A Study on Autonomic Nervous System Responses and Feauture Selection for Emotion Recognition

Emotion Recognition using Machine Learning Algorithms

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Abstract: This study is related with emotion recognition based on autonomic nervous system responses. Three different emotional states, fear, surprise and stress, are evoked by stimuli and the autonomic nervous system responses for the induced emotions are measured as physiological signals such as skin temperature, electrodermal activity, electrocardiogram, and photoplethysmography. Twenty-eight features are analysed and extracted from these signals. The results of one-way ANOVA toward each parameter, there are significant differences among three emotions in some features. Therefore we select eight features from 28 features for emotion recognition. The comparative results of emotion recognition are discussed in view point of feature space with the selected features. For emotion recognition, we use four machine learning algorithms, namely, linear discriminant analysis, classification and regression tree, self-organizing map and naïve bayes, and those are evaluated by only training, 10-fold cross-validation and repeated random sub-sampling validation. This can be helpful to provide the basis for the emotion recognition technique in human computer interaction as well as contribute to the standardization in emotion-specific ANS responses.

1 INTRODUCTION

Physiological signal is one of the most commonly used emotional cues. In recent emotion recognition research, the one of main topics is to recognize human's feeling or emotion using multi-channel physiological signals for the implementation of emotional intelligence in human computer interaction (Wagner, Kim and Andre, 2005). Emotion recognition has been studied using facial expression, gesture, voice and bio signal. Bio signal may happen to artifact due to motion, and have difficulty mapping emotion-specific responses pattern. However, bio signals have some advantages which are less affected by environment than any other modalities as well as possible to observe user's state in real time. In addition, they also can be acquired spontaneous emotional responses and not caused by responses to social masking or factitious emotion expressions (Drummond and Quah, 2001). In that respect, correlation between emotion and autonomic nervous system (ANS) responses in human may have a major influence from development and test of emotion theory to human computer interaction (HCI) studies (Eom, Park, Noh and Sohn, 2011).

Many previous studies on emotion have reported that there is correlation between basic emotions (happiness, sadness, anger, etc.) and physiological responses (Kreibig, 2010; Bailenson, Pontikakis, Mauss, Gross, Jabon, Hutcherson, Nass, and John, 2008; Calvo, Brown and Scheding, 2009; Liu, Conn, Sarkar, and Stone, 2008). Also, experimental studies to distinguish specific emotions by using ANS response are being carried out and suggesting common ANS responses of some emotions (Stemmler, 1989; Ekman, Levenson and Friesen, 1983; Kreibig, 2010). Recently, emotion recognition using physiological signals based on ANS response has been performed by various machine learning algorithms, e.g., Fisher Projection (FP), k-Nearest Neighbor algorithm (kNN), Linear Discriminant analysis, and Support Vector Machine (SVM). Previous researches have conducted a recognition accuracy of over 80% on average seems to be acceptable for realistic applications (Picard, Vyzas and Healey, 2001; Haag, Goronzy, Schaich and

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Williams, 2004; Calvo, Brown and Scheding, 2009).

In this study, we discuss the feature selection using correlation with the specific ANS responses and negative emotions and the emotion recognition using machine learning algorithms. It is important to recognize negative emotions (e.g., fear, surprise and stress) because they are primarily responsible for gradual declination or downfall of our normal thinking process, which is essential for our natural (unforced) survival, even in the struggle for existence. We have already reported the recognition results of three negative emotions (Jang, et al., 2012, 2013). As a follow-up work, we perform extra analysis of emotion recognition on the reduced feature space with various criteria. To classify three negative emotions four machine learning algorithms, which are Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Self Organizing Map (SOMs), and Naïve Bayes, are used. The results will offer information about the emotion recognizer with feature selections using physiology signals induce by negative emotions.

2 NEGATIVE EMOTION AND PHYSIOLOGICAL SIGNALS

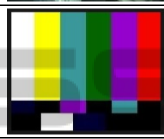
Negative emotions play an important role in adaptation of living and surviving the evolution of human. In particular, Negative emotion is described 'protection reaction' such as flight, withdrawal, vomiting, crying and 'destruction reaction' such as aggressive.

2.1 Emotional Stimuli

Thirty emotional stimuli (3emotions x 10sets) which are the 2-4 min long audio-visual film clips captured originally from movies, documentary, and TV shows are used to successfully induce three emotions. Fear-inducing films are the scene which have tense and dreary atmosphere. Surprise clips are a section in which startling accident occurred and stress clip is TV adjustment scene that was mixture of black and white with white noise sound as shown in Table 1.

