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RBF 커널과 다중 클래스 SVM을 이용한 생리적 반응 기반 감정 인식 기술

Physiological Responses-Based Emotion Recognition Using Multi-Class SVM with RBF Kernel

마카라 완니, 고 광 은, 박 승 민, 심 귀 보*
(Makara Vanny[1], Kwang-Eun Ko[1], Seung-Min Park[1], and Kwee-Bo Sim[1])
[1]Chung-Ang University

Abstract: Emotion Recognition is one of the important part to develop in human-human and human computer interaction. In this paper, we have focused on the performance of multi-class SVM (Support Vector Machine) with Gaussian RFB (Radial Basis function) kernel, which has been used to solve the problem of emotion recognition from physiological signals and to improve the accuracy of emotion recognition. The experimental paradigm for data acquisition, visual-stimuli of IAPS (International Affective Picture System) are used to induce emotional states, such as fear, disgust, joy, and neutral for each subject. The raw signals of acquisited data are splitted in the trial from each session to pre-process the data. The mean value and standard deviation are employed to extract the data for feature extraction and preparing in the next step of classification. The experimental results are proving that the proposed approach of multi-class SVM with Gaussian RBF kernel with OVO (One-Versus-One) method provided the successful performance, accuracies of classification, which has been performed over these four emotions.

Keywords: emotion recognition, biofeedback system, physiological signals, visual-stimuli, multi-class SVM with Gaussian RBF

I. INTRODUCTION

The concept of emotion involves three major components, such as experience, expressions, and biological arousal. The emotion is treated as psycho-physiological process that produced by the limbic system activity in response to a formal stimulus [3]. Various researches have tried to measure the psycho-physiological signals and used to them as novel source for HCI (Human-Computer Interaction) system. This system provided interactive services for human and has been proved to be a particularly successful in recent and future industry [11]. Especially, the automatic emotion recognition system in the HCI fields can be increasingly playing a significant role in practical applications, such as affective computing, smart phone application, assistance robot in household, and so on.

So far, there have been some kind of problems that the researchers have occurred and solved in the study of emotion recognition such as the experimental paradigm for acquisition data, means that the methods of induced emotion in which have proved receiving low level of acquired data, the method for designing filter for noisy reduction and translating the meaningful data into the feature vector, and the method with algorithm for classifying data.

There were many previous methods that various researchers have employed to express and elicit emotions through visualization, audition, gesture with tone of voice, body movement, facial expressions, and other elicitation methods in order to detect which respond to the effective state [3]. In this paper, visual-stimuli of IAPS was used to elicit emotions in the experimental paradigm and it was an effective picture standard to induce emotions for each subject [1]. And some emotions were difficult to induce and recognize by human, and inner states of emotion was not expressed outwardly. The physiological patterns might be used to recognize distinct emotions through the remained questions [2]. And the importance of physiological responses-based emotion recognition proved the evidence to express some gestural activities such as shaking, leg movement, facial impression (lips, nose, cheek, eyebrows, and chin) would be preferable, as well as other behavior-based models, such as gestural activity or time to complete a test. However, it is a mistake to think of physiology as something that people do not naturally recognize. As the real example, a stranger shaking your

* 책임저자(Corresponding Author)
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마카라 완니, 고광은, 박승민, 심귀보: 중앙대학교 전자전기공학부
(makaravanny@cau.ac.kr/kkeun@cau.ac.kr/sminpark@cau.ac.kr/kbsim@cau.ac.kr)
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hand can feel its clamminess (related to skin conductivity) and a friend learning next to you might sense your heart pounding.

In this paper, multi-class SVM with Gaussian RBF (Radial Basis Function) kernel was proposed to solve the problem for classifying data and improving accuracy in the study of automatic emotion recognition. The goal of this paper is to show and improve the efficiency of emotional detection system in the real time with the knowledge of the current advancement in this technology through the methods and algorithms as we mention above. The remained sections show the next step respectively, such as related works in section II, meaningful feature selection from physiological responses in section III, Physiological response-based automatic emotion recognition in section IV, and the last section is conclusion.

