A Real-Time Model Based Support Vector Machine for Emotion Recognition Through EEG

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***Abstract*— Recently, there has been a significant amount of work on the recognition of human emotions. The results of the work can be applied in real applications, for example in market survey or neuro-marketing. This interesting problem requires to recognize naturally human emotions which come from our mind but ignore the external expressions fully controlled by a subject. A popular approach uses key information from electroencephalography (EEG) signals to identify human emotions. In this paper, we proposed an emotion recognition model based on the Russell's circumplex model, Higuchi Fractal Dimension (HFD) algorithm and Support Vector Machine (SVM) as a classifier. Moreover, we also proposed a method to determine an emotion label of a series of EEG signals. Our model includes two main approaches in machine learning step. In a first approach, machine learning was utilized for all EEG signals from numerous subjects while another used machine learning for each particular subject. We extensively implemented our model in several test data. The experimental results showed that the first approach is impossible to apply in practical applications because EEG signal of each subject has individual characteristic. In addition, in the second, our model can recognize five basic states of human emotion in real-time with average accuracy 70.5%.**

I. INTRODUCTION

Research on brain-computer interface (BCI) was begun in the 1970s. BCI allows us to interact with computer and electronic devices through the Electroencephalography (EEG) signals. Nowadays, it has been a promising approach for many areas of life, for example in health, criminal, entertainment, market survey or neuro-marketing, ... Most of practical applications need computer to understand human emotions. Since emotion is an important aspect in the life, emotion recognition by computer is becoming increasingly popular. In this paper, we are interested in a problem in which we develop an emotion recognition model of human being through the EEG signals.

Several works which related to the emotion recognition problem have been proposed. K. Ishino et al. [7] proposed a system for feeling estimation with accuracy of 54.4% for joy, 67.7% for anger, 59% for sorrow and 62.9% for relaxation. Berkman et al. [1] used a layer neural network to predict the emotions including positive, negative and neutral with accuracy of 43%. Lin et al. [10] presented several different schemes of multi-class SVM (support vector machine) classifier. The result was about 82.37% accuracy to distinguish the feeling of joy, sadness, anger and pleasure. Chanel et al. [4] showed that arousal assessment of emotion could be obtained with a maximum accuracy of 58% for three emotion classes estimated by the Naive Bayes classifier. SVM was used in [6] for emotion classification with the accuracy for valence and arousal identification as 32% and 37%, respectively. In [14], optimization approaches and dimensionality reduction techniques were considered. The experimental results indicated that accuracy obtained about 62.07% by SVM after using these optimizations. Recently, Y. Liu et al. [11] proposed fractal dimension based algorithm of quantification of basic emotions. They also indicated that fractal dimension model provided a better accuracy and performance in EEG-based emotion recognition. Their model could recognize six emotions such as sad, frustrated, fear, satisfied, pleasant and happy.

Currently, a main issue of the works is that accuracy in recognizing emotions is not high enough. Some works used support vector machine and achieved a higher accuracy of emotion recognition but only recognized emotions in the off-line way. There was an exception in [11] since their model could run in real-time. However, two issues in their approach need to be mentioned. Firstly, they used the Higuchi Fractal Dimension (HFD) algorithm to receive *FD* values of the electrodes. In order to recognize an emotion, they compared the *FD* values with predefined thresholds. However, they did not show how to define the threshold as well as evaluate accuracy of it. Second, they implemented their model with several test data. However they did not indicate accuracy of recognition from their experiments.

