EMOTION CLASSIFICATION BASED ON PHYSIOLOGICAL RESPONSES INDUCED BY NEGATIVE EMOTIONS

Discrimination of Negative Emotions by Machine Learning Algorithms

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Abstract: The one of main topic of emotion recognition or classification research is to recognize human's feeling or emotion using physiological signals, which is one of the core processes to implement emotional intelligence in HCI research. The aim of this study was to identify the optimal algorithm to discriminate negative emotions (sadness, anger, fear, surprise, and stress) using physiological features. Physiological signals such as EDA, ECG, PPG, and SKT were recorded and analysed. 28 features were extracted from these signals. For classification of negative emotions, five machine learning algorithms, namely, LDF, CART, SOM, Naïve Bayes and SVM were used. Result of emotion classification showed that an accuracy of emotion classification using SVM was the highest (100.0%) and that of LDA was the lowest (41.3%). 78.2%, 45.8%, and 73.3% were shown as the accuracy of emotion classification in CART, SOMs and Naïve Bayes, respectively. This can be helpful to provide the basis for the emotion recognition technique in HCI.

1 INTRODUCTION

Emotion recognition or classification is one of the core processes to implement emotional intelligence in human computer interaction (HCI) research (Wagner, Kim, Andre, 2005). It is highly desirable (even mandatory) that the response of the computer takes into account the emotional or cognitive state of the user in HCI applications such as computer aided tutoring and learning (Sebe, Cohen, Huang, 2005). In basic emotions, negative emotions 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.

Emotion classification has been studied using facial expression, gesture, voice, and physiological signals. In particular, 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 are related to emotional state (Drummond, Quah, 2001).

Recently, emotion classification using physiological signals has been performed by various machine learning algorithms, e.g., Fisher Projection (FP), k-Nearest Neighbor algorithm (kNN), Linear Discriminant Function (LDF), Sequential Floating Forward Search (SFFS), and Support Vector Machine (SVM). Previous works conducted a recognition accuracy of over 80% on average seems to be acceptable for realistic applications (Picard, Vyzas, Healey, 2001; Cowie et al., 2001; Haag et al., 2004; Healey, 2000; Nasoz et al., 2003; Calvo, Brown, Scheding, 2009).

In this paper, we were to identify the best emotion classifier with feature selections using physiology signals induced by negative emotions (sadness, anger, fear, surprise, and stress). For this, electrodermal activity (EDA), electrocardiogram (ECG), skin temperature (SKT), and photoplethysmography (PPG) are acquired and analysed to extract features for emotional pattern dataset. Also, to identify the best algorithm being able to classify negative emotions, we used 5 machine learning algorithms, which are Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Self

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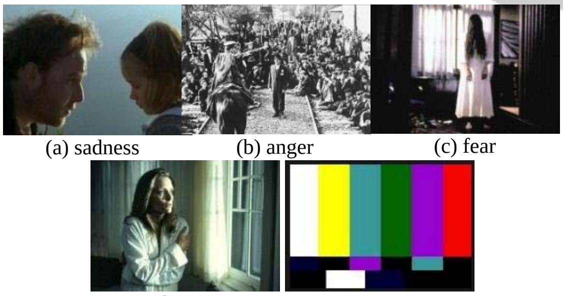
Organizing Map (SOM), Naïve Bayes, and SVM, which are used the well-known emotion algorithms.

2 EMOTION CLASSIFICATION TO DISCRIMINATE NEGATIVE EMOTIONS

12 college students (21.0 years ± 1.48) have participated in this study. They reported that they have no history of medication due to heart disease, respiration disorder, or central nervous system disorder. They filled out a written consent before the beginning of the study and compensated $20 per session for their participation.

2.1 Emotional Stimuli

Fifty emotional stimuli (5 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, anger, fear, surprise, and stress) in this study (Figure 1).



(a) sadness (b) anger (c) fear

(d) surprise (e) stress

Figure 1: The example of emotional stimuli.

The stimuli were examined their appropriateness and effectiveness by preliminary study which 22 college students rated the category and intensity of their experienced emotion on questionnire after they were presented each film clip. The appropriateness means the consistency between emotion intended by experimenter and participanats' experienced. 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 91% and the effectiveness of 9.4 point on average.

2.2 Experimental Settings and Procedures

The laboratory is a room of 5m x 2.5m size having a sound-proof (lower than 35dB) of the noise level where any outside noise or artifact are completely blocked. A comfortable chair is placed in the middle of the laboratory and 38 inch TV monitor set for presentation of film clips is placed in front of the chair. An intercommunication device is placed to the right side of chair for subjects to communicate with an experimenter. A CCTV is installed on the top of the monitor set to observe participants' behaviours.

Prior to the beginning of experiment, experiment procedure was introduced to participants, and electrodes on their wrist, finger, and ankle were attached for measurement of physiological signals. Physiological signals were measured for 1 min prior to the presentation of the stimulus (baseline) and for 2 to 4 min during the presentation of the stimulus (emotional state) then for 1min after presentation of the stimulus as recovery term.

