Clustering of EEG data using maximum entropy method and LVQ

Yuji Mizuno, Hiroshi Mabuchi, Goutam Chakraborty, and Masafumi Matsuhara

***Abstract*—** The study of extracting electroencephalogram (EEG) data as a source of significant information has recently gained attention. However, since EEG data are complex, it is difficult to extract them as a source of intended, significant information. In order to effectively extract EEG data, this paper employs the maximum entropy method (MEM) for frequency analyses and investigates an alpha frequency band and beta frequency band in which features are more apparent. At this time, both the alpha and beta frequency bands are divided further into several sub-bands so as to extract detailed EEG data where the loss of data is small. In addition, learning vector quantization (LVQ) is used for clustering the EEG data with features extracted. In this paper, we will demonstrate the effectiveness of the proposed method by applying it to the EEG data of one subject and two subjects and comparing the results with other related studies. By applying the proposed method further to the EEG data of three subjects, and comparing the results with a related study, the effectiveness of the proposed method will be determined.

***Keywords*—**Brain-Computer Interface(BCI), Clustering, EEG, LVQ, Maximum Entropy Method(MEM)

I. Introduction

RECENTLY, there have been many studies on the brain-computer interface (BCI), which interprets EEG data of brain activities generated by picturing images and human physical actions and then serves as an interface between the human brain and a computer. The process flow of BCI is: measurement of brain activities, preprocessing, feature extraction, learning, recognition, and postprocessing. When creating a BCI, it is important to note that postprocessing cannot be carried out correctly unless recognition is properly completed. Therefore, determining the method by which the BCI executes the processes from preprocessing to learning is crucial for accurate recognition. This paper proposes an effective method for processing from preprocessing to learning.

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The measurement methods of brain activities fall into two approaches: invasive [13]-[17] and noninvasive. In a noninvasive approach, studies on the BCI using EEG data have been actively conducted [4]-[10]. The EEG is the oldest, popular noninvasive measuring technique and, owing to its simplicity, used widely. However, satisfactory results in terms of recognition accuracy have yet to be obtained through BCI studies using noninvasive approaches. This study uses the EEG data released from the Colorado State University [1].

For the BCI to be realized, it is important to recognize the meaning the recorded EEG data contain. For this purpose, processing for feature extraction and learning is of particular significance. Although various methods have been used for these processing [11],[12], [18]-[22], there is not yet a definite, established approach, leaving today's researchers following a process of trial and error.

With regard to recognition accuracy studies using the EEG data released from the Colorado State University, Inagaki et al. proposed a method by which EEG features were extracted through the Fourier transform and the EEG data was clustered using back propagation (BP), one of the learning algorithms in neural networks [2]. Also, Anderson et al. proposed a method by which EEG features were extracted through the short-time principal component analysis (STPCA) and the EEG data was clustered by the linear discriminant analysis (LDA) [3].

This study uses maximum entropy method (MEM) to effectively extract EEG features and investigates both an alpha frequency band and a beta frequency band. At this time, both the alpha and beta frequency bands are divided further into several sub-bands to capture precise features of the EEG data. Then, all these frequency sub-bands are used as features. Moreover, LVQ, which is a model of neural networks, is used in this study for clustering the EEG data.

In this paper, we will demonstrate the effectiveness of the proposed method by applying it to the EEG data of one subject and two subjects and comparing the results with other related studies. Moreover, each subject will be examined to determine which task is more likely to be recognized falsely as what task and, based on these examinations, we will seek a combination of tasks that has a higher positive recognition rate.

In addition, by applying the proposed method further to the EEG data of three subjects, and comparing the results with a related study, the effectiveness of the proposed method will be determined.

This paper is organized as follows. Section 2 explains maximum entropy method and LVQ, and Section 3 describes EEG data and mental tasks used in this study. Section 4 explains a method for extracting features, more specifically, segmentation, feature extraction, normalization. Section 5 explains an experimental method, and shows the experimental results. We will demonstrate the effectiveness of the proposed method by comparing the experimental results with other related studies. In addition, the combination of tasks by which the recognition rate increases is examined. Section 6 shows the experiment results of the case where three more subjects have been added in the experiment, again demonstrating the effectiveness of the proposed method. Lastly, the conclusion is provided in Section 7.