In this paper, we proposed a new model based on the Russell's circumplex model, Higuchi Fractal Dimension (HFD) algorithm and Support Vector Machine (SVM) as a classifier. Our model automatically recognizes through learning machine with SVM instead of using threshold as in [11]. Additionally, we also proposed a method in mapping between the Russell's circumplex model and SAM to identify an emotion label of a series of EEG signals. Our model

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included two main approaches. In a first approach, machine learning was applied for all EEG signals from numerous subjects. In another, we used machine learning for each particular subject. Moreover, in order to recognize in real-time, a suitable sliding window technique was incorporated into our model. We extensively implemented our model with several test data. From the experiments, we concluded that each subject owned a particular characteristic. Therefore, the second approach was suitable to practical applications. The experimental results showed that our approach can recognize five emotions (happy, angry, sad, relaxed and neutral) with average accuracy 70.5%.

The rest of this paper is organized as follows: section 2 describes preliminaries. The proposed model is presented in section 3. The experimental results are reported in section 4. Section 5 concludes the paper.

II. PRELIMINARIES

In this section, we describe several notations and theories which are used in this paper.

A. The Russel's model

Recently, many emotion models have been proposed based on psychology research [13]. In this paper, we used the continuous emotion model of Russel [13]. The Russel's model is shown in Fig. 1. In this model, the two primary dimensions include an affective valence (ranging from negative to positive) and an arousal (ranging from calm to excited). A third, less strongly-related dimension is variously called 'dominance' or 'control'. However, Russel et al. showed that two valence and arousal dimensions are sufficient enough for determining an emotion. Therefore, each emotion is corresponding to a point on the two dimension-coordinate such as neutral, happy, excited, afraid, angry, sad, calmness, ... However, Russel et al. did not indicate valence and arousal values of each emotion. It is implied that even valence and arousal values of an emotion are specified, we cannot define label of the emotion.

B. The IAPS data

In order to stimulate a subject in exposing his emotions, we use IAPS (International Affective Picture System) which includes photos for exciting emotions and SAM (Self Assessment Manikin) [9]. The IAPS has 1200 photos divided into 20 sets in which each set consists of 60 photos. A photo is labelled with valence and arousal values. In order to build the IAPS, a numerous volunteers saw these photos to stimulate their emotions. They then evaluated their emotions by SAM. The SAM is a model for rating emotions proposed by P.J. Lang et al. [9]. The SAM has two versions but only a paper and pencil version is used in this paper. The Paper and pencil version has three rows for rating such as valence, arousal and dominance values. Each row has nine items for rating. In the Russell's model, they showed that two valence and arousal dimensions are sufficient enough for defining an emotion. Therefore, only the two first rows of SAM are considered. Fig. 2 describes two rows for valence

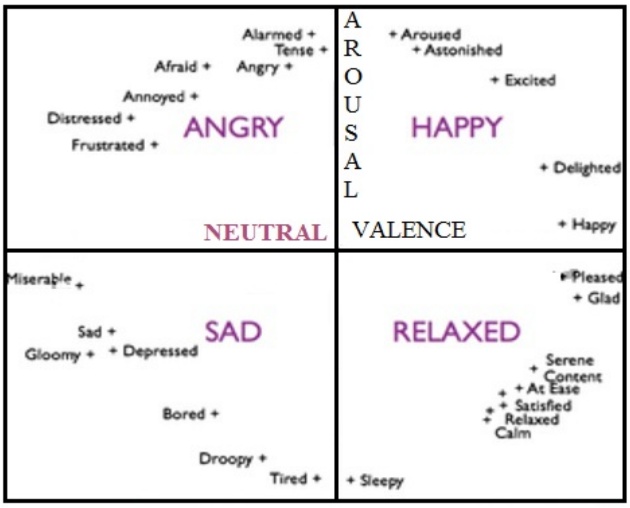

Fig. 1. The circumplex model of Russell

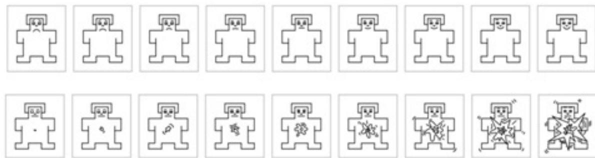

Fig. 2. The original SAM

and arousal dimensions, respectively. In order to evaluate a current emotion, each volunteer needs to tick on items which are suitable to his emotion on two rows. However, P.J. Lang et al. also did not showed valence and arousal values for items. As the result, we cannot evaluate exactly volunteers' emotions by valence and arousal values from SAM.

