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Brain Machine Interface using Portable Near-InfraRed Spectroscopy – Improvement of Classification Performance based on ICA analysis and Self-proliferating LVQ -

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***Abstract*— Recently, the Brain-Machine Interface (BMI) has been expected to be applied to robotics and medical science field as a new intuitive interface. BMI measures human cerebral activities and uses them directly as an input signal to various instruments. The future goal of our research is to design a practical BMI system that can be used reliably in daily lives. In this paper, we will discuss a design method of a BMI system using a portable Near-InfraRed Spectroscopy (NIRS) device and then we will consider improving the performance of the learning vector quantization (LVQ) classifier by using the independent component analysis (ICA) and the self-proliferating function of neurons. The effectiveness of the proposed method is investigated in human imagery classification experiments.**

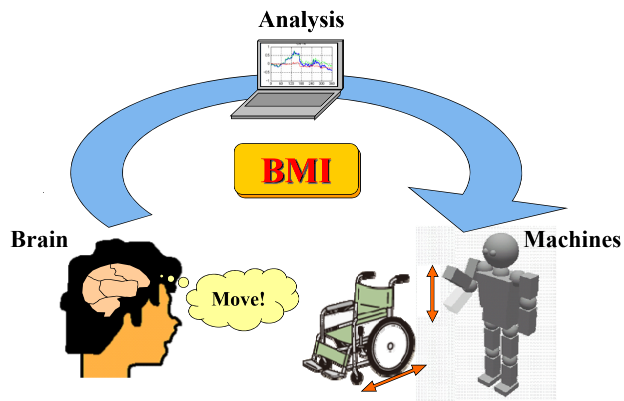

Fig.1 Outline of brain-machine interface system

I. Introduction

Recently, the Brain-Machine Interface (BMI) has been expected to be applied to robotics and medical science field as a new intuitive interface. BMI measures human cerebral activities and uses them directly as an input signal to various instruments as shown in Fig.1. If a practical and intuitive BMI system is realized, it could have pioneering applications in various new fields, e.g., human-robot interaction, supportive care for amyotrophic lateral sclerosis (ALS) patients and other persons with special needs. Various researches have been conducted to develop effective BMI systems. For example, in invasive and less-invasive measurement methods, M. D. Serruya et al.[2] and L. R. Hochberg et al.[3] measured the spike activity of neurons by inserting electrodes and translated brain signals into cursor movement on a PC monitor. Hirata et al. [3] applied ECoG to control a robotic arm. With regard to noninvasive measurement methods, Kamitani et al. [4] studied an fMRI-based method for decoding visual and subjective contents in a human brain. Q. Zhao et al. [5] used the scalp EEG to drive a car in a 3D virtual reality environment. Honda Research Institute Japan Co., Ltd. (HRI-JP), Advanced Telecommunications Research Institute International (ATR), and Shimadzu Corp. demonstrated a BMI system using both EEG and NIRS in which human body motion images of "right hand", "left hand", "foot", and "tongue" are classified as commands to be used for robot control. RIKEN, Toyota Motor Corp., Toyota Central R&D Labs, Inc., and Genesis Research Institute, Inc. have demonstrated an EEG-based BMI system that classifies the motion images of "walking", "right arm movement", and "left arm movement" to control a powered wheelchair. Although research on BMI has been progressing rapidly, it is not yet sufficient clear that to what extent BMI can classify human thoughts and imageries and emotions etc.

In this research, we aim to design a practical BMI system using a Near-InfraRed Spectroscopy (NIRS) device. NIRS is one of the non-invasive measuring methods for cerebral activities and it enables to measure the cerebral blood flow by using a headset fitted with optical probes. NIRS has various potential applications, because it is intrinsically safe and easy to equip and realize the relatively high spatial resolution and multi-channel simultaneous measurement. But the relationship between blood flow patterns and cerebral activities corresponding human physical motions or mental imagery is not yet sufficiently clear. So, we will focus on the design and application problem of NIRS-based BMI system.

In our previous research[7], we proposed a LVQ-based cerebral state classifier for NIRS-measured cerebral blood flow patterns and we succeeded in classifying not only human physical motions but also mental imageries (mental motions, mental commands to robots and emotions.) In [7], we used a large size NIRS instrument for medical use and measured blood flow data in an ideal medical lab room. But in the practical use of BMI, users are limited to utilizing a simpler NIRS device with lower sampling rate and fewer measuring points. Additionally, in the daily living environment, the measurement suffers from the influence of various conditions and human blood flow patterns tend to fluctuate according to the changes of conditions such as the human mental and physical condition, the environmental condition (e.g.