II. MAXIMUM ENTROPY METHOD AND LVQ

This section explains MEM and LVQ used in this study.

Today, the fast Fourier transform (FFT) is widely used as a frequency analysis. The FFT, however, is unsuitable for analyzing ever-changing frequencies. The wavelet transform, also, is one of the frequency analysis methods but is unsuitable for analyzing continuous and steady frequencies. In this study, we use MEM, which has higher spectral resolutions than other frequency analysis methods and provides the ability to analyze even short-time data. From the above, it can be said that MEM is an optimal analysis method for EEG data.

In LVQ, several reference vectors, each of which is a representative of a cluster, are set first and then updated for the formation of ideal clusters. A learning algorithm of LVQ is simple while the learning time of it is shorter than that of the BP method [23]. Since LVQ can be applied to a large-scale recognition problem, it can be considered that LVQ is suitable for problems requiring recognition of a character with many data or classification of EEG data. There are several models, such as LVQ1, LVQ2.1, and LVQ3, for LVQ. In this study, we use the LVQ2.1 model for which the recognition rate is said to be the highest [24].

III. MENTAL TASKS AND EEG DATA

This study utilizes EEG data, which is released by Colorado State University, as experimental data [1]. The mental tasks used in the EEG measurement are as follows.

- Task1 : Resting task
- Task2 : Mental multiplication of two multi-digit numbers
- Task3 : Mental letter writing
- Task4 : Visual rotation of a three dimensional block figures
- Task5 : Visual counting

EEG signals are measured at the points C3, C4, P3, P4, O1, and O2 designated by the ten-twenty electrode system (Fig.1). Also, signals generated from eye movements are recorded by the electrooculogram (EOG). Accordingly, a total of seven

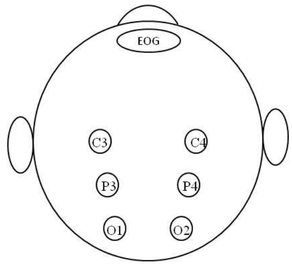

Fig.1: Positions of EEG electrodes measured and released by Colorado State University

channels are used. Because EEG signals are measured for 10 seconds at the sampling frequency of 250Hz against each mental task, there will be 2,500 (250Hz $\times$10 seconds) sample data for each channel. Data from the seven channels will constitute a data set.

IV. FEATURE EXTRACTION METHOD

The feature extraction is carried out in the order of segmentation, frequency analysis, and normalization.

A Segmentation

The segmentation is to eliminate fluctuations in EEG data. Because of this, EEG data can be analyzed in real time. In this study, 10-second recording of EEG data are segmented by 0.4 seconds, and a frequency analysis is conducted on each segment.

Experiments were undertaken within various segment division times, and we adopted the segment time which brought the best results among them. Moreover, experiments were undertaken in two cases: a case by which there was an overlap of segments and a case by which there was no overlap of segments. As result of this experimentation, we adopted the case in which there is no overlap of segments as it produced the best results.

B Frequency Analysis and Normalization

The maximum entropy calculation method (MemCalc), which is developed from MEM, is used for frequency analysis. In MemCalc, the frequency of time-series signals can be analyzed with minimum noise interference, and it is possible to process a signal that is of only a few seconds duration.

In this study, the power spectra of alpha frequency and beta frequency bands, where changes readily appear in EEG data, are used. The alpha frequency band from 8Hz to 12Hz is divided into three frequency sub-bands: alpha1 frequency band of 8Hz; alpha2 frequency band from 9Hz to 10Hz; and alpha3 frequency band from 11Hz to 12Hz. Similarly, the beta frequency band from 13Hz to 30Hz is divided into two frequency sub-bands: beta1 frequency band from 13Hz to 19Hz and beta2 frequency band from 20Hz to 30Hz.