The audio-visual film clips used as emotion stimuli are examined their suitability and effectiveness by preliminary study which 22 college students rated the category and intensity of their experienced emotion on emotional assessment scale. The suitability of emotional stimuli means the consistency between the experimenters' intended emotion and the participants' experienced emotion and the effectiveness is determined by the intensity of emotions reported by the participants. The result showed that emotional stimuli had the suitability of 89% and the effectiveness of 9.1 point on average.

Table 1: The examples of emotional stimuli.

Emotion	Contents	Example
Fear	ghost, haunted house, scare, etc.	
Surprise	sudden or unexpected scream etc.	
Stress	audio/visual noise on screen, etc.	

Prior to the experiment, participants are introduced to detail experiment procedure and have an adaptation time to feel comfortable in the laboratory's environment. Then an experimenter attaches electrodes on their wrist, finger, and ankle for measurement of physiological signals. Physiological signals are 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. Participants rate the emotion that they experience during presentation of the film clip on the emotion assessment scale. This procedure is repeated 3 times for elicitation of 3 differential emotions. Presentation of each film clip is count-balanced across each emotional stimulus. This experiment is progressed by the same procedures over 10 times.

2.2 Measurement of Physiological Signals and Feature Extraction

The ANS responses of emotions induced by stimuli are measured using MP100 of Biopac Systems Inc. (USA) and AcqKnowledge (version 3.8.1) is used for signal analysis. Electrodermal activity (EDA) is measured from two Ag/AgCl electrodes attached to the index and middle fingers of the non-dominant hand. Electrocardiogram (ECG) is measured from both wrists and one left ankle (reference) with the two-electrode method based on lead I. Photoplethysmography (PPG) and skin temperature (SKT) are measured from the little finger and the ring finger of the non-dominant hand, respectively. Appropriate amplification and band-pass filtering are performed.

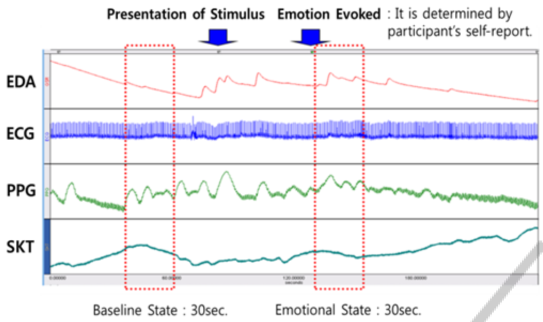


Figure 1: Analysis of physiological signals.

Table 2: Features extracted from physiological signals.

<table>
<tr><th colspan="3">Signals</th><th colspan="2">Features</th></tr>
<tr><td colspan="3">EDA</td><td colspan="2">SCL, NSCR, meanSCR</td></tr>
<tr><td colspan="3">SKT</td><td colspan="2">meanSKT, maxSKT</td></tr>
<tr><td colspan="3">PPG</td><td colspan="2">meanPPG</td></tr>
<tr><td rowspan="4">ECG</td><td rowspan="2">Time domain</td><td>Statistical Parameter</td><td colspan="2">meanRRI, stdRRI, meanHR, RMSSD, NN50, pNN50</td></tr>
<tr><td>Geometric parameter</td><td colspan="2">SD1, SD2, CSI, CVI, RRtri, TINN</td></tr>
<tr><td rowspan="2">Frequency domain</td><td>FFT</td><td colspan="2">FFT_apLF, FFT_apHF, FFT_nLF, FFT_nHF, FFT_LF/HF ratio</td></tr>
<tr><td>AR</td><td colspan="2">AR_apLF, AR_apHF, AR_nLF, AR_nHF, AR_LF/HF ratio</td></tr>
</table>

The physiological signals for emotions are acquired for 1 minute long baseline state prior to presentation of emotional stimuli and 2-4 minutes long emotional states during presentation of the stimuli. 270 data except severe artifact are used for analysis. To extract features, the obtained signals are analyzed for 30 seconds from the baseline and the emotional state as shown in Figure 1. The emotional states are determined by the result of participant's self-report (scene that emotion is most strongly induced during presentation of each stimulus).

