

## **Three Differential Emotions and Classification Using Physiological Signals**

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**Abstract.** In HCI researches, human emotion classification has been done by machine learning algorithms based on physiological signals. In this study, we discuss the comparative results of emotion classification by several algorithms which classify three different emotional states (happiness, neutral, and surprise) using physiological features. 217 students participated in this experiment. While three kinds of emotional stimuli are presented to participants, physiological signal responses (EDA, SKT, ECG, RESP, and PPG) were measured. Participants rated their own feelings to emotional stimuli on emotional assessment scale after presentation of emotional stimuli. The emotional stimuli had 96% validity and 5.8 point efficiency on average. There were significant differences of autonomic nervous system responses among three emotions by statistical analysis. The classification of three differential emotions was carried out by Linear Discriminant Analysis (LDA, SPSS 15.0), Support Vector Machine (SVM), and Multilayer perceptron (MLP) using difference value which subtracts baseline from emotional state. The result of LDA showed that the accuracy of classification in three different emotions was 83.4%. 75.5% and 55.6% have obtained as the accuracy of classification by SVM and MLP, respectively. This study confirmed that the three emotions can be better classified by LDA using various physiological features than SVM and MLP. Further study may need to get those results to obtain more stability and reliability, as comparing with the accuracy of emotions classification by using other algorithms.

**Keywords:** Emotion classification, Physiological signals, Machine learning

### **1. Introduction**

Recent emotion recognition studies have tried to detect a human emotion by using physiological signals. It is important to detect emotions for applying on human-computer interaction system. Various physiological signals have been widely used to recognize a human's emotion and feeling because signal acquisition using non-invasive sensors is relatively simple and physiological responses are less sensitive in social and cultural difference [1]. Physiological signal may happen to artifact due to motion, and have difficulty mapping emotion-specific responses pattern, but this has 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, those can be acquired spontaneous emotional responses and not caused by responses to social masking or factitious emotion expressions. Finally, measurement of emotional responses by multi-channel physiological signals offers more information for emotion recognition, because physiological responses are related to emotional state [2]. Various physiological signals offer a great potential for the recognition of emotions in computer systems. In order to fully exploit the advantages of physiological measures, standardizations of experimental methods have 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 [3].

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In this paper, we introduce classification of three differential emotions using physiological signals. For this, three kinds of emotion, namely, happiness, neutral, and surprise are evoked by stimuli constructed by audio-visual film clips and then physiological signals are measured as the reactions of stimuli. The suitability and effectiveness of the used stimuli have been examined in preliminary study. In addition that, we identified the optimal algorithm being able to classify three emotions. We used Linear Discriminant Analysis (LDA) which is one of the linear models as a statistical method and Support Vector Machine (SVM) and Multilayer perceptron (MLP) as a machine learning algorithm [4]-[7]. The comparative analysis of classification results by those algorithms showed that the LDA exhibits higher accuracy for three emotions.

## 2. Methods for Emotions Classification

129 college students (60 males, 69 females and  $22 \pm 2.2$  years) and 88 high school students (37 males, 51 females and  $16 \pm 1.3$  years) have participated in this study. They reported that they have not any history of medical illness or psychotropic medication and any kind of medication due to heart disease, respiration disorder, or central nervous system disorder. A written consent was obtained before the beginning of the study from the participants and they were also paid \$20 USD per session to compensate for their participation.

The emotional stimuli, 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 (happiness, neutral, and surprise) in this study as shown in Fig. 1.



Fig. 1: Example of a stimulus for inducing an emotion

Prior to the experiment, we introduced detail experiment procedure to participants. They had an adaptation time to feel comfortable in the laboratory's environment and then an experimenter 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. Participants rated the emotion that they experienced during presentation of the film clip on the emotion assessment scale. This procedure was repeated 3 times for elicitation of 3 differential emotions. Presentation of each film clip was count-balanced across each emotional stimulus.

EDA, ECG, PPG, and SKT as physiological signals 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 physiological signals were analyzed for 30 sec from the baseline and the emotional state by AcqKnowledge (Ver. 3.8.1) software (USA) and 13 features were extracted from these signals as shown in Fig. 2.