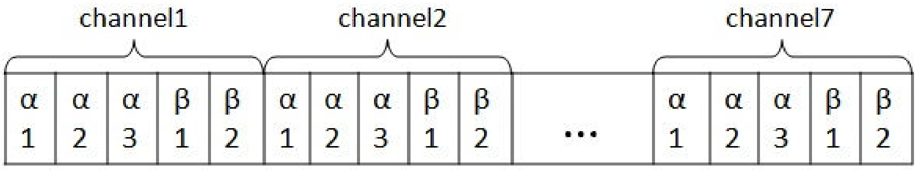

Fig.2: Input data

After a power spectrum of each frequency band is derived, linear normalization of the power spectrum is carried out for each frequency band. The power spectrum of all frequency bands (alpha1, alpha2, alpha3, beta1, and beta2) from each of the seven channels is used as input data. Therefore, as shown in Fig.2, 35 (7×5) power spectrum values, which are the features, become the input data of LVQ.

V. Experimental method and results, comparisons and considerations

In this section, we give an experimental method and experimental results.

This study uses EEG data [1] released by Colorado State University. These data are obtained in the following manner.

- EEG data are measured 10 times, each time for a duration of 10 seconds, against each mental task.
- This measurement is conducted for each of the five mental tasks.

In this study, 40 data sets out of a total of 50 are used for learning data and the remaining 10 for test data, as in the method adopted by Inagaki et al. Experiments were conducted with a set of test data, which was combined with consistency without producing biased data. Then, the average recognition rate derived from all the combined data sets was determined as the final recognition rate.

The experimental conditions in LVQ are: a total of 10 reference vectors (2 vectors a class × 5 classes); the learning rate of 0.01; and the learning count of 10000. The reference vectors are drawn at random from vectors in the learning data.

The task-specific recognition rates observed in the proposed method are shown in Table 1. It can be noted from Table 1 that the recognition rate varies according to tasks and subjects. It can also be said that the higher the number of subjects is, the lower the recognition rate becomes.

Next, we will demonstrate the effectiveness of the proposed method by comparing the results with other related studies [2],[3].

A Comparing the proposed method with the method by Inagaki et al.

In this section, we compare the proposed method with the method by Inagaki et al.

The differences between the proposed method and the method by Inagaki et al. are shown in Fig.3.

As shown in Table 2, the average of task-specific recognition rates in the proposed method are compared with those in the method used by Inagaki et al.

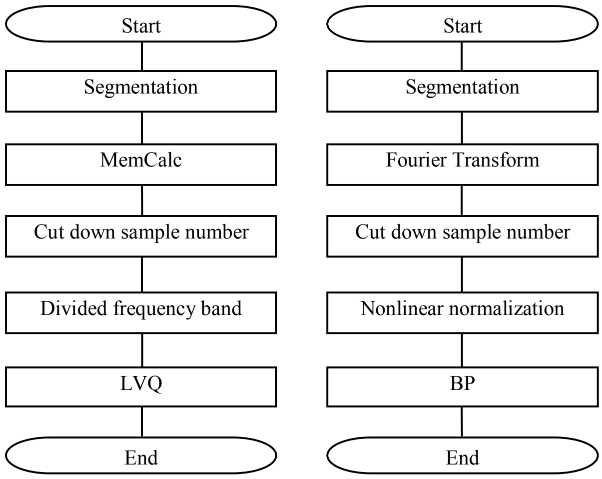

Fig.3: The differences between the proposed method and the method by Inagaki et al.

TABLE 1
Task-specific recognition rates in the proposed method

	Task1	Task2	Task3	Task4	Task5	Average
Subject1	73.2	97.8	66.4	93.2	74.2	81.0
Subject2	66.5	99.0	77.5	81.0	69.0	78.6
Subject3	65.3	61.4	73.7	50.8	15.4	53.3
Subjects of 1 and 2	49.8	96.0	81.0	95.3	35.5	71.5
Subjects of 1 and 3	57.9	79.3	53.1	66.1	30.2	57.3

TABLE 2
COMPARING WITH RECOGNITION RATES IN THE METHOD BY INAGAKI ET AL.

Subject	Proposed Method	Method by Inagaki et al.
Subject1	81.0	78.0
Subject2	78.6	72.0
Subject3	53.3	42.0
Subjects of 1 and 2	71.5	65.0
Subjects of 1 and 3	57.3	53.0

B Comparing the proposed method with the method by Anderson et al.

