Classification of Three Negative Emotions based on Physiological Signals

- Classification of fear, surprise and stress

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Abstract—**Physiological signal is one of the most commonly used emotional cues. In recent emotion classification research, the one of main topics is to recognize human's feeling or emotion using multi-channel physiological signals. In this study, we discuss the comparative results of emotion detection using several classification algorithms, which classify negative emotions (fear, surprise and stress) based on physiological features. Physiological signals, such as skin temperature (SKT), electrodermal activity (EDA), electrocardiogram (ECG), and photoplethysmography (PPG) were recorded while participants were exposed to emotional stimuli. Twenty-eight features were extracted from these signals. For classification of negative emotions, four machine learning algorithms, namely, Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Self Organizing Map (SOMs), and Naïve Bayes were used. The 70% of the whole datasets were selected randomly for training and the remaining patterns are used for testing purposes. Testing accuracy by using the 30% datasets ranged from 32.4% to 46.9% and, consequently the selected physiological features didn't contribute to classify the three negative emotions. In the further work, we intend to improve emotion recognition accuracy by applying the selected significant features, such as NSCR, SCR, SKT, and FFTap_HF.**

Keywords-emotion classigication; physiological signals; negative emotions; machine learning algorithm

I. INTRODUCTION

Emotion detection is one of the core factors for implementing emotional intelligence in human computer interaction research [1]. In particular, it is important to recognize negative emotions (e.g., anger, fear, etc.) because they have direct or indirectly effects gradual deviance or interruption of our normal thinking process, they are essential for our natural (unforced) survival or struggle for existence. Emotion recognition has been done using by facial expression, gesture, voice, and physiological signals. In particular, physiological signals have advantages; they are less affected by social and cultural difference as well as signal acquisition by non-invasive sensors is relatively simple and is possible to observe user's state in real time. They aren't robust to social masking or factitious emotion expression and are related to emotional state [2]. Recently, emotion recognition based on physiological signals has been performed by using various machine learning algorithms, e.g., Fisher Projection (FP), k-Nearest Neighbor algorithm (kNN), and Support Vector Machine (SVM). Previous results that have showed the over 80% accuracy on average seems to be applicable in real world settings [3-8]. We have already reported the recognition accuracy on the three emotions, i.e., fear, surprise, and stress, derived from only training data [9]. As a follow-up work, we performed supplementary analysis by using machine learning algorithms for these emotions based on physiological signals. We performed each classifier by 10 fold cross-validation for solution of the overfitting problem and divided the dataset into 70% training and 30% testing subsets for testing purposes. The results were compared with the previous result that used the only training dataset. To classify three negative emotions, four well-known machine learning algorithms, i.e., were Linear Discriminant Analysis (LDA), Classification And Regression Tree (CART), Self Organizing Map (SOMs), and Naïve Bayes, were used. For dataset of physiological signals, twenty-eight features were extracted from physiological signals, i.e., skin temperature (SKT), electrocardiogram (ECG), electrodermal activity (EDA), and photoplethysmography (PPG).

II. PHYSIOLOGICAL SIGNALS OF EMOTIONS

Twelve male and female college students (mean age: 21 ± 1.48 yrs) participated in this study. They reported that they had not any medical illness or psychotropic medication and any kind of medication due to heart disease, respiration disorder, or central nervous system disorder. They participated in an experimental session for 10 weeks on a weekly basis over 10 times. A written consent was obtained prior to the study from the participants and they were paid $20 USD per session to compensate for their participation.

Thirty emotional stimuli (3 emotions x 10 sessions), 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 (fear, surprise, and stress) in this study (Figure 1). Audio-visual film clips have widely used because they have a relatively high degree of ecological validity as well as they have the desirable properties of being readily standardized and being dynamic rather than static [10-13].