C. The proposed method to map between SAM and the Russel's model

As our knowledge, we do not define exactly valence and arousal values of an emotion from the model of Russel. In addition, some emotions are very close together (ie. happy and delighted). Therefore, it is difficult to recognize all emotions. In this paper, we only consider five main emotions such as happy, angry, sad, relaxed and neutral.

In order to evaluate an emotion, we need to quantify items on each row by arousal and valence values. In the SAM, each row has nine items which correspond to nine scales (one to nine) from left to right as in Fig. 3. If we represent these scales on the model of Russel, then we obtain a new coordinate as in Fig. 4. Thus we can easily evaluate emotions by arousal and valence values from selected items of volunteer. Specifically, if volunteer selected the item with scale one in the first row and the item with scale nine in the second row, then the emotion corresponds to the A point on the new coordinate with emotion label "angry".

D. Fractal Dimension Algorithm

A fractal dimension analysis is suitable for analysing nonlinear systems and could be used in real-time EEG signal

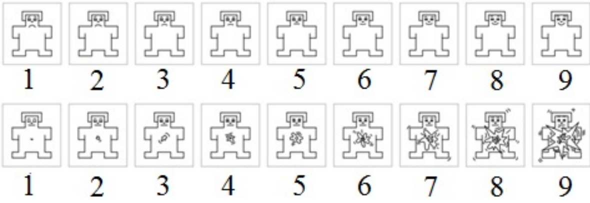

Fig. 3. SAM with nine scales

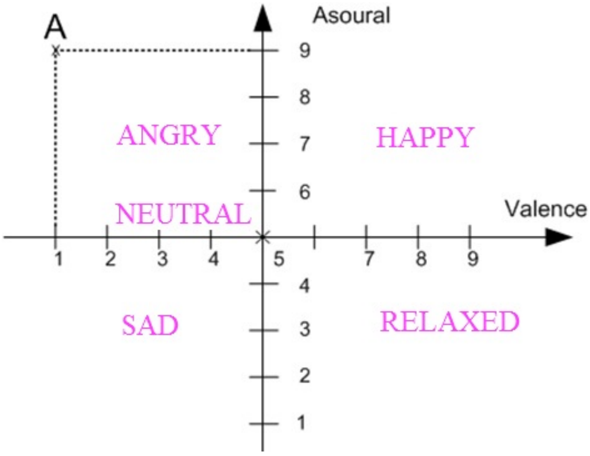

Fig. 4. The scaled arousal and valence coordinate with five main emotions

processing [11][12][15][5]. In this paper, we also considered *FD* as an important feature in recognizing emotions. Higuchi has proposed an algorithm to analysis fractal dimension of an irregular time series [5]. This method has been applied in many researches, especially electroencephalography (EEG). The HFD provides an efficient way to determine a sequence of signals' characteristic. In the problem, finding typical differences between EEG signals is the key to distinguish and classify these signals into right categories before building up a pattern to recognize emotions. Let us consider a finite set of discrete time series samples:

$$X(1), X(2), X(3), ..., X(n)$$

Build up k set of new time series, X_m^k, from the original as follows:

$$X_k^m : X(m), X(m+k), X(m+2k), ..., X(m+[\frac{N-m}{k}]k)$$

where $[], N, m, k$ is Gauss' notation, total number of samples, initial time and interval time, respectively. The length of each curve X_m^k is defined as follows:

$$L_m(k) = \left\{ \left(\sum_{i=1}^{\left[\frac{N-m}{k}\right]} \left| X(m+ik) - X(m+(i-1)k \right| \right) \frac{N-1}{\left[\frac{N-m}{k}\right]k} \right\} / k$$