In this section, we compare the proposed method with the method by Anderson et al.

The differences between the proposed method and the method by Anderson et al. are shown in Fig.4.

Next, we compare recognition rates with those in the method used by Anderson et al. in Table 3.

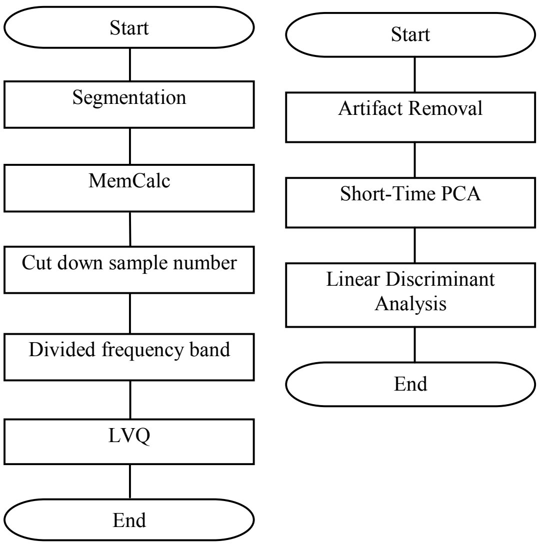

Fig.4: The differences between the proposed method and the method by Anderson et al.

TABLE 3
COMPARING RECOGNITION RATES WITH THOSE IN THE METHOD BY ANDERSON ET AL.

Subject	Proposed Method	Method by Anderson et al.
Subject1	81.0	77.9
Subject2	78.6	69.0

In the method used by Anderson et al., out of 50 data sets, 25 data sets from the first five experiments (trial 1 to trial 5) are used for learning data, and the remaining 25 data sets from the sixth to tenth experiments (trial 6 to trial 10) are used for test data. Moreover, while the number of electrodes used in our study and the study of Inagaki et al. is seven, Anderson et al. used six electrodes in their experiments.

C Comparing the proposed method with the method using MEM and BP

This section shows the effectiveness of the proposed method by comparing with the method using MEM and BP.

The differences between the proposed method and the method using MEM and BP are shown in Fig.5.

First, task-specific recognition rates derived from the method using MEM and BP are shown in Table 4. Then, the average of

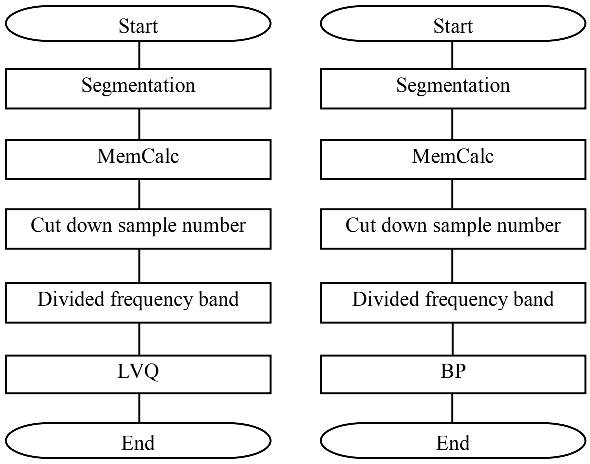

Fig.5: The differences between the proposed method and the method using MEM and BP

TABLE 4
TASK-SPECIFIC RECOGNITION RATES IN THE METHOD USING MEM AND BP

	Task1	Task2	Task3	Task4	Task5	Average
Subject1	67.2	96.4	62.7	86.4	61.8	74.9
Subject2	72.5	93.5	72.0	89.5	48.5	75.2
Subject3	59.0	60.6	63.0	57.6	20.0	52.0
Subjects of 1 and 2	56.8	82.0	71.8	88.3	41.8	68.1
Subjects of 1 and 3	54.3	69.5	47.9	64.3	32.4	53.7

task-specific recognition rates in the proposed method is compared to that of the method using MEM and BP in Table 5.

