F-score Based EEG Channel Selection Methods for Emotion Recognition

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***Abstract*—Emotion, as an advanced function of the human brain, affects kinds of human behaviors. Electroencephalographs (EEG) are widely used in the field of emotion classification owing to their low cost and portability. In this work, we study the effects of a non-linear EEG feature and a channel selection method on emotion recognition. First, the fractal dimension(FD) which could reflect the state of the brain is extracted with a sliding window. The top seven channels are screened out by calculating the F-score from the whole samples. Then, based on the signals from forehead channels, filtered channels and associated channels, emotions on valence and arousal are classified by Support Vector Machine(SVM) and K Nearest Neighbours(KNN). The result shows that the forehead channels Fp2, AF8, Fpz play an important role in valence classification. When combining the forehead channels with other channels that have higher F-score, the SVM classifier has a better accuracy on the whole set with 89.37% on valence and 87.07% on arousal. Besides, the overall accuracy calculated on each participants with associated channels get significant improvement. Especially, the KNN classifier has a much better result on every subject. This phenomenon indicates that by combining the higher F-score channels with the forehead channels, the associated channels can not only take advantage of the forehead channels' ability to categorize emotions but also consider individual differences.**

***Index Terms*—Emotion classification, Channel selection, F-score, EEG**

I. Introduction

As a intuitive expression of internal or external things, emotion can reflect human mental state. Recognition of emotions can not only assist in the study of the mechanisms but also can detect outbreaks of mental illness. Thus, affective computing [1] has attracted considerable attention, resulting in marked advances.

In affective computing, physiological signals [2] such as electromyogram(EMG), electrocardiogram(ECG), electroencephalographs(EEG) and skin temperature(ST) are widely used for emotions classification. For example, in [3], Wagner et al. achieved higher accuracy on four categories of emotion through using multiple physiological signals. In [4], Khalil et al. extracted time-domain features based on EEG signals such as mean value and standard deviation, then used the Quadratic Discriminant Analysis (QDA) classifier to distinguish between three emotions. Cai et al [5] found a pervasive approach to EEG-Based depression detection and a case-based reasoning model for depression based on three-electrode EEG Data [6]. Besides, in [7], they introduced a novel emotion-aware mobile application called iSmile which collected the user's different physiological information and demonstrated its practicality and usefulness for healthy and good sleep. Among these physiological signals, the EEG signal is widely used in investigating mental illnesses. However, the brain-computer interface (BCI) device which is widely used for collecting EEG signals has several channels, the dimension of the features from EEG signals is high and substantial redundant information is recorded. Initially, feature selection methods such as ReliefF and correlation were used to obtain an optimal feature set. With advancing research, studies have concentrated on channel selection algorithms to reduce computational complexity. In [8], Zheng et al. obtained the outstanding 20 features that belonged to 12 channels. And [9], Sun et al. used CFS+KNN algorithm and got a higher accuracy for the valence dimension divided into three classes. Furthermore, Ansari-Asl et al. [10] proposed a channel selection algorithm based on the synchronisation likelihood. Wang et al. [11] used the paired t-test to screen channels based on sample entropy. Recently, Zhang et al. [12] hypothesized a mean-ReliefF-channel-selection (MRCS) method to compute the weights of the features and used its mean as the channel's weight to screen channels. The above researches attempted to find effective channels. In [13], [14], they had already found that the forehead area played an important role in human emotion expression. However, the act of performing a task or expressing our emotions the frontal lobes may not only be activated, their combination with different areas may also cause or affect the resultant emotion. A more universally applicable channel combination highlight its importance.

Herein, we use the F-score to calculate the difference between the channels and extract the fractal dimension as a feature. The channels are divided into three parts: the forehead 7 channels, the top 7 channels according to the F-score and the combination of the preceding channels. Then, comparisons are made with respect to two aspects:(1) the effectiveness on valence and (2) the effectiveness on arousal. Our research reveals a channel combination of forehead channels and other channels which have a higher F-score with higher accuracy on each individual level. However, it still need more researches for a portable design of the brain-computer interface device

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and a more applicable channel-selection.

The remaining part of this article is organised as follows: in Section 2, we introduce the technical components which include the pre-processing, feature extraction and the F-score; in Section 3, we briefly describe the experimental procedures. In Section 4, results and discussion are provided. Finally, we make a conclusion of our work.