where $(N-1)/([(N-m)/k]k)$ is the normalization factor. The length of the curve for such a time interval k, $\langle L(k) \rangle$, is the average value over k sets of $L_m(k)$:

$$\langle L(k) \rangle = \frac{1}{k} \sum_{m=1}^{k} L(m,k)$$

The fractal dimension, *FD*, is calculated from the following equation:

$$\langle L(k) \rangle > \propto k^{-FD}$$

or

$$\log \langle L(k) \rangle = FD \log(\frac{1}{k})$$

FD is the slope of in the $\log\langle L(k) \rangle$ against $\log(1/k)$ graph with $k = 1, 2, 3, ..., k_{max}$. The parameter k_{max} is selected by plotting *FD* against a range of k_{max}. The point where *FD* plateaus is considered a saturation point then the k_{max} is selected. Since most of human emotions appear clearly in a short interval of time, we choose $N = 640$ as number of signals received from the Epoc and $k_{max} = 12$.

E. The FC6, AF3, F4 electrodes

The frontal brain area plays an important role in the reflection of the valence level [8][2]. In [11], the difference between *FD* values from the electrode pair AF3 (left hemisphere) and F4 (right hemisphere) were used to identify the valence level. The *FD* value calculated from FC6 is used to distinguish the arousal level independently by comparing with default threshold extracted from their experiments' results. In this paper, we use the FC6, AF3 and F4 electrodes in our model. The EEG signals obtained from these electrodes by using Emotiv headset Epoc [17].

III. THE PROPOSED MODEL

Now we describe our model which is shown in Fig. 5. The model consists of two phases: The Data Acquisition and Training and the Testing phase.

A. The Data Acquisition and Training phase

- **Data Acquistition**: The step is implemented to collect EEG signals and evaluate emotions based on SAM. Initially, a volunteer is evoked his emotion by photo stimuli in the IAPS database. The EEG signals are gathered by the Emotiv headset Epoc [17]. For more simply, let us consider a set of signals in an acquisition time of the volunteer as an EEG sample. The volunteer then evaluates emotion himself by ticking on items of SAM. Using the proposed method in section 2, we easily define the arousal and valence values (AV values) of this emotion. Therefore, each EEG sample now owns the AV values. This step will be described in more detail in section 4.

- **Elimination**: In some cases, volunteer's emotion about a photo stimuli is not suitable to targeting emotion of that photo, for example targeting emotion of the photo is relaxed but volunteer's emotion is neutral. The step aims at removing the EEG sample which does not match the targeting emotion given in the IAPS database. The removal is done by comparing the arousal, valence values of each EEG sample to those in the IAPS database. If the difference

