Multi-Class ERP-Based BCI Data Analysis Using A Discriminant Space Self-Organizing Map

Akinari Onishi[1] and Kiyohisa Natsume[2]

***Abstract*— Emotional or non-emotional image stimulus is recently applied to event-related potential (ERP) based brain computer interfaces (BCI). Though the classification performance is over 80% in a single trial, a discrimination between those ERPs has not been considered. In this research we tried to clarify the discriminability of four-class ERP-based BCI target data elicited by desk, seal, spider images and letter intensifications. A conventional self organizing map (SOM) and newly proposed discriminant space SOM (ds-SOM) were applied, then the discriminabilites were visualized. We also classify all pairs of those ERPs by stepwise linear discriminant analysis (SWLDA) and verify the visualization of discriminabilities. As a result, the ds-SOM showed understandable visualization of the data with a shorter computational time than the traditional SOM. We also confirmed the clear boundary between the letter cluster and the other clusters. The result was coherent with the classification performances by SWLDA. The method might be helpful not only for developing a new BCI paradigm, but also for the big data analysis.**

I. INTRODUCTION

The brain computer interface (BCI) translates human brain signals, typically electroencephalogram (EEG), into commands for manipulating devices [1]. Brain signals such as the P300 component of the event-related potential (ERP) can be used to drive the BCI [2]. The BCI is usually independent of muscle activities so that devices such as a robotic arm, wheelchair, rehabilitation system, game, and smart phone can be handled only by our brain signals. The BCI research is helpful for us, especially for handicapped persons, to improve the quality of life.

The conventional P300-based BCI and ERP-based BCI employs a binary classifier to perform multi-class classification: the binary classifier is trained on target ERPs that contain specific components and the other non-target ERPs. Facial images were recently employed and reported that it performed better than the traditional P300-based BCI [3], [4]. We also found that the ERP-based BCI with desk, seal and spider image intensifications showed significantly better classification accuracies than the traditional P300-based BCI intensification [5]. But BCIs that employ a multi-class ERP classifier are not major for now. Employing the classifier that discriminates ERP elicited by desk, seal and spider image intensifications contributes to develop a new BCI paradigm and to improve the information transfer rate.

In this paper, we proposed a discriminant space self-organizing map (ds-SOM), a tool for visualizing the discriminability of data using the self-organizing map (SOM) [6], and preliminary evaluated ERPs elicited by desk, seal and spider image intensifications in addition to traditional P300 letter intensifications. The SOM is an artificial neural network trained by unsupervised learning, which is used for clustering and data mining. Using the SOM, high dimension data is projected into a low dimensional space keeping the data topology. The low dimensional space is usually visualized by a 2D topographical visualization called the U-matrix and the data relationship can be clarified [7]. The multi-class ERP-based BCI data were first evaluated by the SOM and the ds-SOM. The ds-SOM was compared to the conventional SOM on the U-matrix visualization and the computation time. In addition the discriminability of ERPs using ds-SOM was verified by the classification performance of stepwise linear discriminant analysis (SWLDA). The ds-SOM is useful to visualize multi-class ERP data in terms of the discriminability. The discriminability of ERPs elicited by 4 different intensifications were first evaluated toward developing an ERP-based BCI using a multi-class classifier.

II. METHODS

Four ERP data recorded in [5] were concatenated, then the data set was analyzed by the ds-SOM and SOM. This research is intended to clarify the discriminabilites between 4 ERPs, and to reveal the advantages of the proposed ds-SOM compared to the SOM.

A. Subjects

We employed five healthy male subjects aged 22–26 years old, two of whom have experienced to control P300-based BCI once. The mental task, experimental time and possible risk were explained to all subjects. Then they gave written informed consent before the experiment. This research plan was approved by the Internal Ethics Committee at Kyushu Institute of Technology.