II. RELATED WORKS

In this paper, the emotion recognition procedure was performed by using the physiological responses through the different ways, which the responses were composed of SC (Skin Conductance), SKT (Skin Temperature), and BVP (Blood Volume Pulse). Skin conductance changing was related to the activity of sweat gland which was controlled by the sympathetic nervous system and skin conductance was used as an indication of psychological or physiological arousal. SKT might be taken as a representative sample of bodily activity correlated with changes in affective states. A fall in the skin temperature of the extremities in response to mental work had like so stress, fear, and pain. Conversely, a rise in the skin temperature showed about the relaxation and sleep state. BVP changed in the blood flow causes fluctuations in the brightness of the reflected or transmitted light. These fluctuations were filtered out, amplified, and displayed as the BVP parameter relative change in blood flow.

The physiological signals are varied depending of the range of the number of emotional categories and whether the systems were user-dependent or user-independent as followings: the emotion recognition system was developed by Picard et al. [3] was able to recognize eight different emotions and performed with the accuracy of 81.25% for a single subject. Four biometric sensors of physiological signals were collected over a period of 20 days. The statistical features were then calculated over a period of one-day, and the hybrid of SFFS (Sequential Forward Feature Selection) and FP (Fisher Projection) were used to select and classify emotions respectively. Posner et al. was proved an analog, continuous mapping of emotions based on a weighted combination of arousal intensity and emotional valence in which was represented by two-dimensional space [4].

In the case of user-independent emotion recognition system performed the emotion detection procedure by utilizing three physiological signals that the acquisition data was collected from 50 children aged from 5 to 8 years old to recognize 4 emotions of sadness, anger, stress, and surprise. The accuracy of 78.43% and 61.76% were achieved from three and four emotions respectively [5]. In pattern classification, SVM was employed to classify emotion recognition. This system had been developed by Kim et al. [5].

The emotion recognition system used five types of bio-sensors to attach on the subjects in order to make the experiment [6]. The IAPS was employed to elicit emotion for subjects and feature extraction utilized six statistical features of physiological signals. In order to optimize the work procedure, genetic algorithm was used in feature selection.

The classification of emotional recognition was an important step to classify emotion for getting the result of the accuracy that it was focused and attracted by many researchers. Many researchers have used the different classification technique by trying the best as possible in order to solve the emotional recognition problem and improve the accuracy result. four types of classification methods were employed to classify emotions after comparing the accuracy of these methods such as kNN (k-Nearest Neighbor), fuzzy-kNN, discriminant function analysis with linear (LDF), quadratic (QDF) kernels, and support vector machine (SVM) and so on [6]. Especially, SVMs are widely used for many purpose in various field [12]. The introductions of techniques among the above ones which are applied in this work are described as bellow.

1. Binary class support vector machine

Generally, binary SVM algorithm has shown a good performance in classification that it has received input data during a training phase, build model of the input and output a hypothesis function that could have been used to predict the future data [8,9].

Given the training samples $s=\{(x_1,y_1),\ldots,(x_l,y_l)\}$, $x_i \in R^m$ (x_i: feature vector, m: dimensionality of input space) with two-classes and $y \in \{1,-1\}$ denotes the class label of x_i. In the training of SVM has been to find the optimal hyperplane, one should have maximized the margin which separates two-class samples. Gaussian optimization can be applied to solve the non linear margin separation [13]. In order to minimize the problem, we have used a convex QP (Quadratic Program) as follows:

Find the Lagrange multipliers $\{\alpha_i\}_{i=1}^{l}$ that maximize the objective function:

$$w_1(\vec{\alpha}) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j K(x_i,x_j) \tag{1}$$

$$\sum_{i=1}^{l}\alpha_i y_i = 0, 0 \le \alpha_i \le C,\ i=1,2,...,l\ , \tag{2}$$

where K is a kernel function and C is a positive constant specified by user.