TABLE 5
COMPARING THE PROPOSED METHOD WITH THE METHOD USING MEM AND BP

Subject	Proposed Method	MEM and BP
Subject1	81.0	74.9
Subject2	78.6	75.2
Subject3	53.3	52.0
Subjects of 1 and 2	71.5	68.1
Subjects of 1 and 2	57.3	53.7

D Considerations

From Sections of A, B and C, we can make the following statement.

It can be noted from Table 1 that, except a portion of Task5, the recognition rates are relatively high. In addition, Tables 2 and 3 show that the recognition rates observed in the proposed method are higher than those in the methods used by Inagaki et al. and Anderson et al. for all the cases where the number of participating subjects is either one or two. Especially from Table 2, our recognition rates of Subject2, Subject3, and Subjects of 1 and 2 are shown to far exceed those of Inagaki et al.

Although the recognition rate of Subject3 is slightly lower in this record of measurement, it still surpasses that of Inagaki et al. by 11.3%. Table 3 also shows that, compared to the one of Anderson et al., the recognition rate of Subject2 is higher by 10%. Considering these results, it can be said that the proposed method is more effective than the ones adopted by both Inagaki et al. and Anderson et al. We speculate these results are due to the following reasons:

- The use of MEM with higher spectral resolutions allows the time to be segmented into shorter divisions, thereby extracting features effectively and letting LVQ exert its maximum classification potential.
- By subdividing alpha frequency and beta frequency bands, differences of features found in each frequency band are revealed to some extent, contributing to improvement in recognition accuracy.

In addition, it is demonstrated from Table 1 and Table 4 that, with some exceptions, the proposed method shows higher recognition rates. Also from Table 5, it is demonstrated that the recognition rates of the proposed method are higher than those of the method using MEM and BP for all the cases where the number of experimental subjects is either one or two. While Subject3 shows little difference in recognition rate, the recognition rates of other subjects are significantly higher with the proposed method than the method using MEM and BP. These findings confirm that LVQ employed in our proposed method acquires a higher recognition rate than the BP-employed method. We believe that this is because LVQ is capable of handling a large-scale recognition problem and, therefore, has well adapted to the problem, such as EGG data used in this study, which is complex and extensive.

E Searching for a task combination with a higher recognition rate

In this section, we will examine each subject to determine which task is more likely to be recognized falsely as what task and then seek a combination of tasks that has a higher positive recognition rate.

The relation of tasks is shown in Table 6, Table 7, Table 8, Table 9 and Table 10.

TABLE 6
RELATIONSHIP BETWEEN TASKS IN SUBJECT1

		predicted				
		Task1	Task2	Task3	Task4	Task5
Actual	Task1	73.2	9.2	15.0	1.3	1.2
	Task2	0.8	97.8	0.8	0.4	0.2
	Task3	11.2	7.6	66.4	3.2	11.6
	Task4	1.9	0.3	1.8	93.2	2.8
	Task5	8.0	2.3	12.2	3.2	74.2

TABLE 7
RELATIONSHIP BETWEEN TASKS IN SUBJECT2

		predicted				
		Task1	Task2	Task3	Task4	Task5
Actual	Task1	66.5	0.5	17.5	0.0	15.5
	Task2	0.0	99.0	0.0	0.0	1.0
	Task3	4.0	0.5	77.5	1.0	17.0
	Task4	5.0	0.0	14.0	81.0	0.0
	Task5	6.0	6.0	19.0	0.0	69.0

TABLE 8
RELATIONSHIP BETWEEN TASKS IN SUBJECT3

		predicted				
		Task1	Task2	Task3	Task4	Task5
Actual	Task1	65.3	16.4	5.3	8.3	4.6
	Task2	4.0	61.4	24.6	4.2	5.8
	Task3	7.3	5.2	73.7	4.3	9.4
	Task4	10.4	15.3	11.4	50.8	12.0
	Task5	9.1	18.3	31.4	25.7	15.4

TABLE 9
RELATIONSHIP BETWEEN TASKS IN SUBJECTS OF 1 AND 2

		predicted				
		Task1	Task2	Task3	Task4	Task5
	Task1	49.8	16.8	23.3	2.5	7.8
	Task2	1.5	96.0	0.5	0.0	2.0
Actual	Task3	14.5	0.3	81.0	0.3	4.0
	Task4	2.0	0.5	1.0	95.3	1.3
	Task5	5.8	13.0	26.5	19.3	35.3