B. Data recording

ERPs in response to four different visual intensifications were recorded by an ERP-based BCI (see [5] for more detail). We employed four different emotional/non-emotional stimuli as shown in Fig. 1: N004 (desk: neutral), P079 (seal: positive), Sp036 (spider: negative) and a traditional letter

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[1]A. Onishi is with the Department of Brain Science and Engineering, Graduate School of Life Science and Systems Engineering, Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-ku, Kitakyushu, 808-0196, Japan `onishi-akinari at edu.brain.kyutech.ac.jp`

[2]K. Natsume is with the Department of Brain Science and Engineering, Graduate School of Life Science and Systems Engineering and the Biomedical Informatics R&D Center, Kyushu Institute of Technology, 2-4 Hibikino, Wakamatsu-ku, Kitakyushu, 808-0196, Japan `natume at brain.kyutech.ac.jp`

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intensification, where those images were selected from the Gevena affective picture database (GAPED) [8]. Our ERP-based BCI has 36 gray letters on the center of the screen. A target letter was selected randomly and cued at the top center of the screen. The subject must count the occurrence of intensifications when the target letter among gray letters is intensified or overlaid with images. The ERPs when the target is intensified are called target ERPs. In total, 200 target ERPs in the training sessions and 90 target ERPs in test sessions were gathered for each intensification. We used an amplifier BA1008 (TEAC Co., Ltd., Japan), A/D converter AIO-163202FX-USB (CONTEC Co., Ltd., Japan), a TFT LCD display (HTBTF-24W, 24.6 inches wide with 1920×1080 dpi; Princeton Technology, Ltd., Japan). EEG was measured at Fz, Cz, P3, Pz, P4, PO7, Oz and PO8 scalp site according to the international 10-20 system, where the ground and reference electrodes were at AFz and both mastoids, respectively. The sampling rate was 128 Hz.

C. Self-organizing map (SOM)

The SOM is an artificial neural network proposed by T. Kohonen [6]. The SOM has K units that spread over a low dimensional topological space. Given d dimensional N_s data $\mathbf{f}_n \in \Re^d, n = 1, 2, ..., N_s$, the SOM finds a non-linear projection from the feature space to the topological space. The position of the kth unit in the l dimensional topological space is denoted by $\mathbf{v}_k \in \Re^l, k = 1, 2, ..., K$. Those units have a topological lattice: neighbor units make a square or hexagon. Each unit has a codebook vector $\mathbf{u}_k$ that represents the relationship between the feature space and the topological space. In this research, 20×20 units were spread over 2D space with the hexagonal lattice. The SOM is advantageous because the projection keeps the original data topology and the SOM enables us to visualize the input data in an understandable 2D visualization using a U-matrix.

The batch learning algorithm of the SOM [9] finds $\mathbf{u}_k$ via three processes: the competitive process, cooperative process and adaptive process. In the competition process, the closest unit in feature space or the best matching unit k_n^* is found for all data:

$$k_n^* = \arg\min_k \|\mathbf{f}_n - \mathbf{u}_k\|^2, \tag{1}$$

where $\|\cdot\|$ represents the Euclidian distance. Then a learning coefficient α_{nk} was computed in the cooperative process:

$$\alpha_{nk} = \frac{h(k_n^*, k, \sigma)}{\sum_{n'=1}^{N_s} h(k_{n'}^*, k, \sigma)}, \tag{2}$$

where $h(k_n^*, k, \sigma)$ is a neighborhood function that defines the distance between $\mathbf{v}_{k_n^*}$ and $\mathbf{v}_k$. We employed the Gaussian neighborhood function that is defined as

$$h(k_n^*, k, \sigma) = \exp\left(-\frac{\left\|\mathbf{v}_{k_n^*} - \mathbf{v}_k\right\|^2}{2\sigma^2}\right). \tag{3}$$

The radius of the Gaussian curve is determined by σ. The σ is a decreasing function of time $t = 1, 2, ..., t_{\max}$ that takes

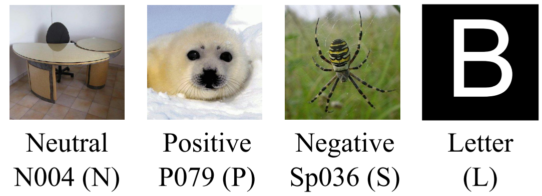


Fig. 1. Types of stimuli for eliciting ERPs. We employed a desk image as a neutral (N), a seal image as positive (P), a spider image as negative (S) and a traditional letter intensification (L). Those three images were selected from GAPED [8].