In our experiment, we applied Gaussian kernel function:

$$K(x_i,x_j) = \exp\left(-\frac{\| x_i - x_j \|^2}{2\sigma^2}\right), \tag{3}$$

where σ is a constant specified by user.

From Eq. (1), we could see the size of the QP problem is equal to the number of training samples. Therefore, usually SVM is slow, especially for large size problem. Solving the Lagrange multiplier above, we could get a decision function:

$$f(x) = \sum_{i=1}^{l}\alpha_i^* y_i K(x_i,x) + b, \tag{4}$$

where b is a bias.

From Eq. (2), we know $0 \le \alpha^* \le C$ holds for $i=1,2,...,l$. All training samples corresponding to $\alpha_i^* > 0$ are called SVs (Support Vectors). Let $\alpha_i^* > 0$ for $i = l_{sv}+1, l_{sv}+2,...,l$, so Eq. (4), could be written as:

$$f(x) = \sum_{i=1}^{l_{sv}}\alpha_i^* y_i K(x_i,x) + b \tag{5}$$

In general, [10] the distance (d) between two points x and y in a Euclidean space R^n, we then could have calculated the distance by using the formula below:

$$d = |x-y| = \sqrt[2]{\sum_{i=1}^{n}|x_i - y_i|^2}\quad , \tag{6}$$

where $x_i = (x_1, x_2, ..., x_n)$ and $y_i = (y_1, y_2, ..., y_n)$.

2. OVO (One-Versus-One) method

After we have already extracted the features, we have to calculate the distance between each feature vector of emotion for dividing the emotions into two classes, because the multi-class SVM could not have been directly solved and applied to the multi-class problems, and then it has to design the multi-class problems into the binary problems by using binary class SVM for solving it [8]. After that, we have trained a statistical classifier with the goal of learning the corresponding emotion by making the binary classification decision function for a set of features with which it has been shown. In order to address this problem, the OVO method has been used to solve this emotion recognition and the feature vectors that have extracted from the multiple subjects under the same emotional stimulus form a distribution in high dimensional space.

We have employed OVO method to solve the multi-class our emotion recognition problems [7-9]. Given k-class training samples $D = \{(x_i, y_i)\}_{i=1}^{l}$, where $x_i \in R^m$, $y_i \in \{1,2,...,k\}$. An algorithm for realizing OVO method is described as follows: Given training samples D, a kernel K, and a constant C, execute the following steps.

Step 1: Divide D into k subsets as $\{D^j\}_{j=1}^{l}$, where D includes the samples $\{x_i\}$ with $y_i = j$. Set $n_1 = 1$ and $n_2 = n_1 + 1$.

Step 2: Get a two-class training set $s = \{D^{n_1}, D^{n_2}\}$. Solve Lagrange multiplier on s by using SMO (Sequential Minimal Optimization) algorithm and get a classifier.

Step 3: Add 1 to n_2. If $n_2 \le k$, go to step 2; if not, go to step 4.

Step 4: Add 1 to n_1. If $n_1 \le k-1$, set $n_2 = n_1 + 1$ and go to Step 2; if not, stop.

From the above algorithm, we can see the final obtained classification model includes $k(k-1)/2$ classifiers. For unknown sample $k(k-1)/2$ decision functions should be calculated and x_i, $k(k-1)/2$ are obtained. The unknown sample would be determined to belong to class j, whose frequency of appearing in the results is highest.

In this work, according to the previous works of the other researchers and our researches, we proposed the classification algorithm of multi-class SVM with Gaussian RBF kernel in order to improve the accuracy of emotion recognition. We have also proposed our interested classification technique, multi-class SVM with Gaussian RBF kernel, by combining with OVO method in order to solve the emotional recognition problem and improve the accuracy result.

III. MEANINGFUL FEATURE SELECTION FROM PHYSIOLOGICAL RESPONSES

1. Preprocessing data

We first have verified that the recorded data properly during the experimental session by generating and examining plots of each channels over time as the following Fig. 1.