TABLE 10
RELATIONSHIP BETWEEN TASKS IN SUBJECTS OF 1 AND 3

		predicted				
		Task1	Task2	Task3	Task4	Task5
	Task1	57.9	14.2	19.0	4.8	4.1
	Task2	4.8	79.3	10.6	2.7	2.6
Actual	Task3	19.8	6.8	53.1	7.4	12.8
	Task4	10.2	7.9	6.4	66.1	9.4
	Task5	14.2	12.9	21.2	21.4	30.2

Extracting two data sets of the same trial for each task, test data consists of 10 data sets (2 data sets × 5 tasks). To have the test data recognized, two out of 10 data sets are recognized individually, and the recognition rate is obtained for the number of possible combinations. The values shown on each table are the averages of these recognition rates. The vertical scale of the tables indicates from which tasks two data sets are derived.

Table 6 shows that the percentage of Task1 and Task5 falsely recognized as Task3, out of all five tasks, is relatively high with 15.0% and 12.2% respectively. Similarly, the percentage of Task3 falsely recognized as Task1 or Task5 is also high with 11.2% and 11.6% respectively. The percentage of Task2 positively recognized as Task2 is significantly high with 97.8% while Task4 falsely recognized as Task2 with the low percentage of 0.3%. From these, it can be noted in Subject1 that combinations of Task1 and Task3 and of Task3 and Task5 are more likely to be recognized falsely while Task2 and Task4 are less likely.

From Table 8, the percentage of Task1 falsely recognized as Task2, out of all five tasks, is high with 16.4% and Task2 as Task3 with 24.6%. The percentage of Task4 falsely recognized as Task1, Task2, Task3 or Task5 is also high with 10.4%, 15.3%, 11.4% and 12.0% respectively. The percentage of Task5 falsely recognized as Task2, Task3 and Task4 is significantly high with 18.3%, 31.4% and 25.7% respectively. Therefore, in Subject3, it is observed that combinations of Task2 and Task3 and of Task3 and Task5 are more likely to be recognized falsely while Task4 and Task5 are most likely to be recognized falsely.

A tendency similar to that found in Table 6 is observed in Table 7 and Table 9. Moreover, a similar tendency to Table 8 is indicated in Table 10.

From the findings above, it is clear that Task3 and Task5 do not make a good match for they are often recognized falsely one another.

When using these five tasks, any task combinations that exclude a pairing of Task3 and Task5, such as a combination of Task1, Task2, Task3 and Task4 or of Task1, Task2, Task4 and Task5, are expected to produce higher recognition rates.

VI. RECOGNITION RATES IN THE EEG DATA OF THREE

In general, it is said that the more the number of subjects, the lower the recognition rate.

In this section, by applying the proposed method to the EEG data of three subjects, and comparing the results with a related study, the effectiveness of the proposed method will be determined. Experimental results are shown in Table 11.

From the average rates in Table 11, several recognition rates

TABLE 11
RECOGNITION RATES IN THE EEG DATA OF THREE SUBJECTS

	Task1	Task2	Taask3	Task4	Task5	Average
Subjects of 1,3, and 4	49.8	66.6	66.7	59.8	31.0	54.8
Subjects of 1,3, and 5	53.2	67.1	73.4	62.9	31.1	57.5
Subjects of 1,3, and 6	70.0	74.5	47.0	74.8	39.5	61.2
Subjects of 1,4, and 5	42.4	72.0	72.0	61.8	41.7	58.0
Subjects of 1,4, and 6	66.9	78.7	53.6	74.8	51.0	65.0
Subjects of 1,5, and 6	56.1	46.8	62.3	80.9	59.6	61.1
Subjects of 3,4, and 5	54.5	57.0	86.3	44.9	47.7	58.1
Subjects of 3,4, and 6	62.9	56.2	68.4	53.2	41.6	56.5
Subjects of 3,5, and 6	63.0	55.2	79.9	65.0	59.0	64.4
Subjects of 4,5, and 6	58.7	63.0	75.0	60.0	68.3	65.0

in the proposed method are similar to those of Subjects of 1 and 2, as shown in Table 2, in the method used by Inagaki et al. This means that, in some cases, the proposed method still can produce recognition rates similar to those of the method followed by Inagaki et al. even though one more subject was added, bringing the total to three subjects. Moreover, depending on a task, such as Task3, relatively high recognition rates were obtained.