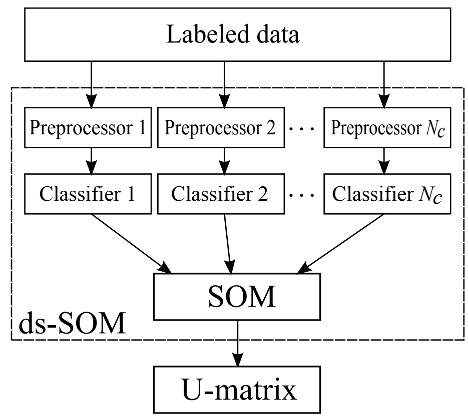


Fig. 2. Structure of the ds-SOM. It has multiple preprocessors and classifiers. Labeled data are preprocessed then classifiers are trained on the data before learning SOM. Then all data are projected into N_c discriminant spaces, then they are used to learn SOM.

values from $\sigma_{\max}$ to $\sigma_{\min}$:

$$\sigma = \sigma_{\min} + \frac{t_{\max} - t}{t_{\max}}(\sigma_{\max} - \sigma_{\min}). \tag{4}$$

Using the learning coefficients, $\mathbf{u}_k$ is updated in the adaptive process as follows:

$$\mathbf{u}_k := \sum_{n=1}^{N_s} \alpha_{nk} \mathbf{f}_n \tag{5}$$

The above procsses are repeated for $t_{\max}$ times. Learning parameters for the SOM and ds-SOM are shown in Table I. We used SOM toolbox for computing SOM and visualizing the U-matrix [10].

D. Discriminant space SOM (ds-SOM)

The ds-SOM translates high dimensional data such as ERP-based BCI data into N_c dimensional data in discriminant spaces. The ds-SOM has N_c supervised binary classifiers and preprocessors focusing on specific features as shown in Fig. 2. The traditional SOM uses data without classification, e.g., vectorized images. In that case the vectorized images are usually high dimensional so that the dimension of codebook vectors also becomes high dimensional. This implies that the computational time of the SOM becomes high depending on data and important features for a distance measure are not enhanced. On the other hand, lower dimensional informative feature vectors are used to learn the SOM in the ds-SOM.

Though many ways to employ and train classifiers inside the ds-SOM can be considered, we preliminary implemented four one-versus-rest linear discriminant analysis (LDA) classifiers ($N_c = 4$). ERP data recorded from 8 channels for 700 ms were denoted by $\mathbf{X}_n \in \Re^{8\times 89},\ n = 1,2,...,N_s$. We prepared 200 ERP training data for each intensification labeled by $l_n \in \{1,2,...,N_c\}$. Thus we have 800 ERP data ($N_s = 800$). First a preprocessing is applied to the data: for the simplicity, we used the same smoothing (moving average with a window size of 4), downsampling to 32 Hz and vectrization for all preprocessors. Then we have preprocessed column vectors $\mathbf{x}_n \in \Re^{184}$. Then the stepwise method [11] was applied for each intensification. The mean vector of class $i \in \{1,2,...,N_c\}$ and the other classes denoted by $\boldsymbol{\mu}_i$ and $\boldsymbol{\mu}_{\bar{i}}$ can be computed as

$$\boldsymbol{\mu}_i = \frac{1}{N_i}\sum_{n:l_n=i}\mathbf{x}_n, \quad \boldsymbol{\mu}_{\bar{i}} = \frac{1}{N_{\bar{i}}}\sum_{n:l_n\neq i}\mathbf{x}_n, \tag{6}$$

where, $N_i = 200$ is the number of data in class i, $N_{\bar{i}} = 600$ is the rest of data number. The covariance matrices of data in class i and $\bar{i}$ were calculated by

$$\begin{aligned} \boldsymbol{\Sigma}_i &= \frac{1}{N_i - 1}\sum_{n:l_n=i}(\mathbf{x}_n - \boldsymbol{\mu}_i)^2, \\ \boldsymbol{\Sigma}_{\bar{i}} &= \frac{1}{N_{\bar{i}} - 1}\sum_{n:l_n\neq i}(\mathbf{x}_n - \boldsymbol{\mu}_{\bar{i}})^2. \end{aligned} \tag{7}$$

The maximum likelihood estimation of common covariance matrix can be derived by

$$\boldsymbol{\Sigma}_{i\bar{i}} = \frac{N_i}{N_s}\boldsymbol{\Sigma}_i + \frac{N_{\bar{i}}}{N_s}\boldsymbol{\Sigma}_{\bar{i}}. \tag{8}$$