In order to preprocess the meaningful data in feature extraction step, the raw data has considered as the meaningful data and has applied directly for proceeding to the next step due to the data acquisition of each physiological signal has been the low level of the noise artifact and environment. In this paper, any kinds of noisy reduction approaches are not employed in the feature extraction step. The reason of we do not consider about noisy reduction in feature extraction is the physiological responses (SC, ST, BVP) what we have an interest in are

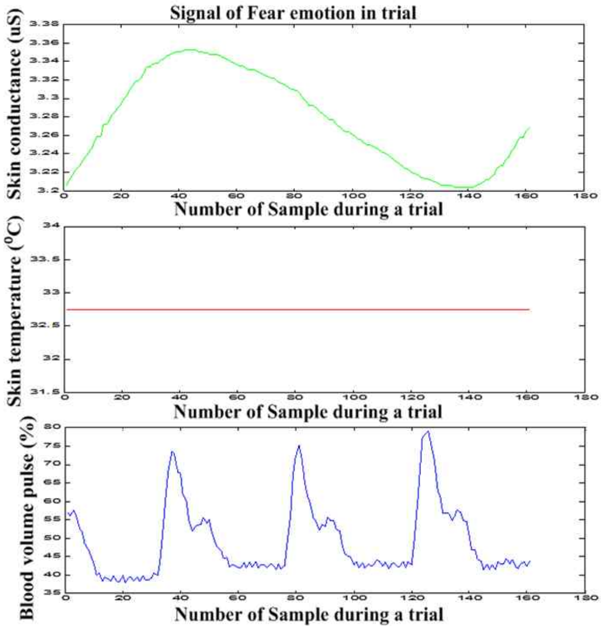


그림 1. 생리적 신호들에서 분포된 공포 감정 관련 실험측정치.

Fig. 1. An experimental measurements of fear emotion signal plotted in physiological signals.

already simply noisy-canceled by the data-acquisition device module with its sensing interface S/W (biofeedback 2000 x-pert). And the major contribution of this paper is that figure out the experimental paradigms for artificially inducing the responses correspond to emotional states and acquire the validated physiological responses instead of focusing on the optimal feature extraction or optimization of class labeling process in the field of emotion recognition. Also, we try to design of automatic emotion recognition framework using the validated responses. Therefore, the additional noisy filtering methods are unnecessary in the feature extraction step. The data acquisition of each physiological signal was segmented according to the time duration of the stimulating effects sections as you could see in the Fig. 4. And then these segments were prepared to process to the next step, means that we cut the meaningful signal as the trial from the session of the experiment procedure.

2. Feature selection

Feature selection has been necessary to define a methodology in order to enable the system to translate the signals coming from the physiological signals into the specific emotions. For this study, emotion recognition training or testing, the features of physiological signals have been extracted using two parameters. Mean and standard deviation are used to extract the features from the data of each trial after the preprocessing step, so we have received 160 features from four subjects, four emotions (four sessions) and one trial equals to 10 trials.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i\,, \quad s = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}(x_i - \mu)^2}\,, \tag{7}$$

where i is the trial number and n denotes the total number of trial.

By using these two parameters of Eq. (7), that computed the three physiological signals of our recording data, thus, we received our feature vector as follow:

$$x = [\mu_{sc}\, s_{sc}\, \mu_{st}\, s_{st}\, \mu_{bvp}\, s_{bvp}] \tag{8}$$

IV. PHYSIOLOGICAL RESPONSE-BASED AUTOMATIC EMOTION RECOGNITION

1. Concepts of experiments

The equipment for data acquisition of emotion-specific physiological signals has been MULTI module of biofeedback 2000 x-pert combined multi-sensor such as SC, SKT, and BVP. These three physiological signals have been selected to record the raw data for extracting the emotion recognition features. This equipment has been attached on the finger tip of the non-dominant hand of subject as the following Fig. 2. The temperature and relative humidity of the experimental room have been between 20°C and 26°C.