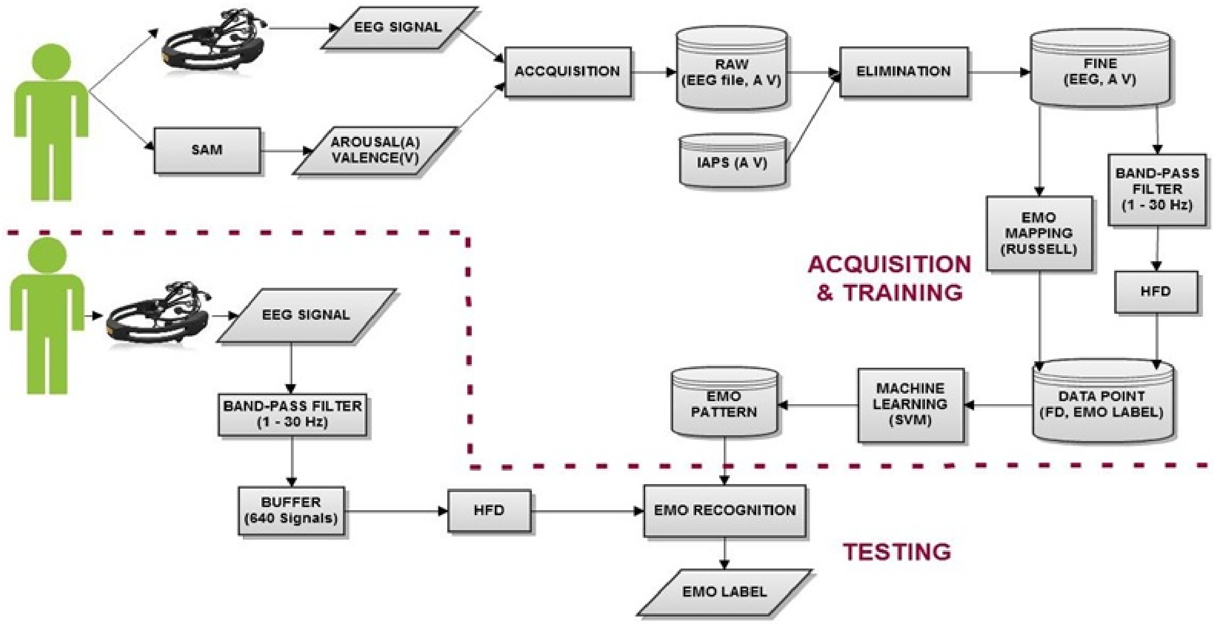

Fig. 5. The proposed model for emotion recognition

of them is larger than the predefined standard deviation (as seen in the last page), then the sample is discarded.

- **Band-pass Filter**: The signals receive from 14 electrodes Epoc in which each electrode includes many types of wave from human brain. In order to extract several necessary EEG waves in emotion recognition such as Delta, Theta, Alpha, Beta, we use 1-30 Hz band-pass filter to obtain the waves Delta (1-4 Hz), Theta (4-7 Hz), Alpha (7-13 Hz), Beta (13-30 Hz) [16].

- **Higuchi Fractal Dimension (HFD)**: In [11], Y. Liu et al. indicated that signals obtained from the FC6, AF3, F4 electrodes are useful signals in recognizing human emotions (as seen in Fig. 6). They are input of the HFD algorithm to receive their *FD* values. The *FD* value of FC6 (it is named as FD_1) is used to define arousal level while the difference of two *FD* values of AF3 and F4 (it is named as FD_2) is for valence level. Each EEG sample thus also owns a pair of FD_1 and FD_2 values.

- **Emo Mapping**: Each EEG sample owns two features which are AV values and pair of FD_1 and FD_2 values. In the step, we need to determine a relationship between them. At first, we label the EEG sample by using the circumplex model's coordinate plane of Russell [13] and its AV values (as seen in Fig. 4). The AV values of each EEG sample are mapped to the coordinate plan to determine an emotion label of the sample according to the proposed method in section 2. Since each EEG sample also has *FD* values, we can determine an emotion label according to *FD* values instead of AV values.

- **Machine Learning**: SVM is a learning system based on statistical learning theory. It has been used as a classifier in many real-world applications. In this paper, we used LIB-SVM [3], an implimentation of SVM, which is an effective tool for the problem. We take *FD* values and emotion label of the EEG sample as input of SVN machine. As a result, we obtain an emotion pattern which is used in the Testing phase. In the step, we use two approaches in the machine learning step. In the first approach, the *FD* values and emotion labels of EEG samples of all volunteers are input for the SVM. The second approach uses the SVM for each particular volunteer.

B. The Testing phase

In the phase, we need to recognize a human emotion which is an input of our model. We use the Emotiv Epoc to receive the EEG signals. The EEG signals then are processed with the Band-pass Filter, HFD algorithm before they are recognized with the SVM. The achieved result is an emotion label printed on the screen. In addition, our model is able to recognize human emotion in real-time. Since any change of emotion is made, our model immediately catches this change automatically. In order to implement our model in real-time, we use a buffer with window size of 640 signals gathered by the Epoc and the number of over lapping signals is 16.