Thus the weight vector and bias of the ith one-versus-rest LDA can be computed by

$$\mathbf{w}_i = \boldsymbol{\Sigma}_{i\bar{i}}^{-1}(\boldsymbol{\mu}_i - \boldsymbol{\mu}_{\bar{i}}), \tag{9}$$

$$b_i = -\frac{1}{2}\left(\boldsymbol{\mu}_i^{\mathrm{T}}\boldsymbol{\Sigma}_{i\bar{i}}^{-1}\boldsymbol{\mu}_i - \boldsymbol{\mu}_{\bar{i}}^{\mathrm{T}}\boldsymbol{\Sigma}_{i\bar{i}}^{-1}\boldsymbol{\mu}_{\bar{i}}\right) + \log\frac{N_i}{N_{\bar{i}}}. \tag{10}$$

We finally used feature vectors $\mathbf{f}_n = (f_{ni})$ defined as follows:

$$f_{ni} = \mathbf{w}_i^{\mathrm{T}}\mathbf{x}_n + b_i. \tag{11}$$

Vectorized data $\mathbf{x}_n \in \Re^{184}$ are directly used as an input data set in the traditional SOM ($\mathbf{x}_n = \mathbf{f}_n, \forall n$), while $\mathbf{f}_n \in \Re^4$ computed by Eq. (11) is used to learn SOM in the ds-SOM.

The result of the ds-SOM is also verified by the SWLDA ($p_{\mathrm{in}} = 0.1, p_{\mathrm{out}} = 0.15$) [11]. The test data were preprocessed as well as the training data, then Eq. (11) is applied. Then the predicted class the test data belong to was estimated by finding maximum value among the test feature vectors. In total 360 test ERPs (90 ERPs × 4 stimuli) were classified by SWLDA and the classification accuracy was computed.

III. RESULTS

ERP data elicited by desk (N), seal (P), spider (S) and letter (L) intensifications were analyzed by the ds-SOM and SOM. The clustering results of ERP data from subject 1 were shown in Fig. 3 (a) and (b), respectively. The other clustering results were not presented due to page limitation. Labels assigned to units were decided by voting when data with different labels were projected to the same unit. The U-matrix of ERP-based BCI data using the ds-SOM shown in Fig. 3 (a) had 4 uniformed clusters separated by a red or yellow boundary. The letter cluster of the ds-SOM was far from the other 3 clusters, however, the desk, seal and spider cluster were closer to each other. On the other hand, U-matrix visualization using SOM shown in Fig. 3 (b) did not have uniformed cluster and meaningful information cannot be seen. In this way the ds-SOM produced much clearer clusters than the traditional SOM.

TABLE I

LEARNING PARAMETERS OF THE SOM AND DS-SOM.

Parameters	Values
Unit size	20×20
Lattice	Hexagon
$\sigma_{\max}$	15
$\sigma_{\min}$	3
$t_{\max}$	1000

TABLE II

COMPUTATIONAL TIME FOR LEARNING SOM AND DS-SOM

Algorithms	Computational time [s]
ds-SOM	9.31 ± 0.47
SOM	15.60 ± 0.03

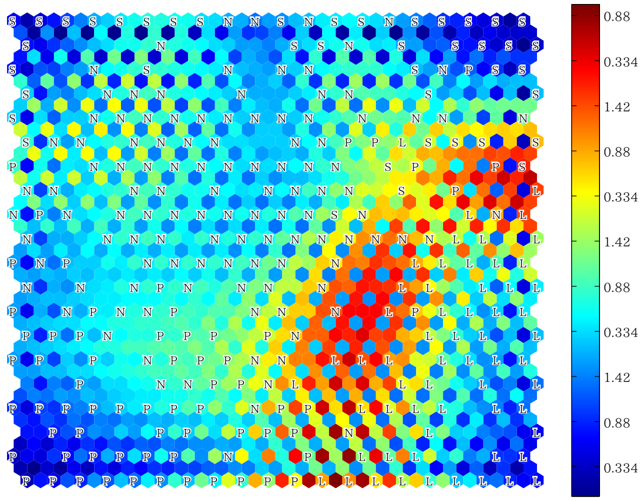
Computational time of the ds-SOM and the SOM were presented in Table II. The computational time of the ds-SOM was shorter than that of the traditional SOM. This difference came from the dimension size of feature vectors.