그림 2. Biofeedback 2000 xpert MULTI 모듈장비 기반 실험 과정.

Fig. 2. The Experiment procedure of MULTI module equipment of Biofeedback 2000 x-pert.

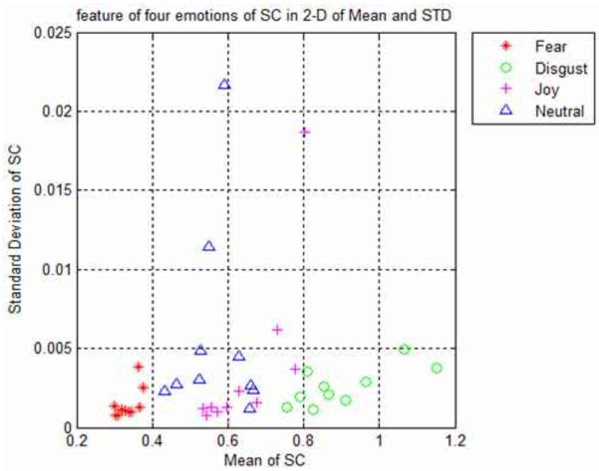


그림 3. 2차원 상의 평균 및 표준편차로 나타낸 4가지 감정들의 생리적 신호 특징: 피부전도반응.

Fig. 3. The features of four emotions of physiological signals in 2-D of mean and standard deviation: *skin conductance*.

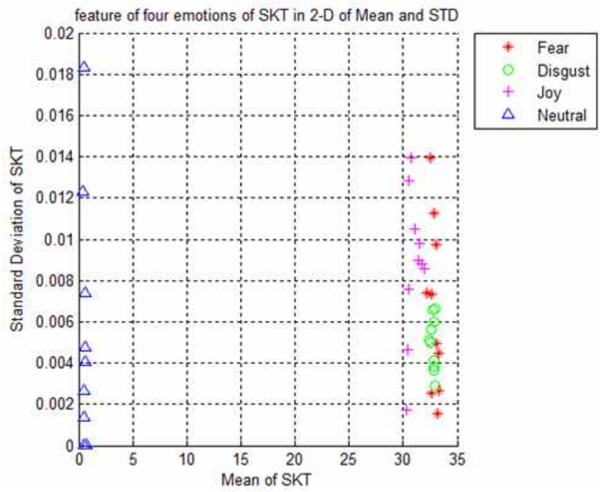


그림 4. 2차원 상의 평균 및 표준편차로 나타낸 4가지 감정들의 생리적 신호 특징: 피부온도.

Fig. 4. The features of four emotions of physiological signals in 2-D of mean and standard deviation: *skin temperature*.

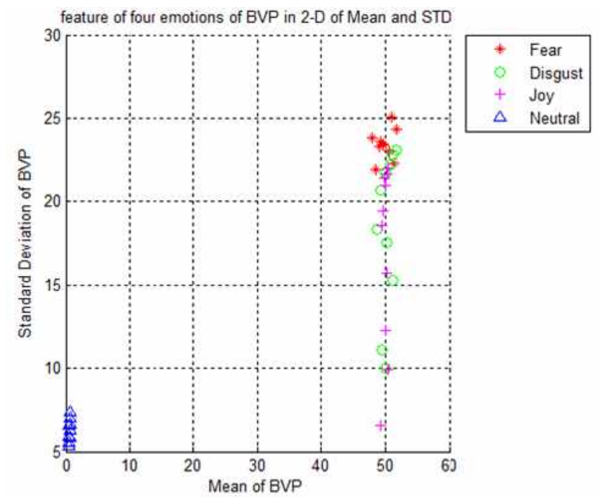


그림 5. 2차원 상의 평균 및 표준편차로 나타낸 4가지 감정들의 생리적 신호 특징: 혈류량.

Fig. 5. The features of four emotions of physiological signals in 2-D of mean and standard deviation: *blood volume pulse*.