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

Figure 1. Examples of emotional stimuli

The appropriateness and effectiveness of the stimuli were examined through a preliminary study. The appropriateness of emotional stimlus means the consistency between emotion intended by experimenter and 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 92% and the effectiveness of 9.4 points on average. The appropriateness and effectiveness of each emotional stimuli were as follows; appropriateness and effectiveness of fear were 89.0% and 9.6 points, 89% appropriateness and 9.5 points effectiveness in surprise. Stress had the appropriateness of 98% and the effectiveness of 9.1 points.

Prior to the experiment, participants were introduced detailed experiment procedure. 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 the measurement of physiological signals. Physiological signals were measured for 60 sec as baseline prior to the presentation of emotional stimulus and for 2 to 4 min as emotional state during the presentation of the stimulus, then for 60 sec as recovery term after presentation of the stimulus. Participants reported the emotion that they had experienced during the presentation of the film clips and the intensities of experienced emotions on the emotion assessment scale. This procedure was repeated 3 times in three different emotion conditions.

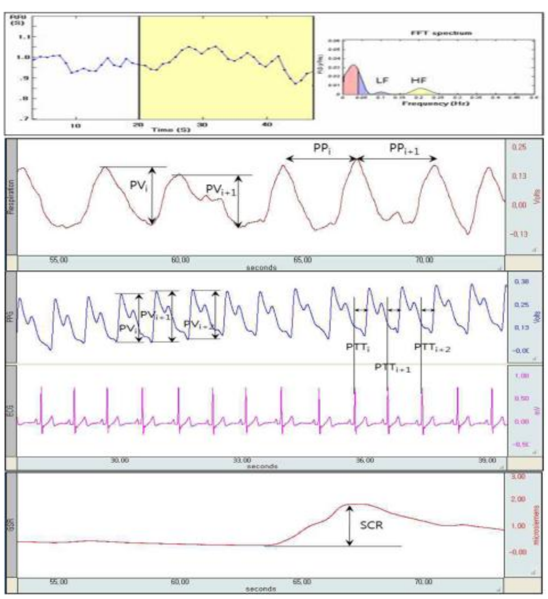

Figure 2. Analysis of physiological signals

The dataset of physiological signals were collected using by MP150 (Biopac system Inc., USA). SKT electrode was attached on the first joint ring finger of non-dominant hand and EDA was measured with the use of 8 mm AgCl electrodes placed on the volar surface of the distal phalanges of the index and middle fingers of the non-dominant hand. Electrodes were filled with a 0.05 molar isotonic NaCl paste to provide a continuous connection between the electrodes and the skin. ECG electrodes were placed on both wrists and one left ankle with two kinds of electrodes, sputtered and AgCl ones. The left-ankle electrode was used as a reference. PPG electrode was attached on the first joint of the thumb of the non-dominant hand. To extract features, the obtained signals for 30 seconds from the baseline and the each emotional state are analyzed by AcqKnowledge (Ver. 3.8.1) software (USA) as shown in Fig. 2. Twenty-eight features were firstly extracted from the physiological signals, which have been used for emotion recognition in the study (shown in Table I).

TABLE I. 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 colspan="2">Statistical parameter</td><td>meanRRI, stdRRI, meanHR, RMSSD, NN50, pNN50</td></tr>
<tr><td colspan="2">Geometric parameter</td><td>SD1, SD2, CSI, CVI, RRtri, TINN</td></tr>
<tr><td rowspan="2">Frequency domain</td><td colspan="2">FFT</td><td>FFT_apLF, FFT_apHF, FFT_nLF, FFT_nHF, FFT_LF/HF ratio</td></tr>
<tr><td colspan="2">AR</td><td>AR_apLF, AR_apHF, AR_nLF, AR_nHF, AR_LF/HF ratio</td></tr>
</table>

Two hundred-seventy physiological signal data (3 emotions x 10 sessions x 9 cases) were used for emotion classification except for data having severe artifacts by movements, noises, etc. To classify three negative emotions by the twenty-eight physiological features, four machine learning algorithms, namely, LDA, which is one of the oldest classification systems, CART, which is a robust classification and regression tree, unsupervised SOM, and Naïve Bayes classifier based on density were used in data analysis.

