR	12.6	24.3	42.7	20.4	100.0
STR	15.0	12.0	16.0	57.0	100.0

SAD : sadness, FEA : fear, SUR : surprise, STR : stress

CART provided accuracy of 84.0% when it classified all emotions and the classification accuracy of each emotion was range of 80.2% to 93.3%. In sadness, accuracy of 93.3% was achieved with CART, 80.2% in fear, 80.5% in surprise, and 82.0% in stress (Table 4).

Table 4. The results of emotion classification by CART

	SAD	FEA	SUR	STR	Total
SAD	93.3	3.9	0.00	2.8	100.0
FEA	9.9	80.2	5.9	4.0	100.0
SUR	12.6	3.9	80.5	2.9	100.0
STR	9.0	3.0	6.0	82.0	100.0

The result of emotion classification using SOM showed that accuracy to classify all emotions was 51.2%. According to orders of sadness, fear, surprise, and stress, recognition rates of 76.0%, 45.5%, 46.6%, and 36.0% were obtained by SOM (Table 5).

Table 5. The results of emotion classification by SOM

	SAD	FEA	SUR	STR	Total
SAD	76.0	5.8	7.7	10.6	100.0
FEA	31.7	45.5	12.9	9.9	100.0
SUR	31.1	9.7	46.6	12.6	100.0
STR	37.0	8.0	19.0	36.0	100.0

The accuracy of Naïve Bayes algorithm to classify all emotion was 76.2%. And each emotion was recognized by Naïve Bayes with 80.8% of sadness, 82.2% of fear, 62.1% of surprise, and 80.0% of stress (Table 6).

Table 6. The results of emotion classification by Naïve Bayes

	SAD	FEA	SUR	STR	Total
SAD	80.8	2.9	4.8	11.5	100.0
FEA	5.9	82.2	3.0	8.9	100.0
SUR	9.7	12.6	62.1	15.5	100.0
STR	15.0	2.0	3.0	80.0	100.0

4. Conclusion

We have identified the optimal emotion classification algorithm for classifying 4 negative emotions (sadness, fear, surprise, and stress). Our result showed that CART is the best algorithm being able to classify sadness, fear, surprise and stress emotions. However, because our physiological signals didn't linear variables and the extracted features didn't linearly separable and large variability between the features used, in further analysis, we needed performance of some normalization of features being able to reduce large variability. And for more accurate and realistic applications, a novel method to identify basic emotions and more various emotions such as boredom, frustration, and love must be devised before it is mentioned that emotion recognition based on physiological signals is a practicable and reliable way of enabling HCI with emotion-understanding capability.

Although some algorithm showed lower accuracy of emotion classification, ore results led to better chance to recognize human emotions and to identify the optimal emotion classification algorithm by using physiological signals. This will be applied to the realization of emotional interaction between man and machine and play an important role in several applications, e.g., the human-friendly personal robot or other devices.

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Author listings

Eun Hye Jang: cleta4u@etri.re.kr

Highest degree: PhD, Department of Psychology, Chungnam National University
Position title: Senior Member of Engineering Staff, BT Convergence Technology Research Department, Electronics and Telecommunications Research Institute
Areas of interest: Emotion Recognition, Cognition Convergence

Sang Hyeob Kim: shk1028@etri.re.kr

Highest degree: PhD, Department of Apply Physics, Tohoku University
Position title: Principle Member of Engineering Staff, BT Convergence Technology Research Department, Electronics and Telecommunications Research Institute
Areas of interest: Cognition Convergence, Emotion Recognition

Jin Hun Sohn: jhsohn@cnu.ac.kr

Highest degree: PhD, Department of P sychology, University of Korea
Position title: Professor, Department of Psychology, Chungnam National University
Areas of interest: Brain Science, Neuroscience, Electro Physiology

Myoung Ae Chung: machung@etri.re.kr

Highest degree: PhD, Department of P hysical Chemistry, Clausthal Technical University
Position title: Managing Director, Principle Member of Engineering Staff, IT Convergence Services Future Technology Research Department, Creative & Challenging Research Division, Electronics and Telecommunications Research Institute
Areas of interest: Cognition Convergence, Brain Science

Byoung Jun Park: bj_park@etri.re.kr

Highest degree: PhD, Department of Electrical Engineering, Wonkwang University
Position title: Senior Member of Engineering Staff, BT Convergence Technology Research Department, Electronics and Telecommunications Research Institute
Areas of interest: Computational Intelligence, Pattern Recognition, Cognition Convergence