SC was measured by recording the electrical potential and it had the sample rate of 2 KHz. It was a square wave signal with frequency 20 Hz and amplitude of ±1.42 V that was applied to the skin. The maximum measuring range of SC was defined from 0 to 50μS and resolution 0.001μS with maximum error of 0.65μS.

SKT was processed in the sensor and transmitted to the multi-module in digital form and data rate of 4 values per second. Within a range of 10-40^{0}C, the temperature was measured at a resolution of 0.01^{0}C and an accuracy of 0.5^{0}C.

BVP was the measurement of the mean flow of blood near the surface of the skin with the range of the value was 0-100% at a resolution of 0.25%. And the range of parameter was 30-200 bpm (beats per minute) at a display resolution of 1 bpm. The sample rate was 500Hz and integration time constant of 100ms with 10 data rate per second.

2. Experimental methods

Subjects and emotion elicitation protocol, four subjects (Male and aged from 25 to 30 years old) graduate students have been healthy subjects and have not been taken any medicine in a week for making the experimental paradigm. The participants have been introduced the method how to induce emotions and make the experiment. The consent form of participant has been seated in a comfortable chair in front of a computer screen at an approximate distance of 70 cm. All target emotion states are elicited from the subject by using IAPS image slide-show to induce emotion.

Data collection: One session has taken the time of 4 minutes 50 seconds that each emotion has displayed 10 images and one image has been displayed 4 seconds to induce emotion. In order to process the experiment, we first have started showing the black screen which represent the rest time for the subject, after we have showed the image stimulus to elicit emotion. The black screen also has been shown in the time duration of 25 seconds and it has been shown between of the images to stimulus emotion that it has been done 10 times until finish the experiment of each session. There have been 10 trials in one session as shown in the Fig. 4 and these 10 trials of image stimuli have been displayed the same emotion in a session.

The accuracy has strongly depended on the experimental data which has been obtained in laboratory conditions because the observation and verification have shown that the results were achieved for specific users in specific contexts and it has been very difficult to label emotion classes in physiological signals such as wave forms without uncertainty.

3. Class labeling for emotion recognition

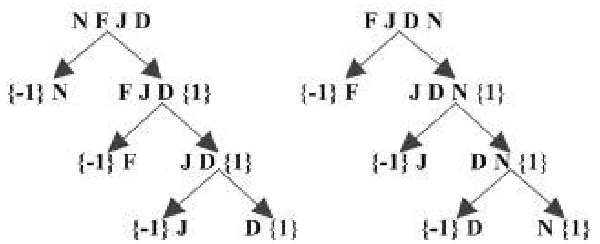
We have compared our classification results due to our preparing the training data using the distance between each class as Eq. (10), follows:

$$d_{NF} > d_{NJ} > d_{ND} > d_{FJ} > d_{FJ} > d_{JD} \qquad (10)$$

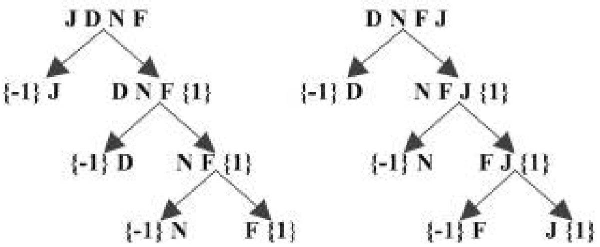
where F: Fear, D: Disgust, J: Joy, and N: Neutral. For d_{NF} denotes the distance between (N) and (F) and so on.

그림 6. 본 실험에서 감정유발을 위한 피험자의 감정 유발 과정.

Fig. 6. The process of eliciting emotions for the subject in our experiment.



(a) Reference Emotion = Neutral. (b) Reference Emotion = Fear.



(c) Reference Emotion = Joy. (d) Reference Emotion = Disgust.

그림 7. 감정의 가능한 4가지 조합 기반 학습을 위한 OVO 방법.
Fig. 7. The OVO method is illustrated for training with four possible combinations of set of emotion.