Classification performances of the SWLDA were shown in Table III. In the binary classification, pairs that contain letter intensifications (L) achieved 91.7–92.4% mean classification accuracies. However, the other binary mean classification performances were 62.0–71.6%. Three-class and four-class mean classification accuracies were 75.0% at best, and 59.9%, respectively. An obvious boundary can be seen between the letter cluster and the other clusters, but the other boundaries were more blurred (see Fig. 3 (a)). Thus the pairs of classes that is divided only by clear boundaries showed better classification performances, which was coherent with the classification performance by the SWLDA.

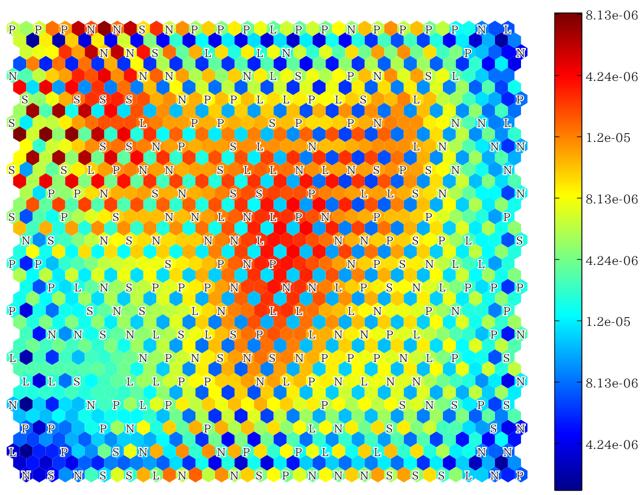
IV. DISCUSSION

The proposed ds-SOM was applied to ERP-based BCI data and clustering performances were compared between the ds-SOM and SOM. As a result, the ds-SOM showed clearer cluster boundaries than the traditional SOM. Moreover, the ds-SOM requires much shorter computation time than the traditional SOM. The result was coherent with the classification performance of SWLDA. In this way, the ds-SOM is applicable to supervised high dimensional data with a shorter computational time.

Since the clear boundary between the letter (L) cluster and the other clusters can be seen, a new BCI paradigm that uses the letter and image intensification can be realized.



(a) ds-SOM



(b) SOM

Fig. 3. U-matrix visualization of ERP-based BCI data using (a) ds-SOM and (b) SOM. The color represents distances of neighbor codebook vectors. The area surrounded by red or yellow cells is considered as a cluster.

This result implies that the two simple yes-no questions can be efficiently asked by simultaneous letter and image intensifications. Better applications can be imagined if the varieties of ERPs can be discriminable between each other.

In the future research, we would like to clarify the pairs of ERPs that can be separated in high classification accuracy to develop better ERP-based BCI paradigms. The proposed ds-SOM will be helpful in finding similarity or discriminability between ERPs. The SWLDA was employed in this research, however, the ds-SOM can be improved more by applying different classifiers such as the support vector machines. This method may be applied to the other types of biomedical signals such as an electromyogram (EMG). The proposed method may also be applied to the (labeled or partially labeled) big data analysis, saving the computation time.

TABLE III
CLASSIFICATION PERFORMANCE OF THE SWLDA

Compared Stimuli	Classification accuracy (%)
N v.s. P	71.6 ± 6.3
N v.s. S	62.0 ± 7.9
N v.s. L	$\mathbf{91.7 \pm 1.9}$
P v.s. S	68.7 ± 3.4
P v.s. L	$\mathbf{92.4 \pm 1.9}$
S v.s. L	$\mathbf{91.9 \pm 3.8}$
N v.s. P v.s. S	54.7 ± 4.5
N v.s. P v.s. L	75.0 ± 5.4
N v.s. S v.s. L	71.1 ± 5.0
P v.s. S v.s. L	71.8 ± 4.4
N v.s. P v.s. S v.s. L	59.9 ± 3.8

V. CONCLUSIONS

We proposed the ds-SOM to clarify relationships between four ERP-based BCI data. Our experiment showed that ds-SOM showed more understandable clustering result than the traditional SOM for labeled ERP-based BCI data. The results were coherent with the classification performances by SWLDA. We also found that ERPs elicited by letter intensification had clearly uniformed and isolated cluster from the others.

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