II. METHODS

A. Preprocessing

The EEG signals are recorded using a 64-channel braincap produced by Brain Products Corporation with a sample rate of 1000Hz. The electrodes are sited according to the International 10-20 system. After removing the channels that record signals of HEOG (Horizontal Electro-oculogram), VEOG (Vertical Electro-oculogram) and the channel (FT10) which does not have a symmetrical channel and the remaining 61 electrodes signals are used for further processing. The raw EEG signals are sampled down to 256Hz. Then, 1Hz high-pass and 49-51Hz band-stop filters are applied to reduce the baseline drift and the power line interference. A 45Hz low-pass filter is used to remove irrelevant frequency components. Next, we dash-out the signals which are recorded at the rating and resting period (between blocks) and the remaining signals are integrated. Then, signals of every subject are reduced to their corresponding baseline to eliminate the individual's influence. Subsequently, we use the Independent Component Analysis (ICA) algorithm to remove the artifacts. We also use the adjust plugin to automatically eliminate the eye potentiometer and muscle artifacts. All of these steps are conducted using EEGLAB [15]. Our research aims to explore the classification effect of different emotions. Consequently, epochs induce inappropriate emotions and poor experiment signals are excluded. The exclusion criteria are based on the scores of the individuals' Self-Assessment Manikin (SAM) [16] rating. Each movie is presented for 2-4mins and during this period, the emotions of the subjects are induced. The details of the selected videos are listed in Table I. We use the whole signals to extract the feature as every subject might see a different movie to induce the same emotion.

B. Feature Extraction

Many methods have been proposed for extracting time-domain features, frequency-domain features, or time-frequency domain features from the EEG signals, including Fast Fourier Transform(FFT) and wavelet transform. With the development of chaos theory, more attention has been paid to the non-linear features of EEG signals such as sample entropy and the fractal dimension(FD). In [17], Liu et al. discovered that emotions had a spatiotemporal location and fractal dimension could be used to distinguish it. Therefore, herein, we used FD as the only feature. Higuchis algorithm was widely used even though different methods were available for to estimating the fractal dimension. [18]. Higuchi's fractal dimension calculation procedure is as follows:

TABLE I: Statistics of The Chosen Movies In Our Emotion Experiment

Type	Arousal	Valence	Specificity	Consistency
Fear	7.26	7.08	3.58	97.78%
Angry	7.05	6.44	1.81	85.93%
Sad	7.11	6.69	2.86	93.33%
Happy	6.54	6.33	2.06	95.56%

Construct the discrete-time series:

$$\{x(i), i = 1, 2, \cdots, n\} \tag{1}$$

Reconstruct it as the following time series:

$$x_m^k = \left\{x[m], x[m+k], \cdots x\left[m + \operatorname{int}\left(\frac{N-m}{k}\right) \times k\right]\right\} \tag{2}$$

where m is the time starting point, k is the time interval and int() represents rounded down.

The length of the new sequence is given as follow:

$$L_m(k) = {}^1\!/_k \left\{ \sum_{i=1}^{\operatorname{int}\left(\frac{N-m}{k}\right)} \left| \begin{array}{l} x(m+ik) - \\ x(m+(i-1)k) \end{array} \right| \right\} \times \frac{N-1}{\operatorname{int}\left(\frac{N-m}{k}\right)} \tag{3}$$

Then, the average length of the sequence is expressed as:

$$L(k) = \frac{1}{k} \sum_{m=1}^{k} L_m(k) \tag{4}$$

The estimated Higuchi fractal dimension can be calculated as follows:

$$D = \frac{\ln(L(k))}{-\ln(k)} \tag{5}$$

We implement the algorithm with a sliding window with no overlap where the window size is 768 samples(3s) and calculate the FD value from the 61 channels.

