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Half-Against-Half Multi-class SVM Classify Physiological Response-based Emotion Recognition

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Abstract

The recognition of human emotional state is one of the most important components for efficient human-human and human-computer interaction. In this paper, four emotions such as fear, disgust, joy, and neutral was a main problem of classifying emotion recognition and an approach of visual-stimuli for eliciting emotion based on physiological signals of skin conductance (SC), skin temperature (SKT), and blood volume pulse (BVP) was used to design the experiment. In order to reach the goal of solving this problem, half-against-half (HAH) multi-class support vector machine (SVM) with Gaussian radial basis function (RBF) kernel was proposed showing the effective techniques to improve the accuracy rate of emotion classification. The experimental results proved that the proposed was an efficient method for solving the emotion recognition problems with the accuracy rate of 90% of neutral, 86.67% of joy, 85% of disgust, and 80% of fear.

Key Words : Visual-stimuli, Emotion Recognition, Physiological Signals, HAH Multi-class SVM Classification.

1. Introduction

Interactive emotion have been significantly improved the usage of an affective system and provided user with all the benefits of natural interaction as well as, the performance of emotional recognition rate was highly dependent on the quality of emotional data [1]. Emotion was treated as a psycho-physiological process that produced by the limbic system activity in response to a formal stimulus, whereas the physiological signals were varied depending on the range of the number of emotional categories and whether the system were user-dependent or user-independent that the emotion recognition system was developed by Picard et al. [2].

Emotion recognition system obviously was emerged in the Human-Computer Interaction (HCI) research area that could be essentially playing a significant role more and more in practical applications like assistance robot in household with the user, smart phone, affective computing, and so on. Moreover, some emotions also have been the difficulty in order to induce and recognize by human that the inner states of emotion have not been expressed outwardly. As the real example, when some images were looked at by a subject, certain feelings and emotions might be experienced by that subject [3]. And the visual-stimuli of International Affective Picture System (IAPS) have been an affective picture standard for inducing emotions, and have been the most aspect of the experiment protocol. For instance, when the human looked at some objects or pictures, the eyes transformed visual-stimuli into the neural signals. Therefore, in this paper, Radio MULTI module of biofeedback 2000 x-pert with visual information of IAPS were used to make the experiment in order to design the meaningful data for achieving higher recognition rate.

So far, Support Vector Machine (SVM) still has been one of the most popular classification algorithm, and has been used in numerous practical applications that performed a higher accuracy with good generalization capability because of its robust classification tool has effectively overcome many traditional classification problems such as local optimum and curse of dimensionality. Furthermore, it based on the principle of the Structural Risk Minimization (SRM) and employed the convex optimization with unique optimum solution [4], [5], [6], [7]. In addition, two kinds of SVM such as binary and multi-class SVM were presented in the various problems of classifying data that each technique was employed in the other different conditions. For instance, multi-class SVM was used to solve multi-class classification problem in many areas such as pattern

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recognition, computer vision, data mining and bio-informatics. Likewise, most of these problems in classification study also have been tackled by the other methods of SVM classifier like One-Against-One (OAO), One-Against-All (OAA), Directed Acyclic Graph (DAG), and Binary-Tree (BT).

On the other hand, the goal of this paper, we proposed the Hafl-Against-Half (HAH) multi-class SVM with Gaussian Radial Basis Function (RBF) in order to optimize and solve the multi-class problems for improving overall emotion recognition accuracy. For HAH multi-class SVM construction was combined by the other methods such as (OAO), (OAA), and (DDAG) [8-9], and it existed the same as a decision tree which contained the binary SVM classifier in each node. It meant that the classification procedure was run at the beginning of the root node to the leaf led by the binary SVM classifier. Especially, HAH SVM existed the greatest problem which was to find the optimal way in order to distinguish classes in each node as well as the speed of the computational time of this method gave better performance compare to other methods.