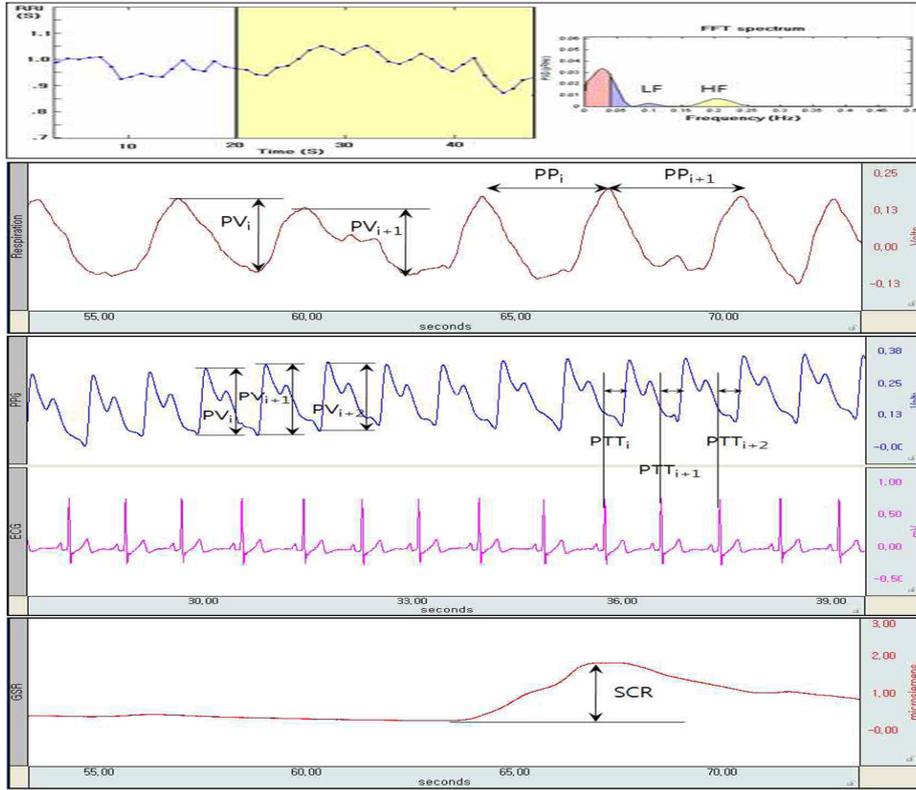


Fig. 2: Analysis of physiological signals

### 3. Emotion Classification

In this study, we have used LDA, SVM and MLP for three emotion classifications. Firstly, LDA finds the direction to project data on so that between-class variance ( $S_B$ ) in maximized and within-class variance ( $S_W$ ) in minimized, and then offers a linear transformation of predictor variables which provides a more accurate discrimination [4].  $S_W$  is proportional to the sample covariance matrix for the pooled d-dimensional data. It is symmetric and positive semidefinite, and it is usually nonsingular if  $n > d$ . Likewise,  $S_B$  is also symmetric and positive semidefinite, but because it is the outer product of two vector, its rank is at most one.

In terms of  $S_B$  and  $S_W$ , the criterion function  $J$  is written as

$$J(\mathbf{w}) = (\mathbf{w}^T \mathbf{S}_B \mathbf{w}) / (\mathbf{w}^T \mathbf{S}_W \mathbf{w}). \quad (1)$$

This expression is well known in mathematical physics and the generalized Rayleigh quotient. It is easy to show that a vector  $\mathbf{w}$  that maximizes  $J$  must satisfy

$$\mathbf{S}_B \mathbf{w} = \lambda \mathbf{S}_W \mathbf{w}, \quad (2)$$

for some constant  $\lambda$ , which is a generalized eigenvalue problem.

In analysis of LDA, accuracy of all emotions was 78.6 % and accuracy of each emotion had range of 78% to 89%. Happiness was recognized by LDA with 78.0%, neutral 88.8 % and Surprise 83.0% as shown in Table. 1.