VII. Conclusions

In this study, we proposed an effective method for increasing recognition rates of EEG data. This study used MEM to effectively extract EEG features and investigated both an alpha frequency band and a beta frequency band. At this time, both the alpha and beta frequency bands are divided further into several sub-bands to capture precise features of the EEG data. Then, all these frequency sub-bands are used as features. Moreover, LVQ, which is a model of neural networks, was used in this study for clustering the EEG data.

In addition, we demonstrated the effectiveness of the proposed method by applying it to the EEG data of one subject and two subjects and comparing the results with other related studies [2],[3]. By applying the proposed method further to the EEG data of three subjects, and comparing the results with related studies, the effectiveness of the proposed method was determined.

However, an issue that an increase in the number of subjects tends to correlate with a decrease in recognition rates has been addressed. There are some cases where the recognition rates presented in this paper are not sufficient. We believe, however, that our study will raise questions regarding the development of practical systems in future.

References

[1] CEBL: CSU Eeg Brain-computer interface Lab. http://www.cs. colostate.edu/eeg/EEG Pattern Analysis. 2009/12
[2] Kiyoto Inagaki, Kenji Nakayama, "Classification of Mental Task by Using Neural Networks Based on Brain Waves", THE INSTITUTE OF ELECTRONICS, INFORMATION AND COMMUNICATION ENGINEERS, vol.105, No.174, pp24-30, SIP2005-54, 2005.
[3] C.W.Anderson, and J.A.Bratman,"Translating Thoughts Into Actions by Finding Patterns in Brainwave", In Proceedings of the Fourteenth Yale Workshop on Adaptive and Learning Systems, Yale University, New Haven, CT, June 2008, pp. 1-6.
[4] C.Anderson and Z.Sijercic,"Classification of EEG Signals from Four Subjects During Five Mental Task," In Solving Engineering Problems with Neural Networks: Proceedings of the Conference on Engineering Applications in Neural Networks (EANN'96), ed. by Bulsari, A.B., Kallio, S., and Tsaptsinos, D., Systems Engineering Association, PL 34, FIN-20111 Turku 11, Finland, 1996, pp.407-414.
[5] B.Blankertz, G.Curio and K.R.Muller, "Classifying Single Trial EEG: Towards Brain Computer Interfacing", Advances in Neural Inf. Proc. Systems(NIP 01), vol.14, 2002, pp.157-164.
[6] K.R.Muller, J.Kohlmorgen, A.Ziehe and B.Blankertz, "Decomposition algorithm for analysing brain signals," Adaptive Systemsfor Signal Processing, Communications and Control, 2000, pp.105-110.
[7] K.R.Muller, C.W.Anderson and G.E.Birch, "Linear and non-linear methods for brain-computer interfaces", IEEE Trans. Neural Sys. Rehab. Eng., vol.11, no.2, 2003, pp.165-169.
[8] P.Sajda, A.Gerson, K.R.Muller, B.Blankertz and L.Parra, "A Data Analysis Competition to Evaluate Machine Learning Algorithms for use in Brain-Computer Interfaces", IEEE Trans. Neural Sys. Rehab. Eng., vol. 11, no. 4, Dec. 2003, pp. 422-426.
[9] K.R.Muller, M.Krauledat, G.Dornhege, G.Curio, and B.Blankertz, "Machine learning techniques for brain-computer interfaces", Biomed. Tech., vol.49, no.1, 2004, pp.11-22.
[10] M.Krauledat, G.Dornhege, B.Blankertz, F.Losch, G.Curio, and K.R. Muller, "Improving Speed and Accuracy of brain-computer interfaces using readiness potential features" in Proceedings of the 26th Annual International Conference IEEE EMBS on Bipmedicine, San Francisco, 2004.