For the remainders of this paper, were organized as the following sections: section 2 demonstrated the related works, section 3 presented the meaning feature extraction from physiological responses, For the physiological response-based emotion recognition was proved in section 4, and conclusion was expressed in the last section.

2. Related Works

2.1 Binary Support Vector Machine

Support vector machine (SVM) is a statistical classification system proposed by Cortes and Vapnik in 1995 [15]. In general, SVM algorithm has been designed and proposed for binary classification which has been shown a good performance in classification for receiving the 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 [7, 11].

Given the training data sets $s=\{(x_1,y_1),...,(x_l,y_l)\}$, $x_i \in R^m$,where x_i represented as a feature vector, m represented the dimensionality of input space, and $y \in \{1,-1\}$ denoted the class label of x_i with two classes. SVM classification was to construct a hyper-plane to classify patterns into two classes. In the case, the linear classifier could be inseparable data and then the nonlinear classifier (kernel function) was appeared to create the separable classifier by mapping data into the high-dimensional space [12] $\Phi : X \rightarrow H;\ x \rightarrow \Phi(x)$, where H was called feature space. And herein the inner product similarity was calculated through $\langle \Phi(x_a),\ \Phi(x_b) \rangle$ for pattern x_a and x_b. So, SVM was realized through the kernel function as shown in Eq. (1).

$$k(x_a, x_b) = \langle \Phi(x_a),\ \Phi(x_b) \rangle \tag{1}$$

In the training of SVM was to discover the optimal hyper-plane, one should be maximized the margin which separates two-class samples. In order to minimize the problem, we employed a convex Quadratic Program (QP) as follows:

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

$$\omega_1(\vec{\alpha}) = \sum_{i=1}^{l}\alpha_i - \frac{1}{2}\sum_{i=1}^{l}\sum_{j=1}^{l}\alpha_i\alpha_j y_i y_j k(x_i,\ x_j) \tag{2}$$

$$\sum_{i=1}^{l}\alpha_i y_i = 0,\ 0 \le \alpha_i \le C,\ i = 1,2,...,l \tag{3}$$

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

From Eq. (2), 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. By 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. (3), we know $0 \le \alpha^* \le C$ holds for $i = 1,2,...,l$. All training samples corresponding to $\alpha_i^* > 0$ are called support vectors (SVs). Let $\alpha_i^* > 0$ for $i = l_{sv}+1, l_{sv}+2, ..., l$, so Eq. (4), could be written as:

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

2.2 Multi-class Support Vector Machine

Support vector machine was originally designed for binary classification, and it could not be directly extended to multi-class problem. Basically, there were two types of approached for multi-class SVM problem. One was constituting all data into the formula optimization [13], and the other was distinguishing the multi-class problem by designing into the series standard techniques of binary SVMs, namely OAO, OAA, and DAG. All of these methods were considered as the efficient and suitable methods to realize the practical multi-class problem in the real world that their structure was constructed briefly by the form of binary SVM as shown below [16], [17], [18], [19].

The OAO method has built the M(M-1)/2 binary SVM classifiers in order to solve the M-class problem, and it was created by training binary SVM between pair-wise classes, (where M >2).

Whereas, the OAA technique has designed the M binary classifiers for replying with M-class problem, and herein the patterns of a class were trained against the patterns of rest classes, (where M >2).

For the DAG has created M(M-1)/2 binary classifiers which have been organized in a tree structure with M layers for dealing with M-class problem. This method has operated in a kernel induced feature space and has utilized binary class at each node of a tree structure (where M >2).