Table. 1: result of three emotion discriminant by LDA

	Happiness	Neutral	Surprise	Total
Happiness	78.0	21.4	0.6	100.0
Neutral	10.6	88.8	0.5	100.0
Surprise	12.5	4.5	83.0	100.0

SVM finds a hyperplane based on support vector to analyze data and recognize patterns. The complexity of the resulting classifier is characterized by the number of support vectors rather than the dimensionality of the transformed space. The goal in training SVM is to find the separating hyperplane with the largest margin [4]. We expect that the larger the margin, the better generalization of the classifier. The distance from any hyperplane to a pattern  $\mathbf{y}$  is  $|\mathbf{g}(\mathbf{y})|/\|\mathbf{a}\|$ , and assuming that a positive margin  $b$  exists

$$z_k \mathbf{g}(\mathbf{y}_k) / \|\mathbf{a}\| \geq b, k = 1, \dots, n; \quad (3)$$

The goal is to find the weight vector  $\mathbf{a}$  that maximizes  $b$ . Here,  $z_k$  is the class of  $k$ -th pattern,  $b$  is margin and  $\mathbf{g}(\mathbf{y})$  is a linear discriminant in an augmented  $\mathbf{y}$  space,

$$\mathbf{g}(\mathbf{y}) = \mathbf{a}^T \mathbf{y} \quad (4)$$

SVM provided accuracy of 75.5% when it classified all emotions. In happiness, accuracy of 64.7% was achieved with SVM, 77.7% in neutral, and 84.1% in surprise, refer to Table. 2.

Table. 2: result of three emotion discriminant by SVM

	Happiness	Neutral	Surprise	Total
Happiness	64.7	30.6	4.6	100.0
Neutral	20.2	77.7	2.1	100.0
Surprise	12.5	3.4	84.1	100.0

MLP is a computational intelligence model inspired by the structure and functional aspects of biological neurons [4]. It is realized by connecting neurons and each neuron processes information using activation function,

$$f_j(\text{net}_j) = 1 / (1 + e^{-\text{net}_j}) \quad (5)$$

where,  $\text{net}_j$  is input of  $j$ -th neuron and computed by,

$$\text{net}_j = \sum_i w_{ji} f_i + \theta_j \quad (6)$$

where,  $w_{ji}$  is the connection weight between  $j$ -th and  $i$ -th neurons and adjusted by

$$w_{ji}(\text{new}) = w_{ji}(\text{old}) + \Delta w_{ji} \quad (7)$$

$\Delta w_{ji}$  is calculated by back-propagation algorithm.

In Table. 3, the result of emotion recognition using MLP showed that accuracy to recognize all emotions was 55.6%. According to orders of happiness, neutral, and surprise recognition rates of 11.6%, 67.0%, and 88.1% were obtained by MLP.

Table. 3: result of three emotion discriminant by MLP

	Happiness	Neutral	Surprise	Total
Happiness	11.6	50.3	38.2	100.0
Neutral	6.9	67.0	26.1	100.0
Surprise	1.1	10.8	88.1	100.0

## 4. Summaries

This study was to identify the difference among happiness, neutral, and surprise emotions using physiological responses induced by these emotional stimuli and to find the optimal emotion recognition algorithm for classifying these three emotions.

Our result showed that LDA is the best algorithm being able to classify three emotions. LDA, which is a statistical method to classify data signals by using linear discriminant functions, provides extremely fast

evaluations of unknown inputs performed by distance calculations between a new sample and mean of training data samples in each class weighed by their covariance matrices. The LDA shows a recognition ratio much higher chance probability, i.e. 78.6% for three emotion categories, when applied to physiological signal databases.

Although some algorithm showed lower accuracy of emotion recognition, the results led to better chance to recognize human emotions and to identify the optimal emotion recognition algorithm by using physiological signals. For example, 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. However, for more accurate and realistic applications, a novel method to identify not only basic emotions but also more various emotions such as boredom, frustration, and love, etc. 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.

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