C. F-score

The F-score is used to measure the differentiation of the features among different categories. The larger the value, the more obvious the distinction between the categories. Suppose the x_k represents the sample in the data set $(k = 1, 2, \cdots, N)$, n_+ is the number of positive samples, and n_- is the number of negative samples. Then the F-score of the ith feature in the data set can be calculated as follows:

$$F_i = \frac{\left(\bar{x}_i^{(+)} - \bar{x}_i\right)^2 + \left(\bar{x}_i^{(-)} - \bar{x}_i\right)}{\frac{1}{n_+-1}\sum_{k=1}^{n_+}\left(x_{k_i}^{(+)} - \bar{x}_i^{(+)}\right)^2 + \frac{1}{n_--1}\sum_{k=1}^{n_-}\left(x_{k_i}^{(-)} - \bar{x}_i^{(-)}\right)^2} \tag{6}$$

Here $\bar{x}_i$ is the mean of this feature over the entire set, $\bar{x}_i^{(+)}$ represents the average value of this feature on the positive sample, $\bar{x}_i^{(-)}$ is the mean value of this feature on the negative sample, $\bar{x}_{k_i}^{(+)}$ represents the value of the kth positive sample on the ith characteristic, $\bar{x}_{k_i}^{(-)}$ represents the value of the kth negative sample on the ith characteristic.

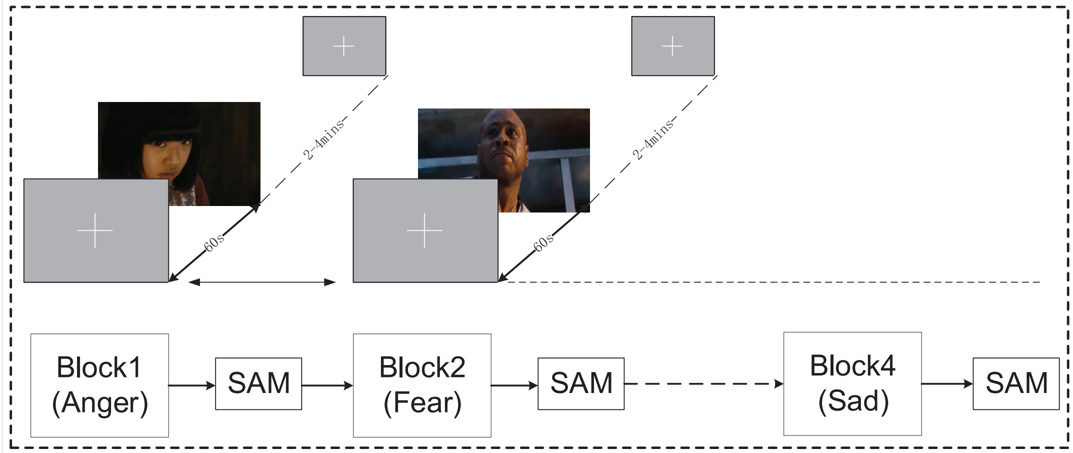

Fig. 1: The Experiment Protocol

We calculated the F-score after data processing based on the whole samples and then extract feature from the destination channels.

III. Experiment

We recruited ten male and nine female student volunteers(mean age 24,SD=0.62) from Lanzhou University. All the subjects had no history of neurological or psychiatric illness and their vision or corrected vision is normal. Because films are the most effective way of inducing a single emotion [19] and and all participants are Chinese, we chose some Chinese videos for better results. First, the subjects were instructed to look at a cross picture and try to relax for obtaining the 60s resting EEG data. The process of the experiment was shown in Fig.1: the process was divided into four blocks and each block featured a 2-4 min video promoting a certain emotion. The four predominant emotions promoted by the constituent videos, are were anger,fear,joy and sadness. After watching a clip, the subjects scored the video according to the SAM scale and calmed down for next video. We removed the signal of two subjects according to the SAM scale and signal quality. Ultimately, all the signals are derived from 17 subjects

IV. Result and Discussion

The Support Vector Machine(SVM) is the most used classifier. Therefor, in our research, we used the SVM with the RBF kernel function. LIBSVM [20], an SVM toolbox, was used to process the features and classify the emotions. We used the fixed c and g parameters(-c 4,-g 7). Moreover, we compared it with the k-Nearest Neighbor(KNN) [21] which was useful in emotion classification [22]. And the parameter k was set to 3. Then, the average accuracy was calculated after 5 trials of 10-fold cross-validation, which was considered as the final result.

In previous research, classifications were mostly performed on each dimension(valence and arousal). Thus, herein, two different classification scenarios were considered:

i) S1: class1: high valence(HV) and class2: low valence(LV)

ii) S2: class1: high arousal(HA) and class2: low arousal(LA)

A. Channel Contrast

The forehead(FH) channels were F7, AF7, Fp1, Fpz, Fp2, AF8 and F8. On scenarios S1, the channels filtered by F-score(FS) were AF4, FP2, T8, AF3, Oz, AF8 and FPz. Both of them had three identical channels Fp2, AF8 and FPz. Feature from these channels had obvious difference on valence.