III. CLASSIFICATION OF EMOTIONS

In this study, we have used LDA, which is one of the oldest mechanical classification systems and linear models, CART which is a robust classification and regression tree, unsupervised SOM, and Naïve Bayes classifier based on density for three emotion classifications. 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. It is a technique for dimensionality reduction that projects the data onto a subspace that satisfies the requirement of maximizing the between-class variance (SB) and minimizing the within-class variance (SW). It then offers a linear transformation of

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the predictor variables, which provides a more accurate discrimination. In LDA, the measurement space is transformed allowing the separability between the emotional states to be maximized. The separability between the emotional states can be expressed through several criteria [14]. SW 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, SB 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 SB and SW, 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 w that maximizes J must satisfy

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

for some constant λ, which is a generalized eigenvalue problem.

CART [14-15] is a non-parametric decision tree technique that produces either classification or regression trees, depending on whether the dependent variable is categorical or numeric, respectively. Given the data represented at a node, either declare that node to be a leaf (and state what category to assign to it), or find another property to use to split the data into subsets. In the generic tree-growing methodology known as CART, the basic principle underlying a tree creation is simplicity. We prefer decisions that lead to a simple, compact tree with few nodes. In formalizing this notion, the most popular measure is the entropy impurity (or occasionally, information impurity)

$$i(N) = -\sum_j P(\omega_j)\log_2 P(\omega_j) \quad (3)$$

where, P(ωj) is the fraction of patterns at node N that are in class ωj. By the well-known properties of entropy, if all the patterns are of the same category, the impurity is 0; otherwise it is positive, with the greatest value occurring when the different classes are equally likely.

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 [14, 16]. This is called a topology-preserving map because there is a topological structure imposed on the nodes in the network. A topological map is simply a mapping that preserves neighborhood relations. The goal of training is that the "winning" unit in the target space is adjusted so that it is more like the particular pattern. Others in the neighborhood of output are also adjusted so that their weights more nearly match that of the input pattern. In this way, neighboring points in the input space lead to neighboring points being active. Given the winning unit i, the weight update is

$$\mathbf{w}_i(\text{new}) = \mathbf{w}_i + h_{ci}\,(\mathbf{x} - \mathbf{w}_i) \quad (4)$$

$$h_{ci} = h_0 \exp(-\|\mathbf{r}_i - \mathbf{r}_c\|^2/\sigma^2) \quad (5)$$

where, hci is called the neighborhood function that has value 1 for i=c and smaller for large value of the distance between units i and c in the output array. h0 and σ are suitable decreasing functions of time. Units close to the winner as well as the winner itself, have their weights updated appreciably. Weights associated with far away output nodes do not change significantly. It is here that the topological information is supplied.

The Naïve Bayes algorithm is a classification algorithm based on Bayes rule and particularly suited when the dimensionality of the inputs is high [14]. When the dependency relationships among the features used by a classifier are unknown, we generally proceed by taking the simplest assumption, namely, that the feature are conditionally independent given the category, that is,

$$p(\omega_k|\mathbf{x}) \propto \prod_{i=1}^{d} p(x_i|\omega_k) \quad (6)$$

This so-called naïve Bayes rule often works quite well in practice, and it can be expressed by a very simple belief net.

The machine learning algorithms were evaluated by only training and the repeated random subsampling validation. The former uses the whole emotional patterns in order to build a classifier model using machine learning algorithms and measure the classification accuracy of those. The repeated random subsampling validation is used to consider overffiting problem for only trained model. This builds and evaluates a classification model using training and testing datasets, respectively. The 70% of the whole emotional patterns are selected randomly for training and the remaining patterns are used for testing purposes. It was repeated 10 times in this study.