In Fig. 7(a), has shown the training data has distinguished from (N) to (F) to (J) and (D). And (N) has considered as class {-1} and the rest as class {1} and so on. Fig. 7(b), has shown the training data has distinguished from (F) to (J) to (D) and (N). And (F) has considered as class {-1} and the rest as class {1}, and so on. Fig. 7(c), has shown the training data has distinguished from (J) to (D) to (N) and (F). And (J) has considered as class {-1} and the rest as class {1} and so on. Fig. 7(d), has shown the training data has distinguished from (D) to (N) to (F) and (J). And (D) has considered as class {-1} and the rest as class {1} and so on.

Table 1 shows that the highest accuracy with 90% for classifying the neutral emotion, 86.67% for joy emotion, 85% for disgust emotion, and the low accuracy 80% for classifying the fear emotion.

Table 2 shows that the highest accuracy with 93.33% for classifying the neutral emotion, 83.33% for disgust emotion, 75% for joy emotion, and the low accuracy 65% for classifying the fear emotion.

Table 3 shows that the highest accuracy with 91.67% for classifying the neutral emotion, 82.50% for disgust emotion, 76.67% for fear emotion, and the low accuracy 55% for classifying the joy emotion.

Table 4 shows that the highest accuracy with 92.50% for classifying the neutral emotion, 86.67% for fear emotion, 69.33% for joy emotion, and the low accuracy 60% for classifying the disgust emotion. Following table 5 shows the comparison of performance of the proposed method of this paper with state-of-the-arts.

표 1. 그림 7 (a)의 학습 데이터 기반 다중 피험자에서의 감정인식 정확도.
Table 1. The accuracy of each emotion for multiple subjects for training data of Fig. 7(a).

Categories of Emotion [%]	***Neutral***	***Fear***	***Joy***	***Disgust***
Accuracy of Classification	90	85	95	95
	*	75	100	85
	*	*	65	75
Total Accuracy of Classification	90	80	86.67	85

표 2. 그림 7 (b)의 학습 데이터 기반 다중 피험자에서의 감정인식 정확도.
Table 2. The accuracy of each emotion for multiple subjects for training data of Fig. 7(b).

Categories of Emotion [%]	***Fear***	***Joy***	***Disgust***	***Neutral***
Accuracy of Classification	65	100	85	100
	*	50	100	80
	*	*	65	100
Total Accuracy of Classification	65	75	83.33	93.33

표 3. 그림 7 (c)의 학습 데이터 기반 다중 피험자에서의 감정인식 정확도.
Table 3. The accuracy of each emotion for multiple subjects for training data of Fig. 7(c).

Categories of Emotion [%]	***Joy***	***Disgust***	***Neutral***	***Fear***
Accuracy of Classification	55	100	80	75
	*	65	95	80
	*	*	100	75
Total Accuracy of Classification	55	82.50	91.67	76.67

표 4. 그림 7 (d)의 학습 데이터 기반 다중 피험자에서의 감정인식 정확도
Table 4. The accuracy of each emotion for multiple subjects for training data of Fig. 7(d).

Categories of Emotion [%]	***Disgust***	***Neutral***	***Fear***	***Joy***
Accuracy of Classification	60	95	85	70
	*	90	100	85
	*	*	75	50
Total Accuracy of Classification	60	92.50	86.67	69.33

4. Results and discussion

In this paper, we have proposed the multi-class SVM with Gaussian RBF kernel by combining with OVO method in order to solve the problem and improve the accuracy of emotion recognition. The technique of this algorithm has been performed as follow: calculating the distance between

표 5. 최근 관련 연구 대비 제안 방법의 성능 비교.
Table 5. The performance comparison of current work with state-of-the-arts (Averaged Accuracy: AA, Maximum Value: MV).