First, using the FH channel, we calculated on the whole set the accuracy, the recall rate and the F1-score; the following results were obtained, 81.39%, 38.61% and 51.30% on SVM and 80.02%, 56.44% and 59.68% on KNN respectively The same indices based on FS channel were 83.02%, 46.97% and 59.91% on SVM and 82.57%, 61.15% and 64.90% on KNN respectively The FS channel is slightly more efficient than the FH channel. Then, we tested the indices on each subject. Table II showed the results calculated for each subject with different channels on valence. From Table II, on SVM, we observed that the overall accuracy was 81.81% on FH and 84.36% on FS. On KNN, it was 92.92% on FH and 93.41% on FS. The test on the FS channels still performed better than the FH channels. Even though, the KNN classifier worked well on each subject, its F1-score was 85.56% on FH and 86.98% on FS which were much higher than the values obtained on the SVM. The FS channels made progress on classification result. However, not all the subject their accuracy got improved and the performance of some subjects declined. On the KNN, from the F1-score we could see that these subjects: 3, 6, 7, 8, 11, 12, 13, 16, 17, had set back which was more than half of the subjects. In scenario S2, the channels filtered by F-score(FS) were C4, C2, CPz, Cz, CP4, Fz and P2. This was totally different from FH channels. Using the FH channel, we calculated the whole signals, and the accuracy, the recall rate and the F1-score. Then, the following results were obtained: 80.13%, 53.98%, 65.33% on SVM and 76.54%, 60.57%, 63.81% on KNN respectively. The same indices were 74.01%, 39.52%, 50.78% on SVM and 72.43%, 54.88%, 57.61% on KNN which was reckoned on FS channels. On the arousal, it was no doubt that the FH channels worked well. Furthermore, Table III shows the results calculated for each subject with