[11] G.Vanacker, J.d.R.Millan, E.Lew, P.W.Ferrez, F.G.Moles, J.Philips, H.V.Brussel and M.Nuttin, "Context-based filtering for assisted brain-actuated wheelchair driving",Computational Intelligence and Neuroscience,2007.
[12] J.R.Wolpaw and D.J.McFarland, "Control of a two-dimensional movement signal by a non-invasive brain-computer interface in humans". In Proceedings of the National Academy of Sciences, volume 101 (51), December 21 2004, pages 17849-17854.
[13] M.D.Serruya, N.G.Hatsopoulos, L.Paninski, M.R.Fellow, J.P.Donoghue, "Instant neural control of a movement signal", Naturre, vol 416, 2002, pp.141-142.
[14] J.R.Wolpaw,N.Birbaumer, W.J.Heetderks, D.J.McFarland, P.H.Peckham, G.Schalk, E.Donchin, L.A.Quatrano, C.J.Robinson, and T.M.Vaughan, "Brain-Computer Interface Technology: A Review of the First International Meeting", IEEE TRANSACTIONS ON REHABILITATION ENGINEERING, VOL.8, NO.2, JUNE 2000, pp.164-173.
[15] M. A. Lebedev and M. A. L. Nicolelis, "Brain-machine interfaces:past, present and future", TRENDS in Neurosciences Vol.29, No.9, September 2006, pp.536-546.
[16] M.C. Casdagli, L.D. Iasemidis, J.C. Sackellares, S.N.Roper, R.L. Gilmore, R.S. Savit, Characterizing nonlinearity in invasive EEG recordings from temporal lobe epilepsy, *Physica D*, Vol.99, 1996, pp. 381-399.
[17] JOSE L. MARTIN, LUCIANO BOQUETE, MANUEL MAZO, SIRA E. PALAZUELOS, "Mental States Discrimination by Independent Component Analysis and LVQ Neural Networks", Proceedings of the WSES International Conference on Mathematics and Computers in Biology and Chemistry 2001, pp.2001-2014, 2001.
[18] TOHRU KAWABE, "A Control Method with Brain Machine Interface for Man-machine Systems", Proceedings of the 11th WSEAS International Conference on APPLIED MATHEMATICS, Dallas, Texas, USA, March 22-24, 2007.
[19] MERCEDES CABRERIZO, MALEK ADJOUADI, MELVIN AYALA, ILKER YAYLALI, ARMANDO BARRETO, NAPHTALI RISHE, "EEG Analysis Using Neural Networks for Seizure Detection", Proceedings of the 6th WSEAS International Conference on Signal Processing, Robotics and Automation, Corfu Island, Greece, February 16-19, 2007.
[20] M.MURUGAPPAN, M.RIZON, R.NAGARAJAN, S.YAACOB,"EEG Feature Extraction for Classifying Emotions using FCM and FKM", RECENT ADVANCES IN SYSTEMS, COMMUNICATIONS & COMPUTERS, Selected Papers from the WSEAS Conferences in Hangzhou, China, April 6-8, 2008.
[21] JOB RAMON DE LA O CHAVEZ, CARLOS AVILES CRUZ, "Mouse Pointer Controlled by Ocular Movements", Proc. of the 7th WSEAS Int. Conf. on COMPUTATIONAL INTELLIGENCE, MAN-MACHINE SYSTEMS and CYBERNETICS (CIMMACS '08).
[22] Nizar KERKENI, FrEdEric ALEXANDRE, Mohamed HEdi BEDOUI, Laurent BOUGRAIN, Mohamed DOGUI", Proceedings of the 5th WSEAS Int. Conf. on SIGNAL, SPEECH and IMAGE PROCESSING, Corfu, Greece, August 17-19, 2005 (pp128-131).
[23] T. Kohonen, "LVQ_PAK Version3.1 The Learning Vector Quantization Program Package", Prepared by the LVQ Programming Team of the Helsinki University of Technology, 1995.
[24] Atsushi SATO, Keiji YAMADA, "A Proposal of Generalized Learning Vector Quantization", THE INSTITUTE OF ELECTRONICS, INFORMATION AND COMMUNICATION ENGINEERS, TECHNICAL REPORT OF IEICE, 1995.

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