In this section, as we have mentioned above, HAH multi-class SVM algorithm has constructed $N=\left(2^{\lceil \log_2(M) \rceil}-1\right)$ binary classifiers in order to tackle M-class problem, (where M >2). The N binary SVM classifiers have been resulted from each node of a decision tree that the level of decision tree was defined by $\lceil \log_2(M) \rceil$, and the M classes were bifurcated randomly into two groups. And the similar or close classes could have been grouped together. The problem was happened due to the separability between the arbitrary two groups was not high that made the accuracy to be unreliable. For reaching problem, the most desirable way was to find the optimum two groups to reduce the expected error. And the hierarchy clustering of classes was selected to progress the optimal division. The first group consisted of a half of the classes with performance of the better separation. After that, the distance between two classes was considered as the mean distance between the training data of both two classes, and likewise each node was repeated. The hierarchy clustering structure for the M classes could be built, and herein the HAH model could be trained accordingly. Therefore, this method was demonstrated sequentially [9-10], as the following steps:

Step 1 : Adopt Gaussian kernel function in Eq. (6), and calculate the Euclidean distances between one class and the others in Eq. (7),

$$k(x_a, x_b) = \exp\left(-\frac{\| x_a - x_b \|^2}{\sigma^2}\right) \tag{6}$$

$$\begin{aligned} d(x_a, x_b) &= \| \Phi(x_a) - \Phi(x_b) \|_2 \\ &= \left(k(x_a, x_a) - 2k(x_a, x_b) + k(x_b, x_b)\right)^{\frac{1}{2}} \end{aligned} \tag{7}$$

Step 2 : Calculate the distance between the two nearest samples which respectively belong to class A and class B as the distance of class A and class B, indicated by $d_{ij}(i, j = 1,2,...,k)$, in Eq. (8).

$$d_{ij} = \min\{ \| \Phi(x_a) - \Phi(x_b) \|, x_a \in A, x_b \in B\} \tag{8}$$

So that, $d_{ij} = 0, d_{ij} = d_{ji}$, x_a and x_b are the sample of class A respectively, and B, and k is the number of classes.

Step 3 : Arrange the distances between each class and the other *k-1* classes from small to large order and then renumber. Take class i for example, we the new order of $d_{ij}(i, j = 1,2,...,k, j \neq i)$: $l_i^1 \leq l_i^2 \leq ... \leq l_i^{k-1}$.

Step 4 : First, arrange the corresponding classes according to $l_i^1(i, j = 1,2,...,k)$. Compare their l_i^2 when two classes have the same l_i^1. If class i and j own the same $l_i^1, l_i^2, ..., l_i^{k-1}$, let's put the smaller label in front of the others. Finally, we get the new arrangement of all types: $n_1, n_2, ..., n_k$.

Step 5 : Built a binary tree according to the arrangement of all types: $n_1, n_2, ..., n_k$.

Step 6 : According to the binary tree at step 5, construct the optimal hyper-plane of every node using binary SVM formulation. Therefore, we could get the multi-class SVM classification model based a binary tree, and each category could be divided completely.

In the Gaussian kernel function, the output of the kernel was dependent on the Euclidean distance of x_a from x_b that one of these would be the support vector and the other would be the testing data point. The support vector would be the center of the Gaussian kernel function and σ would determine the area of influence this support vector that existed over the data space [14]. In order to select the value σ, it was depended on the condition of each data set (over-fitting or under-fitting). For instance, if σ was defined by a larger value, and then the area of the data would be a smoother decision area and provide more regular decision boundary. Thereby, the Gaussian kernel function with large σ would permit the support vector to have a strong influence over a larger area. On the other hand, the large value of σ would reduce the number of support vectors, thus, it must be adapted to some extent of the feature space distribution.

3. Meaning feature extraction from physiological responses

3.1 Preprocessing data

The raw data was really important in the preprocessing step before it was carried out in the feature extraction step. In this work, the raw data in figure 1, was considered as the meaningful data in figure 2, due to the artifacts and the environmental noise of each physiological signal were the low level compared to the meaningful data so the noisy reduction were not used in the preprocessing data. The reason is that the noisy reduction of each channel was already simply-canceled by the data acquisition device module with its sensing interface S/W (biofeedback 2000 x-pert). The acquisition data were segmented depending on duration time of (4 seconds) for stimulating emotions of each trial in the session.