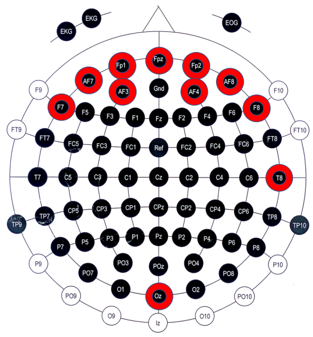

Fig. 2: Selected Channels on Valence level

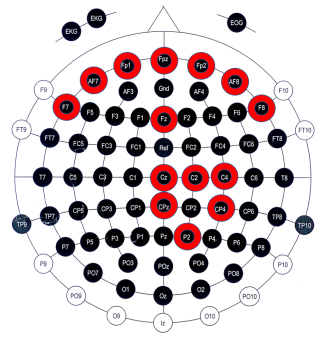

Fig. 3: Selected Channels on Arousal level

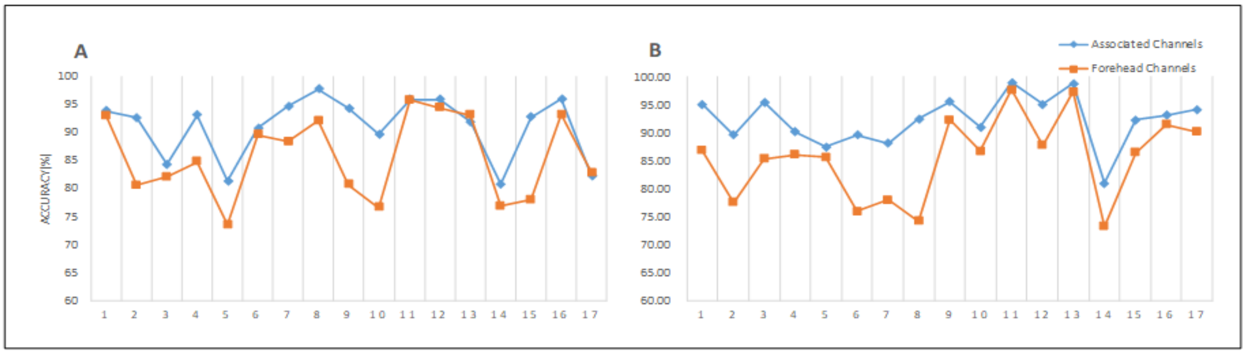

Fig. 4: Comparison of Classification F1-score

TABLE II: Classification Result of Different Channels in Valence

Subject	SVM Accuracy (%)		SVM Recall		SVM F1-score		KNN Accuracy		KNN Recall		KNN F1-score	
	FH	FS	FH	FS	FH	FS	FH	FS	FH	FS	FH	FS
1	91.95	94.29	85.07	88.36	85.95	89.97	95.80	96.80	93.88	94.18	92.85	94.46
2	79.49	90.17	29.38	66.88	43.65	78.67	90.17	96.48	75.16	87.81	80.54	93.11
3	79.42	82.18	40.00	52.37	48.62	58.89	90.90	88.11	85.00	73.42	81.99	75.02
4	78.05	90.10	3.13	60.94	5.97	73.32	93.94	97.18	75.63	88.75	84.72	93.34
5	75.06	77.10	1.56	10.31	3.05	18.38	89.33	90.24	59.06	67.50	73.51	77.57
6	86.22	86.89	66.58	61.05	75.30	74.58	93.57	92.37	87.63	79.08	89.57	86.72
7	85.81	83.82	57.31	48.36	69.14	62.42	93.44	92.61	89.10	82.39	88.30	86.10
8	85.20	70.88	69.06	8.75	74.54	15.84	94.95	92.01	92.50	80.78	92.01	86.36
9	77.66	89.69	8.75	56.25	14.68	70.58	92.51	96.46	71.41	87.66	80.67	91.58
10	70.70	85.58	6.58	61.05	11.60	71.36	87.95	93.95	66.97	84.08	76.58	89.12
11	92.38	95.24	66.57	79.10	79.93	88.33	98.13	97.59	91.94	91.04	95.72	94.50
12	92.80	82.48	84.21	70.79	87.66	71.07	96.40	92.64	98.16	91.18	94.32	88.28
13	89.75	85.38	83.28	82.99	79.58	73.16	96.59	93.98	95.22	89.40	93.09	87.72
14	70.00	69.68	2.11	0.00	4.05	0.00	86.94	88.61	71.84	74.61	76.82	79.75
15	76.96	90.22	13.33	74.85	21.68	78.54	90.58	94.89	69.70	90.76	77.93	89.46
16	83.28	84.96	41.32	49.21	57.69	64.47	96.39	94.23	88.55	87.37	93.15	89.36
17	75.97	75.43	10.75	5.97	18.80	11.19	92.02	89.77	74.18	63.28	82.82	76.19
Average	81.81	84.36	39.35	51.60	45.99	58.87	92.92	93.41	81.53	83.13	85.56	86.98

TABLE III: Classification Result of Different Channels in Arousal

Subject	SVM Accuracy(%)		SVM Recall		SVM F1-score		KNN Accuracy		KNN Recall		KNN F1-score	
	FH	FS	FH	FS	FH	FS	FH	FS	FH	FS	FH	FS
1	91.86	93.33	74.10	82.62	82.71	86.74	93.64	96.62	79.67	91.48	86.86	93.46
2	86.86	77.54	59.67	24.26	70.13	35.61	89.28	88.98	71.80	64.75	77.57	75.15
3	73.46	90.00	29.11	75.18	43.93	84.37	90.35	95.10	78.57	88.84	85.37	92.85
4	73.80	59.93	50.00	76.96	59.81	60.01	89.55	83.28	82.68	84.29	86.06	79.72
5	71.53	71.37	73.04	70.36	69.27	68.34	87.37	85.25	85.89	80.80	85.66	82.80
6	76.27	78.51	8.20	17.70	14.88	29.04	89.42	92.45	66.23	75.08	75.95	83.39
7	78.59	83.90	23.28	63.93	35.42	66.76	89.88	91.87	70.98	89.51	78.00	84.78
8	79.80	76.76	38.36	27.21	53.15	41.17	86.76	91.91	63.77	75.57	74.21	84.80
9	87.49	62.34	80.18	2.14	83.15	4.19	94.02	88.42	92.68	77.59	92.27	83.75
10	78.99	70.16	66.59	28.64	68.37	39.43	90.81	86.05	88.41	80.23	86.78	79.68
11	95.92	77.01	90.18	41.79	94.39	58.01	98.30	93.13	95.71	84.82	97.72	90.38
12	70.40	73.28	20.23	38.18	32.47	48.38	92.28	92.60	79.09	89.55	87.80	89.50
13	98.49	99.00	100.00	97.73	97.67	98.39	98.28	98.60	100.00	97.39	97.35	97.77
14	64.92	61.67	2.50	14.09	4.73	20.38	83.85	83.21	63.75	73.75	73.35	75.39
15	77.54	65.58	46.59	5.45	56.95	9.20	91.52	86.20	85.23	78.98	86.50	78.51
16	79.56	67.08	55.36	25.00	68.89	38.26	93.39	89.12	86.88	82.50	91.47	86.12
17	82.17	68.60	73.21	42.68	78.08	54.01	91.71	88.22	87.59	80.71	90.16	85.60
Average	80.45	75.06	52.39	43.17	59.65	49.55	91.20	90.06	81.11	82.11	85.48	84.92