Skin conductance level (SCL), average of skin conductance response (meanSCR) and number of skin conductance response (NSCL) are obtained from EDA. The mean (meanSKT) and maximum skin temperature (maxSKT) and the mean amplitude of blood volume changes (meanPPG) are gotten from SKT and PPG, respectively. RRI is the interval time of R peaks on the ECG signal. RRI and hear rate (HR) offers the mean RRI (meanRRI) and standard deviation (stdRRI), the mean hear rate (meanHR), RMSSD, NN50 and pNN50. RMSSD is the square root of the mean of the sum of the squares of differences between successive RRIs. NN50 is the number of RRI with 50 msec or more and the proportion of NN50 divided by total number of RRI is pNN50. RRtri is to divide the entire number of RRI by the magnitude of the histogram of RRI density and TINN is the width of RRI histogram. In addition to those, we use the fast Fourier transform (FFT) and the auto regressive (AR) power spectrum. The band of low frequency (LF) is 0.04~0.15 Hz and the high frequency (HF) is 0.15~0.4Hz. The total spectral power between 0.04 and 0.15 Hz is apLF and the normalized power of apLF is nLF. apHF and nHF are the total spectral power between 0.15 and 0.4 Hz and the normalized power, respectively. L/Hratio means the ratio of low to high frequency power. These parameters are resulted by means of FFT and AR. LF and HF are used as indexes of sympathetic and vagus activity, respectively. The L/Hratio reflects the global sympatho-vagal balance and can be used as a measure of this balance.

Twenty-eight features are firstly extracted and analyzed from the physiological signals based on ANS response of each emotion, which have been used in emotion recognition study frequently as shown in Table 2.

3 DIFFERENCES IN AUTONOMIC NERVOUS SYSTEM RESPONSES AMONG NEGATIVE EMOTIONS

The differences of physiological signals among three emotions (alpha level at .05) are analysed by one-way ANOVA (SPSS ver. 15.0). The results of one-way ANOVA using difference value of signals subtracting emotional states from baseline shows statistically significant differences among three emotions in NSCR, mean SCR, mean SKT, max SKT and FFT_apHF (which is value to integrate an absolute value power of HF extracted from FFT) as shown in Table 3.

To verify the difference among three emotions in detail, Figure 2 illustrates data analysed by LSD post hoc test. Here, x axis indicates each emotion, fear, surprise and stress, and y axis presents the difference values between emotion and baseline states. There are significant differences of NSCR among all emotions and mean SCR between fear and stress, and between surprise and stress. SCR and NSCR, which were extracted from EDA, decreased for the response of baseline while all emotions are evoked.

Table 3: Result of one-way ANOVA toward parameters.

ANOVA	Sum of Square	df	Mean of Square	F-score
NSCR	100.398	2	50.199	20.886***
meanSCR	7.363	2	3.681	6.242**
meanSKT	94.884	2	47.442	5.827**
maxSKT	91.563	2	45.781	5.744***
FFT_apHF	2,322.00	2	1,161.00	3.833*

* $p < .05$, ** $p < .01$, *** $p < .001$
df: degree of freedom

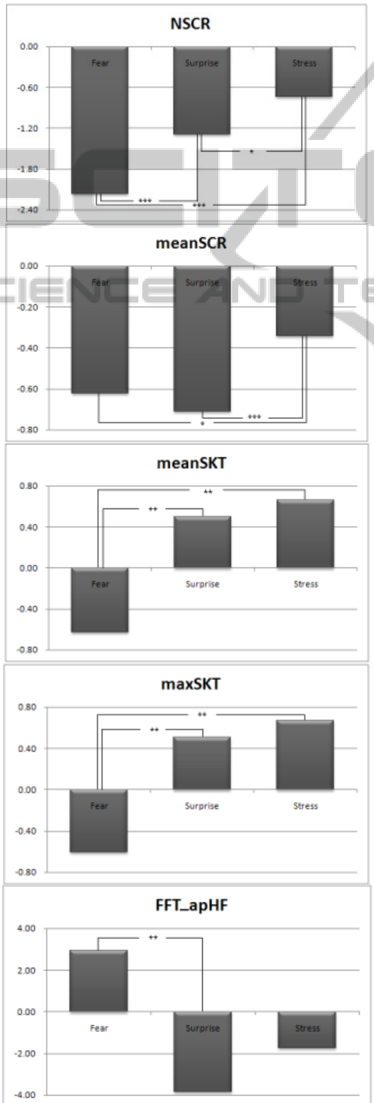


Figure 2: The results of LSD post-hoc test (*p<.05, **p<.01, **p<.001).

Also, mean and max SKT distinguished between fear and surprise and between fear and stress. SKT decreased during fear induction and increased during surprise and stress from baseline. Finally, significant difference between fear and surprise was in FFT_apHF. There were an increase of FFT_apHF in fear and decreases of FFT_apHF in surprise and stress.

To compare results of emotion recognition on feature space, we have select eight feature base on difference in ANS responses among negative emotions. The selected features are SCL, NSCR, meanSCR, meanSKT, meanPPG, meanHR, FFT_LF/HF ratio and AR_LF/HF ratio.

4 EMOTION RECOGNITION

In this study, we have used linear discriminant analysis (LDA), which is one of the oldest mechanical classification systems and linear models, classification and regression tree (CART) which is a robust classification and regression tree, self organizing map (SOM), and Naïve Bayes recognizer based on density for emotion recognition.