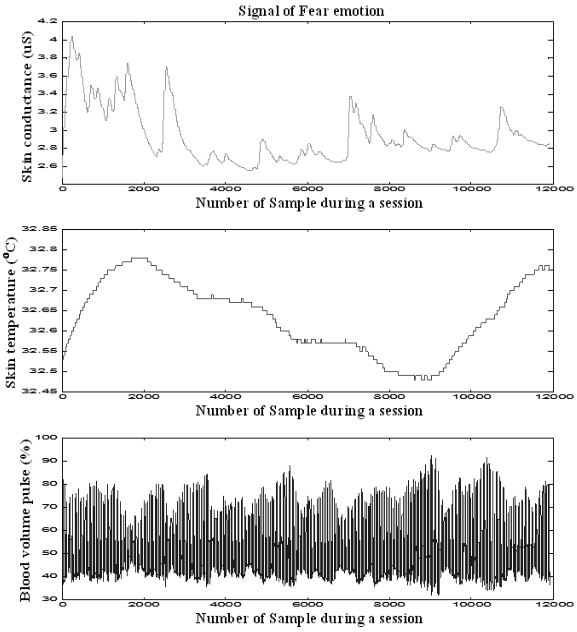

Fig. 1. The raw data of fear emotion recorded by each physiological signal in a session

3.2 Feature extraction

To define the methodology for recognizing emotion, it was essential to translate the meaningful data of the physiological signals into the feature vector that was received from the device sensors. In order to overcome that problem, mean and standard deviation were utilized extracting the features from each trial as shown in the following equations (9) and (10). In this work, we have 160 features from four emotions, four subjects, and 40 trials (1 session has 10 trials). Thus, for deriving a set of features, each physiological signal was combined in order to train in the classification step through the feature vector which expressed in Eq. (11).

$$\overline{X} = \frac{1}{n}\sum_{i=1}^{n} X_i \tag{9}$$

$$s = \sqrt[2]{\frac{1}{n}\sum_{i=1}^{n}\left(X_i - \overline{X}\right)} \tag{10}$$

$$X = \left[\overline{X_{sc}} \quad s_{sc} \quad \overline{X_{st}} \quad s_{st} \quad \overline{X_{bvp}} \quad s_{bvp}\right] \tag{11}$$

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

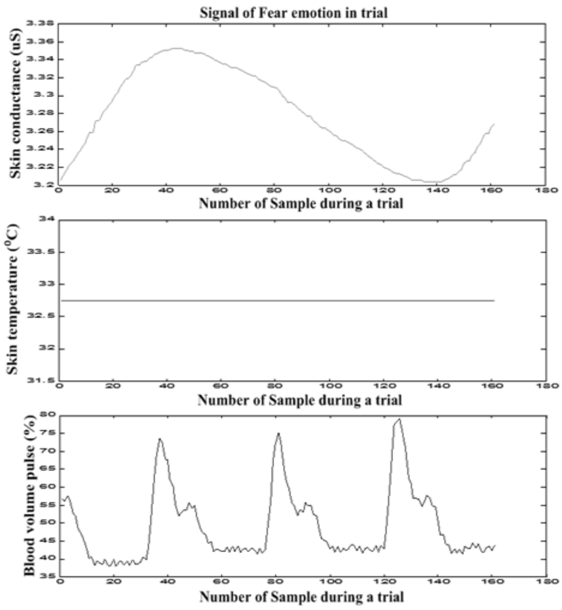

Fig. 2. The meaningful dat of fear emotion in a trial for processing in the feature extraction

4. Physiological response-based emotion recognition

4.1 Equipment and experimental induction method

In this experiment was carried out in a quiet room (temperature: 22-26°C, 4 subjects, sex: male, age: 25-30)) that each subject was seated on the chair with a comfortable state, and at the approximate distance of 70cm in front of a computer monitor. Moreover, the subjects were requested to have enough relaxation and have not take any medicine before running the experiment. For the specific emotional statuses were necessary to represent the databases of physiological signals. Furthermore, each subject was introduced how to induce emotions before the experiment and ask after finish the experiment, whereas the device sensors of Biofeedback 2000 x-pert were attached on the finger tip of non-dominant hand to record physiological signals as shown in the figure 3.