2.3 Physiological Measures

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. EDA was measured from two Ag/AgCl electrodes attached to the index and middle fingers of the non-dominant hand. ECG was measured from both wrists and one left ankle (reference) with the two-electrode method based on lead I. PPG and SKT were measured from the little finger and the ring finger of the non-dominant hand, respectively. Appropriate amplification and band-pass filtering were performed.

The obtained signals were analyzed for 30 sec from the baseline and the emotional states by AcqKnowledge (ver 3.8.1) software (USA). The 28 features were extracted and analyzed from the physiological signals as shown in Table 1 and Figure 2.

Skin conductance level (SCL), average of skin conductance response (mean SCR) and number of skin conductance response are obtained from EDA. The mean (mean SKT) and maximum skin temperature (max SKT) and the mean amplitude of blood volume changes (mean PPG) are gotten from SKT and PPG, respectively.

ECG was analysed in the view point of time (statistical and geometric approaches) and frequency domain (FFT and AR). RRI is the interval time of R peaks on the ECG signal. RRI and heart rate (HR) offers the mean RRI (mean RRI) and standard

Table 1: Features extracted from physiological signals.

Signals			Features
EDA			SCL, NSCR, meanSCR
SKT			meanSKT, maxSKT
PPG			meanPPG
ECG	Time domain	Statistical Parameter	meanRRI, stdRRI, meanHR, RMSSD, NN50, pNN50
		Geometric parameter	SD1, SD2, CSI, CVI, RRtri, TINN
	Frequency domain	FFT	FFT_apLF, FFT_apHF, FFT_nLF, FFT_nHF, FFT_LF/HF ratio
		AR	AR_apLF, AR_apHF, AR_nLF, AR_nHF, AR_LF/HF ratio

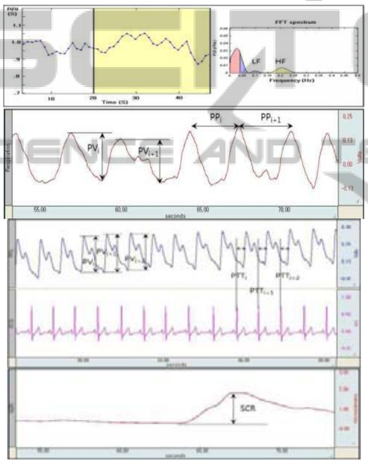


Figure 2: The example of acquired physiological signals.

deviation (std RRI), the mean heart rate (mean HR), 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 50msec or more and the proportion of NN50 divided by total number of RRI is pNN50. In addition to those, RRI triangular index (RRtri) and TINN are extracted from the histogram of RRI density as a geometric parameter. 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 (M-N) as shown in Figure 3.

The relations between RRI(n) and RRI(n+1) are shown in Fig. 6 called Lorentz plot or Poincare plot. Here, n and n+1 are n-th and n+1-th values of RRI, respectively. In the figure, L is the direction that is efficient for representing data, and T is the orthogonal direction of L. The standard deviations, SD1 and SD2, are gotten for T and L directions, respectively. The cardiac sympathetic index (CSI) is calculated by CSI = 4SD2/4SD1 and the cardiac vagal index (CVI) is obtained from CVI = log10 (4SD1 * 4SD2) as an emotional feature. SD1, SD2, CSI and CVI reflect short term HRV (Heart Rate Variability), long term HRV, sympathetic nerve activity and parasympathetic activity, respectively.

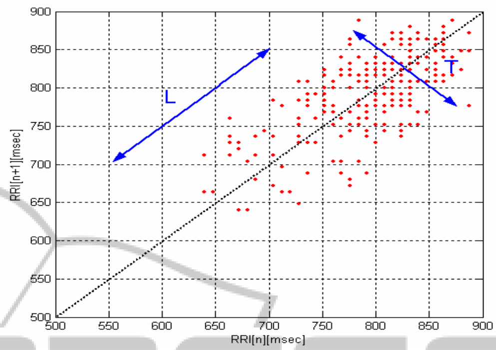


Figure 3: Lorentz plot of RRI.

For extracting an emotional feature based on physiological signals, 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.

2.4 Data Analysis

450 physiological signal data (5 emotions x 10 stimuli x 9 cases) were used for emotion classification except for severe artifact effect by movements, noises, etc. To identify the emotion classification algorithm being able to best recognize 5 emotions by the 28 physiological features, five machine learning algorithms, namely, LDA which is one of the oldest mechanical classification systems, CART which is a robust classification and regression tree, unsupervised SOM, Naïve Bayes classifier based on density, and SVM with the Gaussian radial basis function kernel were used.

3 RESULTS OF EMOTION CLASSIFICATION

The 28 features extracted from physiological signals were applied to emotion classification algorithms, i.e., LDA, CART, SOMs, Naïve Bayes and SVM for emotion classification of 5 emotions. Table 2 shows the result of emotion classification by 5 algorithms.