IV. EXPERIMENTAL RESULTS

Here two experiments are conducted. Under the first experiment, our model with the first approach in the learning machine step is considered. Specifically, EEG signals of all volunteers are input of the SVM. In the second, our model with the other approach which used the SVM for each particular volunteer is tested.

In all experiments, five emotions considered are happy, angry, sad, relaxed and neutral as in Fig. 4. Our model use

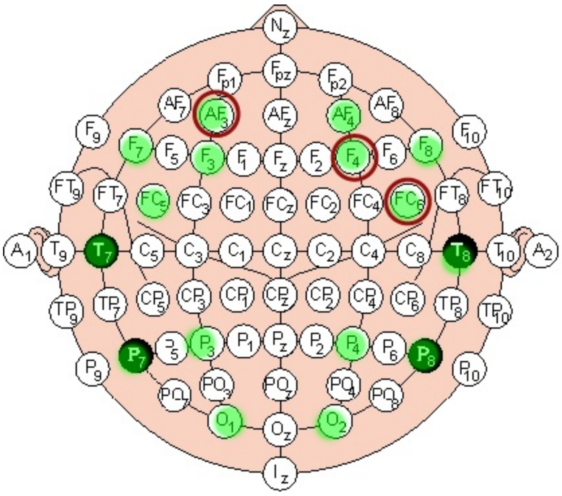

Fig. 6. The electrodes circled with red color are used for emotion recognition

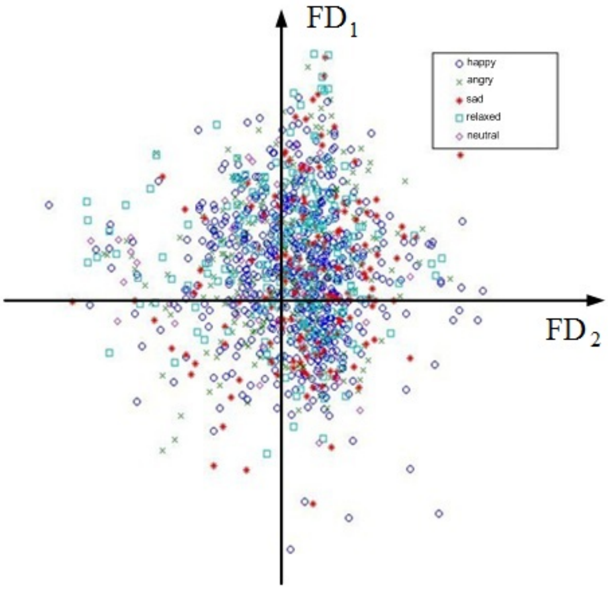

Fig. 7. The representation of EEG samples on the FD-coordinate

a sliding window technique which has a buffer with window size of 640 signals gathered by the Epoc and the number of over lapping of 16 signals. The experimental results let us evaluate efficiency of two approaches and recognition of our model in real-time.

A. The proposed model with machine learning for all subjects

Here we describe in more detail about the data acquisition step and the experimental results. We conducted a data acquisition process about one week with ninety five volunteers. The IAPS was selected as an emotion stimulus. The participants were students who are eighteen to twenty five years old with fifty five males and forty one females. None of the volunteers suffered from mental illness.