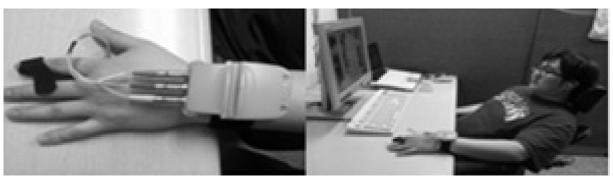

Fig. 3. The attachment and experiment procedure of equipment (Biofeedback 2000 x-pert)

In order to progress the protocols for emotion induction, IAPS material was designed to elicit emotions which would be reflected by the subject's stimuli in the figure 4.

Fig. 4. The process of eliciting emotions for the subject (R=rest and S=stimulus)

In figure 3 illustrated the collecting data of each session of experiments that were taken approximately 5 minutes 40 seconds of the time length, and displayed 10 images, an image was displayed 4 seconds to induce emotion. The experiment was begun showing the black-screen which represents the rest time during 30 seconds. Next, the image stimulus was shown to elicit the target emotion that this model was operated 10 times until finish the session.

4.2 Experimental results

In our work, we had four emotions that would be represented by four different classes such as fear (F), disgust (D), joy (J), and neutral (N). Throughout, the proposed HAH algorithm, we could construct the structure of those emotions in the following figure (5).

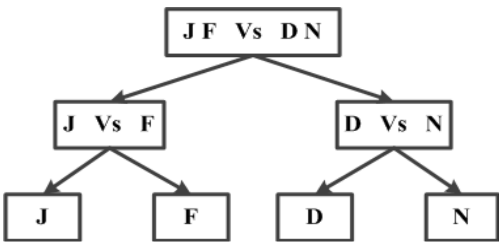

Fig. 5. The corresponding decision tree of HAH algorithm division of the four classes

In the figure 5, illustrated that the similarity of class J and F was grouped together, and the similarity of class D and N was also created into one group. After that, each group was tackled by binary SVM classifier.

Table 1. The accuracy of each emotion for multiple subjects using HAH multi-class SVM

Categories of Emotion	*Neutral*	*Fear*	*Joy*	*Disgust*
Accuracy rate [%]	90	80	86.67	85

In Table 1, the experimental result of HAH algorithm proved that the highest accuracy of 90% for classifying the neutral, 86.67% for joy, 85% for disgust, and the low accuracy of 80% for fear for recognizing emotions in our work.

5. Conclusion

In this paper proved that HAH multi-class SVM with Gaussian RBF kernel is an efficient algorithm for solving the multi-class problem in order to improve the high accuracy of emotion recognition, and it existed the greatest problem which was to find the optimal way in order to bifurcate the classes in each node as well as it proved the better performance of the training speed, testing speed, and the size of model compare to other methods. As the real example, it proved that achieving the higher recognition rate like neutral of 90%, joy of 86.67%, disgust of 85%, and fear of 80% in this work. Although, it had a bit complexity than the others.

In the future work, we will study the efficient optimization methods and algorithms to propose the new ideas for making the experimental paradigm as well as improving the accuracy of emotion recognition in order to develop human-computer and human-machine interaction.

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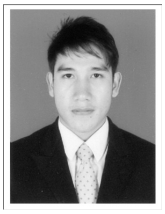

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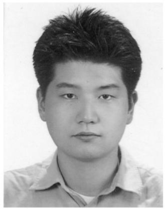

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