LDA is a method used in statistics, pattern recognition and machine learning to find a linear combination of features, which characterizes or separates two or more classes of objects or events (Duda, Hart and Stork, 2000). CART is one of decision tree and nonparametric technique that can select from among a large number of variables those and their interactions that are most important in determining the outcome variable to be explained (Breiman, Friedman, Olshen and Stone 1984). SOMs called Kohonen map, is a type of artificial neural networks in the unsupervised learning category and generally present a simplified, relational view of a highly complex data set (Kohone, 2001). The Naïve Bayes algorithm is a classification algorithm based on Bayes rule and particularly suited when the dimensionality of the inputs is high (Duda, Hart and Stork, 2000).

The four machine learning algorithms were evaluated on only training (TR), 10-fold cross-vallidation (CV) and repeated random sub-sampling validation (RRSV). For TR, the entire dataset is used to build a recognizer and evaluate the built recognizer. TR has the overfitting problem. For solution of the overfitting problem, there are CV and RRSV. In 10-fold cross-validation, the entire dataset is partitioned into 10 equal size subsets. Of the 10 subsets, a single subset is retained as the testing data for testing the recognizer, and the remaining 9 subdatasets are used as training data to build a recognizer. In RRSV, the 70% of the whole emotional patterns are selected randomly for training, the remaining patterns are used for testing purposes and this is repeated 10 times.

Table 4: Result of emotion recognition on feature space with 28 features.

Machine Learning Algorithms		TR	CV	RRSV	
				Training	Testing
LDA		56.9	45.4	58.9±1.7	44.0±3.7
CART		87.2	44.4	87.4±1.9	42.9±4.2
SOM	Supervised	43.1	36.5	43.0±1.8	35.5±4.5
	Unsupervised	59.5	31.9	60.5±1.6	32.4±5.5
Naive Bayes		80.9	54.9	81.9±2.9	46.9±4.8

Table 5: Result of emotion recognition on feature space with 8 features.

Machine Learning Algorithms		TR	CV	RRSV	
				Training	Testing
LDA		52.6	48.0	54.2±2.3	47.0±3.4
CART		85.5	40.5	82.9±1.5	43.3±4.8
SOM	Supervised	47.7	47.4	49.9±2.0	44.2±4.4
	Unsupervised	63.8	39.1	65.1±2.6	40.3±4.3
Naive Bayes		72.7	49.3	73.8±3.2	43.3±5.5

Table 4 and 5 show the recognition results (recognition accrracy) by using the TR, CV and RRSV for 28 features and 8 features, respectively. We used feature normalization and the related parameters of algorithms used default values, which have offered with toolbox. As shown in results, the accraccy of emotion recognition have higher values for trainign than testing. The CV exhibits the results for testing. To apply to real system, we have to discuss in the view point of testing. For 28 features, the results of emotion recogntion for CV has range of 31.9 to 54.9% when all emtions are recognized for test dataset. The accuracy of recognition for RRSV shows in range 32.4 to 46.9 for testing. The similar results accurs when dealing with 8 features. Namlely, we have achieved similar accuracy of emtion recognition with lower dimensionality. In the pattern recognition, a method with low dimensionality offer an intuitive interpretation of the relationship between features and emotions with the use of fewer resoruces. The comparative results reveal that the original feature space has been reduced up to 71% with the similar accurcy of emotion recognition.

5 CONCLUSIONS

The aim of this study is to classify three negative emotions, fear, surprise, and stress, induced by stimuli. For this, we have gotten the physiological signals based on autonomic nervous system responses of the evoked emotions. Also, twenty-eight features have been analysed and extracted from these signals, and we select eight features based on the results of one-way ANOVA. The results of one-way ANOVA using difference value of signals subtracting emotional states from baseline shows statistically significant differences among three emotions in eight features, SCL, NSCR, meanSCR, meanSKT, meanPPG, meanHR, FFT_LF/HF ratio and AR_LF/HF ratio. To classify three emotions, we used four machine learning algorithms, namely, linear discriminant analysis (LDA), classification and regression tree (CART), self-organizing map (SOM) and Naïve Bayes, and the results of those were reported by only training (TR), 10-fold cross-validation (CV) and repeated random sub-sampling validation (RRSV). As shown in results, the similar results have been gotten when dealing with 28 and selected 8 features. Therefore the original feature space has been reduced up to 71% with the similar accurcy of emotion recognition. However, in spite of the reduced feature space, there is a problem with improvement of recognition accuracy for the negative emotions, becuase recognition results showed the low accuracy for testing. We will investigate various methodologies for dealing the accuracy improvement of emotion recognition in the future research. Nevertheless, these results can be useful in developing an emotion theory based on physiological responses in HCI.

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