Table 2: Result of emotion classification by 5 machine learning algorithms.

Algorithm	Accuracy (%)	Features (N)
LDA	41.3	28
CART	78.2	28
SOMs	45.8	28
Naïve Bayes	73.3	28
SVM	100.0	28

In analysis of LDA, sadness was recognized by LDA with 35.6%, anger 33.3, fear 50.5%, surprise 38.8%, and stress 49.0% (Table 3).

Table 3: Result of emotion classification by LDA.

	Sadness	*Anger*	*Fear*	*Surprise*	*Stress*	*Total*
Sadness	35.6	22.1	14.4	6.7	21.2	100.0
Anger	14.3	33.3	23.8	6.7	21.9	100.0
Fear	9.9	12.9	50.5	13.9	12.9	100.0
Surprise	10.7	16.5	15.5	38.8	18.4	100.0
Stress	12.0	15.0	9.0	15.0	49.0	100.0

CART provided accuracy of 78.2% when it classified all emotions. In sadness, accuracy of 85.6% was achieved with CART, 77.1% in anger, 79.2% in fear, 72.8% in surprise and 76.0% in stress (Table 4).

Table 4: Result of emotion classification by CART.

	Sadness	*Anger*	*Fear*	*Surprise*	*Stress*	*Total*
Sadness	85.6	3.8	2.9	2.9	4.8	100.0
Anger	9.5	77.1	1.9	3.8	7.6	100.0
Fear	2.0	7.9	79.2	2.0	8.9	100.0
Surprise	4.9	6.8	9.7	72.8	5.8	100.0
Stress	9.0	5.0	6.0	4.0	76.0	100.0

The result of emotion classification using SOMs showed that according to orders of sadness, anger, fear, surprise, and stress, recognition accuracy of 73.1%, 42.9%, 38.6%, 41.7%, and 32.0% were obtained by SOMs (Table 5).

Table 5: Result of emotion classification by SOMs.

	Sadness	*Anger*	*Fear*	*Surprise*	*Stress*	*Total*
Sadness	73.1	7.7	4.8	9.6	4.8	100.0
Anger	24.8	42.9	11.4	10.5	10.5	100.0
Fear	31.7	14.9	38.6	9.9	5.0	100.0
Surprise	23.3	9.7	15.5	41.7	9.7	100.0
Stress	27.0	13.0	9.0	19.0	32.0	100.0

The accuracy of Naïve Bayes algorithm to classify all emotion was 73.3%. And each emotion was recognized by Naïve Bayes with 77.9% of sadness, 72.4% of anger, 78.2% of fear, 59.2% of surprise and 79.0% of stress (Table 6).

Table 6: Result of emotion classification by NAÏVE BAYES.

	Sadness	*Anger*	*Fear*	*Surprise*	*Stress*	*Total*
Sadness	77.9	3.8	2.9	4.8	10.6	100.0
Anger	1.9	72.4	8.6	4.8	12.4	100.0
Fear	5.0	6.9	78.2	3.0	6.9	100.0
Surprise	5.8	12.6	8.7	59.2	13.6	100.0
Stress	14.0	3.0	2.0	2.0	79.0	100.0

Finally, accuracy of SVM was 100.0% and classifications of each emotion were 100.0% in all emotions (Table 7).

Table 7: Result of emotion classification by SVM.

	Sadness	*Anger*	*Fear*	*Surprise*	*Stress*	*Total*
Sadness	100.0	0.0	0.0	0.0	0.0	100.0
Anger	0.0	100.0	0.0	0.0	0.0	100.0
Fear	0.0	0.0	100.0	0.0	0.0	100.0
Surprise	0.0	0.0	0.0	100.0	0.0	100.0
Stress	0.0	0.0	0.0	0.0	100.0	100.0

4 CONCLUSIONS

This study was to identify the optimal emotion recognition algorithm for classifying negative emotions, sadness, anger, fear, surprise, and stress. Our result showed that SVM is the best algorithm being able to classify these emotions. The SVM showed that an accuracy much higher chance probability when applied to physiological signal databases. SVM is designed for two class classification by finding the optimal hyperplane where the expected classification error of test samples is minimized. This was 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 were carefully extracted (Takahashi, 2004). 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. Therefore, we will perform the average classification in further analysis.

LDA and SOM had the lowest accuracy in emotion recognition. We think that this result in variability of physiological signals. The more or less unique and person-independent physiological response among different emotions may fall off the recognition rate with the number of emotion categories (Kim, Bang, Kim, 2004). These uncertainties could be an important cause that deteriorated the recognition ratio and troubled the model selection of the LDA or SOM. Also, it is possible that result of LDA which is one of the linear models or SOM didn't perform well because our physiological signals didn't linear variables and the extracted features didn't linearly separable and large variability between the features used. To overcome this, we needed performance of some normalization of features being able to reduce large variability.

Nevertheless, our results led to better chance to recognize human emotions and to identify the optimal emotion classification algorithm by using physiological signals. This will be able to apply 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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