At the beginning of the process, a typical data acquisition session lasted forty five minutes before reducing to thirty seven minutes due to volunteers' feedback on the long time issue. In each session, fifteen minutes were used for presenting about BCI, the data acquisition process and SAM. Next seven minutes then were used to place the Emotiv Epoc on the volunteer's head and checked to ensure its functions well. In the rest of time, volunteer saw the photos on the screen. Each photo was shown about eight seconds before SAM was displayed. The volunteer had about ten seconds to tick on items of SAM, which is corresponding to his state of emotion. Each stimulus was repeated 60 times (45-minute per session) or 40 times (37-minute per session). Each stimulus generated a series of EEG signals. The EEG signals were received in eight seconds but only signals from the 2-nd second to 6-th second were used. Several volunteers did not finish their data acquisition session. Therefore, total number of samples was 4658 in which 976 samples were error. We took the valid samples through the Elimination step and received 1341 samples. These samples then were extracted features which included (*FD*-values, emotion labels) and feed into the SVM. As a result, we obtain emotion patterns used in the emotion recognition phase. In the Testing phase, one hundred volunteers took part in the experiment. They were used the Emotiv Epoc to obtain the EEG signals. These EEG signals then were processed with the Band-pass Filter, HFD algorithm and were recognized with SVM. The experimental results are shown in Fig. 8 and Fig. 7. In the Fig. 8, each column is average accuracy of one hundred participants in recognizing an emotion. In the Fig. 7, each point on the *FD*-coordinate corresponds to an emotion.

Fig. 8. Average accuracy of our model with the first approach in emotion recognition

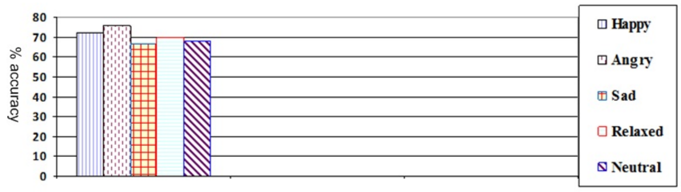

Fig. 9. Average accuracy of our model with the second approach in emotion recognition

B. The proposed model with machine learning for all subjects

Figure. 8 shows that in the first approach, efficiency of our model is very bad since the best average accuracy is about 9%. If we represent all samples on the *FD*-coordinate as in Fig. 7, then points are spread out on the plan instead of

Fig. 10. Average running time of our model with the second approach in emotion recognition

dividing into the five particular groups, in which, each group is corresponding to an emotion label. It is implied that EEG signals of each subject own particular characteristic. Since the FD_2 value is considered as an important characteristic, we realize that right hemisphere (F4) is more active during negative emotion, and left hemisphere (AF3) is more active during positive emotion in several cases. However, in some cases, the opposite observations are yielded. It is impossible to recognize exactly human emotions with this approach.

C. The proposed model with machine learning for a particular subject

In the experiment, we used the SVM for each particular volunteer. Twenty volunteers took part in this experiment. They experienced the data acquisition session as in the first experiment. However, instead of training for all volunteers, we trained for each one. In the Testing phase, the corresponding volunteer in the training step used the Emotiv Epoc to receive the EEG signals. The EEG signals then were processed with the Band-pass Filter, HFD algorithm and were recognized with the SVM. Each volunteer was tested ten times.

The experimental results, shown in Fig. 9 and 10, are extracted from Table 2 and 3 in [18]. Each column corresponds to % average accuracy of our model in recognizing an emotion.

Figure 9 shows that efficiency of our model is high since the worst and best average accuracy in emotion recognition of each volunteer are about 66% and 76%, respectively and average accuracy of all volunteers is 70.5 %. In fig. 3, the average running time of our model in emotion recognition is about 2.2 seconds for all volunteers. It is implied that the second approach is suitable to apply for practical applications in real-time.

V. CONCLUSIONS

In this paper, we proposed the model with two approaches for emotion recognition based on the Russell's circumplex model, Higuchi Fractal Dimension algorithm, and Support Vector Machine as a classifier. Additionally, the method to determine an emotion label of series of EEG signals was also proposed. In this paper, efficiency of our model with each approach was considered from the experiments. The experimental results showed that our model should be only used for recognizing emotions of each particular subject from the training to testing step. It is implied that EEG signals of each subject own individual characteristic. In addition, our model can recognize five basic human emotions in real-time with average accuracy 70.5% from the experiments. However, the accuracy and the number of emotions are still small for real applications. The our model clearly needs to be improved. This is a purpose for future research.

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