Table II summarizes the classification results for the only training dataset and the repeated random subsampling validation (RRSV). The results of RRSV denote the average ± standard deviation for 10 times. The results of emotion classification by only training dataset had range of 43.1% to 87.2% when all emotions are recognized and in similar results, 70% training dataset had range of 43.0% to 87.4%. However, in recognition using 30% of datasets for testing, accuracy of all emotions had only 32.4% to 46.9% and according to orders of Naive Bayes (Kernel Density), LDA, CART, and supervised SOMs, recognition rates were obtained 46.9%, 44.0%, 42.9% and 35.5%.

TABLE II. CLASSIFICATION RESULTS BY ONLY TRAINING DATASET AND THE REPEATED RANDOM SUBSAMPLING VALIDATION (RRSV)

Methods		Only TR Acc	RRSV	
			TR Acc	TE Acc
LDA		57.3	58.9±1.7	44.0±3.7
CART		87.2	87.4±1.9	42.9±4.2
SOMs	**Supervised**	43.1	43.0±1.8	35.5±4.5
	Unsupervised	59.5	60.5±1.6	32.4±5.5
Naive Bayes	**General**	51.0	53.7±2.8	43.7±6.7
	Kernel Density	80.9	81.9±2.9	46.9±4.8

TR : Training, TE : Testing, Acc : Accuracy (%)

TABLE III. THE RESULT ON REPEATED ONE-WAY ANOVA TOWARD EACH FEATURES

ANOVA	*SS*	*df*	*MS*	*F*
dNSCR	100.398	2	50.199	20.886***
dmeanSCR	7.363	2	3.681	6.242**
dmeanSKT	94.884	2	47.442	5.827**
dmaxSKT	91.563	2	45.781	5.744***
FFTap_HF	2,322.00	2	1,161.00	3.833*

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

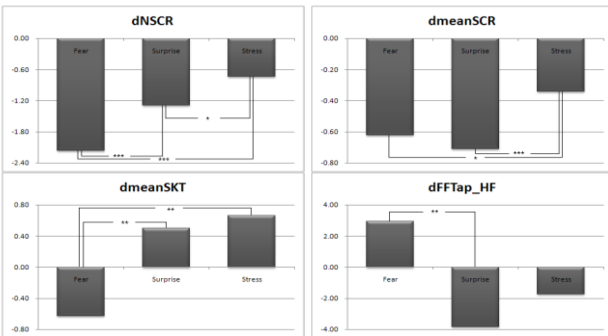

Figure 3. The results of LSD post-hoc test (*p<.05, **p<.01, **p<.001)

IV. CONCLUSION

The aim of this study was to classify three negative emotions, fear, surprise, and stress from physiological signals. We performed each classifier by 10 fold cross-validation for solution of the overfitting problem and divided the dataset into 70% training and 30% testing subsets for testing purposes. We compared this result with the previous result by the only training dataset and our results found no significant differences between the accuracies by the training datasets. However, recognition results by 30% of datasets for testing were lower than that of training dataset and had range of 32.4% to 46.9%. This means that consequently the selected physiological features didn't contribute to classify the three negative emotions. Also, these findings suggest that the given dataset by physiological signals has high nonlinear characteristic and reflects the individual variability of physiological property in emotions. The more or less unique and person-independent physiological response among these emotions may fall off the recognition rate with the number of emotion categories [17].

The values of testing performance are good indicators of the generalization capabilities of the constructed models. As selecting a model, if the approximation capability of a trained model is considered only, the selected model has great recognition accuracy; however, it has deteriorated generalization (prediction) capability and cannot apply to a real system. Especially, this is conspicuous in nonlinear problem. This important question arises, too, as to the selection of the proper structure of the emotion recognition in this study. To overcome these limitation, additional works for the verification of our dataset's statistical distribution and for performance of features' normalization those might be able to reduce large variability should be conducted. Also, for improvement of emotion classification, we have already selected the meaningful features, such as NSCR, SCR, and SKT, which are significantly different among emotions by statistical analysis shown in the Table III and Figure 3 [9]. In the follow-up work, we intend to improve recognition accuracy by applying these features in our classifiers.

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