Sources	*Sensory Info. Type*	*Technology Application*	*Performance*	*Ref.*
Current Paper	SC, BVP, and SKT	Multi-class SVM with GRBF kernel + OVO	AA: 79.5418% MV: 93.33%	-
J. Healey, etc	ECG, EDA, and SKT	Sequential Floating Forward Search with Fisher Projection (SFS-FP)	AA: 80.025% MV: 81.25%	[3]
S. R. Kim, etc	EMG, BVP, SC, and Resp	SVM with Non-linear kernel	AA: 70.095% MV: 78.43%	[5]

each feature vector of emotion, separating the multiple problems into the binary problems, making the binary SVM classification function with Gaussian RBF kernel, training and testing the data of each emotion that has converted into the binary classes by employing the OVO method as mentioned above. Thus, our proposed method has proved that it has been an effective algorithm in the study of emotion recognition. And the accuracies that have shown in Table 1, Table 2, and Table 3, to be better than the accuracies of the other researchers that we have mentioned in the related work.

V. CONCLUSION

In this paper, we have proved that using multi-class SVM with Gaussian Radial Basis Function and add the OVO method have been an efficient method in order to solve the multi-class problems and to improve the accuracy of emotion recognition. The experimental results have shown that the neutral has appeared the high accuracy for all tables as shown above. On the other hand the low accuracies of 80% for fear emotion in Table 1, 65% for fear emotion in Table 2, 60% for disgust emotion in Table 4, and 55% for joy emotion in Table 3. Therefore, Table 1. has been a good performance of the classification that has resulted the high accuracy of 90% for the neutral emotion, 86.67% for joy emotion, 85% for disgust emotion and the low accuracy of 80% for the fear emotion in this work.

In the future work, we would employ the multi-model stimuli (combination of visual-stimuli and audio-stimuli) in order to make the experimental paradigm of acquisition data. And we would study multiple subjects that has much more subjects than this work. Moreover, the multi-class SVM with other kernels such as Radial Basis Function, Gaussian Radial Basis Function, Sigmoid, and Polynomial and two methods for training input data like so OVO and OVA (one-versus-all) would be designed to compare their accuracy and performance of solving emotion recognition for multi-class problem.

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마카라 완니

2011년 Institute of Technology of Cambodia, Electrical and Electronic Department (B.S). 2011년~현재 중앙대학교 대학원 전자전기공학부 석사과정. 관심분야는 Biofeedback System, Brain-Computer Interface, machine learning, and Emotion Recognition.

고 광 은

2007년 중앙대학교 전자전기공학부(공학사). 2007년~현재 중앙대학교 대학원 전자전기공학부 석 · 박사 통합과정 수료. 관심분야는 Human-Computer Interaction, Brain-Computer Interface System, Intention Recognition, Neuro-Science, Neuro-Robotics, 소프트컴퓨팅 등.

박 승 민

2010년 중앙대학교 전자전기공학부(공학사). 2010년~현재 중앙대학교 대학원 전자전기공학부 석 · 박사 통합과정. 관심분야는 Brain-Computer Interface, Intention Recognition, 소프트컴퓨팅 등.

심 귀 보

1984년 중앙대학교 전자공학과(공학사). 1986년 중앙대학교 전자공학과(공학석사). 1990년 The University of Tokyo 전자공학과(공학박사). 1991년~현재 중앙대학교 전자전기공학부 교수. 2002년~현재 중앙대학교 중소기업산학협력센터 센터장. 2006년~2007년 한국지능시스템학회 회장. 2007년~현재 (사)한국산학연협회 서울지역협회 회장. 2009년~2010년 중앙대학교 중앙도서관장 및 박물관장. 2011년~현재 중앙대학교 스마트지능로봇연구센터 센터장. 관심분야는 인공생명, 뇌-컴퓨터 인터페이스, 의도 인식, 감성 인식, 유비쿼터스 지능형로봇, 지능시스템, 컴퓨테이셔널 인텔리젼스, 지능형 홈 및 홈 네트워크, 유비쿼터스 컴퓨팅 및 센서 네트워크, 소프트 컴퓨팅(신경망, 퍼지, 진화연산), 다개체 및 자율분산로봇시스템, 인공 면역시스템, 지능형 감시 시스템 등.