disparate channels on arousal. From the Table III, we can see that the overall accuracy on SVM is 80.45% on FH and 75.06% on FS, whereas on KNN, it is 91.20% on FH and 90.06% on FS. Thus, the FH channels still performed better than the FS channels and the result from KNN was also higher than that obtained using SVM. However, on the KNN, subjects 1, 3, 6, 7, 8, 12 and 14 exhibited improved responses which mean these subjects' signals significantly affected the F-score and the channels chosen from F-score were more suitable on them.

No matter on S1 or S2, choosing one single type of channels was not good for each subject. This also confirmed that different brain area was activated in emotional triggers for diverse subjects.

B. channel selection

Considering the result from the Channel Contrast, we intended to combine the FS channels with the FH channels for a better result on each subject.

For scenarios S1, Fig.2 showed the electrode distribution. Most electrodes were located in the forehead area. Table IV showed the details on the whole set through different levels.

TABLE IV: The Overall Classification Result of Associated Channels in Valence

Channels	SVM			KNN		
	Accuracy(%)	Recall	F1-score	Accuracy	Recall	F1-score
FH	81.39	38.61	51.30	80.02	56.44	59.68
FS	83.02	46.97	59.91	82.57	61.15	64.70
FH+FS(1)	82.37	45.15	57.23	82.17	62.94	64.90
FH+FS(1,3)	85.94	62.69	71.15	85.85	69.89	71.96
FH+FS(1,3,4)	87.75	65.86	73.46	86.14	71.35	72.80
FH+FS(1,3,4,5)	89.37	73.84	78.85	88.08	74.13	76.38

TABLE V: The Individual Classification Result of Associated Channels in Valence

Subject	Associated 11 channels (SVM)			Associated 11 channels (KNN)		
	Accuracy (%)	Recall	F1-score	Accuracy	Recall	F1-score
1	97.49	93.73	95.57	96.36	94.33	93.77
2	92.80	76.56	85.21	96.14	89.53	92.64
3	86.60	66.58	70.78	92.28	84.61	84.23
4	94.29	81.25	86.34	96.97	91.25	93.07
5	87.45	59.69	70.47	91.69	72.19	81.32
6	92.86	82.37	87.92	94.48	85.79	90.74
7	93.20	88.96	87.90	96.89	98.36	94.63
8	98.33	96.56	97.32	98.58	96.25	97.70
9	97.11	88.44	93.09	97.56	91.09	94.25
10	87.67	68.42	76.58	94.07	87.24	89.63
11	95.85	82.39	90.05	98.16	92.54	95.83
12	95.28	96.84	92.58	97.40	97.76	95.82
13	95.13	95.22	90.37	95.91	95.82	91.89
14	72.54	15.26	24.07	88.45	80.53	80.77
15	95.36	85.45	89.78	96.59	89.70	92.65
16	94.60	86.58	89.89	97.81	93.95	95.96
17	82.79	39.70	54.49	91.94	71.79	82.20
Average	91.73	76.71	81.32	95.37	88.98	91.01

By combining these channels together, the indices gradually increased and ultimately the overall accuracy was nearly 90.00% on SVM and 88.08% on KNN which was higher than those obtained using the FH channels. The recall and F1-score rate also created a great progress. Table V showed the result for each subject. Most of the participants achieved a higher rate on every index. The average accuracy reached 95.37% on KNN and its average F1-score was 91.01%. Furthermore, on KNN, the F1-score of each subject exceeded 80.00% and one of them achieved exactly 97.70%. The classification became more practical under the associated channels.

For scenarios S2, Fig.3 showed the electrode distribution. According to Fig.3, most of the FS channels were located on the top of the brain expect the FH channels. According to Table VI, ultimately the overall accuracy was 87.07% on SVM and 85.89% on KNN. The F1-score rate was around 80.00% whether on SVM or KNN. It also got a improvement by comparing with the FH and the FS channels. Based on Table VII, the indices were also higher than the previous ones and subject 13 achieved a 100% rate on the SVM. On KNN, the F1-score of 12 subjects exceeded 90.00% and all F1-scores were exceeded 80.00%. The KNN classifier still performed well on the arousal classification.

Then, we compared the F1-score of the FH channels with that of united channels' for each subject. Fig.4A described the difference on the valence and Fig.4B showed the result of the arousal. Based on Fig.4, after combining the channels, most of the subjects achieved a higher rate than the FH channels. Even though some of them did not improve, they remained nearly constant with the previous results. The classification result improved in this manner whether on the valence or the arousal. The classifier KNN seemed more suitable for each subject classification

TABLE VI: The Overall Classification Result of Associated Channels in Arousal

Channels	SVM			KNN		
	Accuracy (%)	Recall	F1-score	Accuracy	Recall	F1-score
FH	80.13	53.98	65.33	76.54	60.57	63.81
FS	74.01	39.52	50.78	72.43	54.88	57.61
FH+FS(1)	81.12	59.93	68.28	78.51	64.31	67.05
FH+FS(1-2)	81.34	64.23	70.61	80.18	66.08	69.50
FH+FS(1-3)	85.41	70.87	76.88	83.25	71.45	74.36
FH+FS(1-4)	85.98	75.84	78.38	84.08	74.71	76.12
FH+FS(1-5)	85.49	72.40	77.27	84.67	74.35	76.72
FH+FS(1-6)	86.17	74.91	78.50	85.53	76.13	78.10
FH+FS(1-7)	87.07	78.00	80.27	85.89	76.81	78.71

TABLE VII: The Individual Classification Result of Associated Channels in Arousal

Subject	Associated 14 Channels(SVM)			Associated 14 channels(KNN)		
	Accuracy (%)	Recall	F1-score	Accuracy	Recall	F1-score
1	97.84	92.79	95.77	97.45	92.95	95.06
2	92.46	79.67	84.51	94.87	85.74	89.61
3	98.01	96.07	97.20	96.86	92.14	95.46
4	81.39	79.11	76.87	92.13	92.23	90.14
5	80.47	82.50	78.77	89.14	86.70	87.51
6	88.30	61.31	72.53	94.94	86.89	89.66
7	93.20	80.00	85.57	94.36	82.62	88.11
8	95.49	84.92	91.84	95.83	86.56	92.52
9	97.04	96.61	96.18	96.60	94.55	95.53
10	87.52	75.68	80.53	93.84	91.36	91.00
11	98.98	97.68	98.65	99.25	99.02	99.02
12	93.60	90.91	90.90	96.56	94.89	95.10
13	100.00	100.00	100.00	99.25	97.95	98.80
14	67.22	11.36	19.39	87.26	77.73	80.96
15	93.19	91.36	89.53	94.89	95.45	92.26
16	88.76	83.04	85.79	94.45	91.43	93.09
17	88.22	89.46	86.80	94.92	94.38	94.16
Average	90.69	81.91	84.17	94.86	90.74	92.23

V. Conclusion

In this work, we used the F-score as the basis for channel selection and calculated the FD as a feature. Then, we compared the classification results for different channel combinations. The result for each subject showed that the accuracy of the valence could reach 91.73% on SVM and 95.37% on KNN. The F1-score on the KNN was higher than that on SVM. In the case of arousal, the accuracy was 90.69% on SVM and 94.86% on KNN. The F1-score on the KNN was 92.23% which was the highest rate. Regardless of the classifier, the index improved on the united channels and provided a better result for each subject. The selected channels were showed on Fig.2 and Fig.3. By combining the filtered channels and the forehead channels, the accuracy of the valence and the arousal increased and this combination approach was more appropriate for all subjects. However, the results were only calculated using this experimental data. In the future work, we aim to explore more practicable channel combinations and many other efficient channel selection algorithms using more data incorporating different ages, different educational levels, and different experimental conditions.

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