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surrounding noises, the temperature, the variation and the uncertainty of the fitted probe position) and so on. Therefore, we need to develop a robust cerebral state classifier for a portable NIRS device. In our previous paper in MHS2012[8], we showed the possibility of 1) the disturbance removal based on the independent component analysis (ICA) and 2) the imagery evoking training and additional learning. So, in this paper, we will define new performance indices to evaluate the classification stability and robustness and we will confirm the ICA-based performance improvement through the imagery classification experiment. In addition to that, we will also improve the classification performance by modifying the LVQ-based classifier to have the self-proliferating function of LVQ neurons and will confirm the validity thorough the additional learning experiment in the daily living environment.

In the following, we will explain the proposed portable NIRS-based BMI system, at first (Chapter II). Then, we will describe a LVQ-based online cerebral state classifier for a portable NIRS device which enables to classify several categories of human mental imageries (e.g., motion imagery, mental commands to a robot, human emotions) in Chapter III and IV. After that, we will discuss the performance improvement problem in the daily living environment. In Chapter V, the performance indices will be revised to indicate the stability and robustness of the classification, at first (Section A), and then we will confirm the performance of the ICA-based disturbance removal through the imagery classification experiments in which the influence of the subject's breath hold will be removed from the measured blood flow data (Section B). Next, in Section C, we will modify the LVQ-based classifier to have the neuron self-proliferating function and we will investigate the effect of the additional learning with the modified classifier.

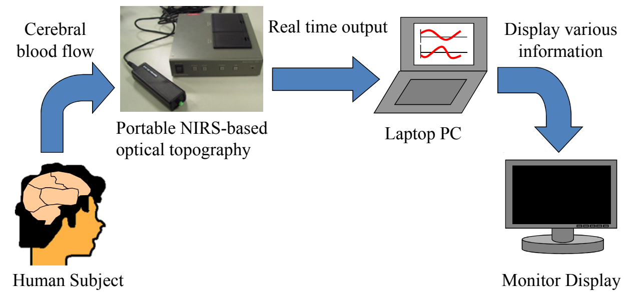


Fig.2 Portable NIRS-based BMI system

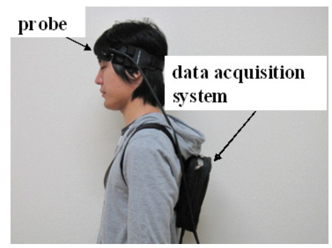


Fig.3 Portable NIRS device (OEG-16)

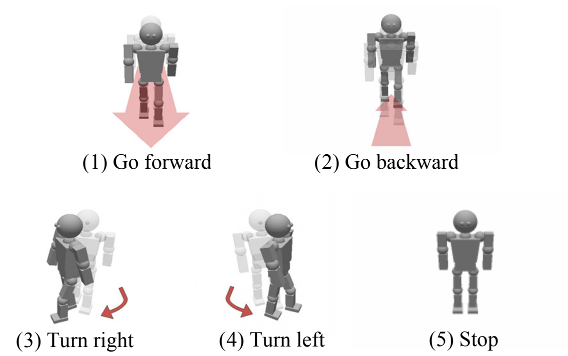


Fig.4 Classification of Mental commands to robot

II. Measurement of Human Cerebral Blood Flow And Experimental Imagery Classification Tasks

A. Portable NIRS-based Measurement of Cerebral Blood Flow (Experimental System)

We will explain the experimental system to measure and classify the human cerebral blood flow. Fig.2 shows a schematic overview of our experimental BMI system. A portable NIRS-based optical topography device (OEG-16 manufactured by Spectratech, Inc,) is used in the system and it can noninvasively measure the concentrations of oxygenated hemoglobin and reduced hemoglobin and total hemoglobin in the cerebral blood flow at 16 different measurement points on the prefrontal cortex. OEG-16 consists of a headset with optical probes and a data acquisition box as shown in Fig.3. It is very compact and can be driven by built-in batteries, so we can measure human cerebral activities under various experimental conditions in the living environment. Its sampling interval is 0.65 s. The measured blood flow data are transmitted to a laptop through USB. Then, the proposed LVQ-based online state classifier analyzes the human blood flow pattern and classifies the human thought and imageries online. A LCD is used for displaying the various information. In experiments in this paper, the LCD was used to display the experimental instructions and directions to the subject persons.

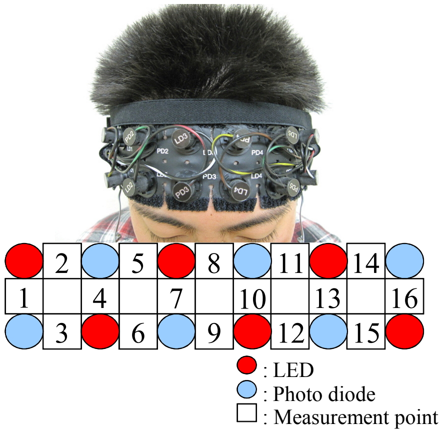
B. Cerebral State Classification Tasks and Experimental Setting in this Paper

In this paper, we conducted cerebral state classification experiments to verify the performance of the NIRS-based BMI system. In this section, the details of experimental tasks and measurement settings will be described.

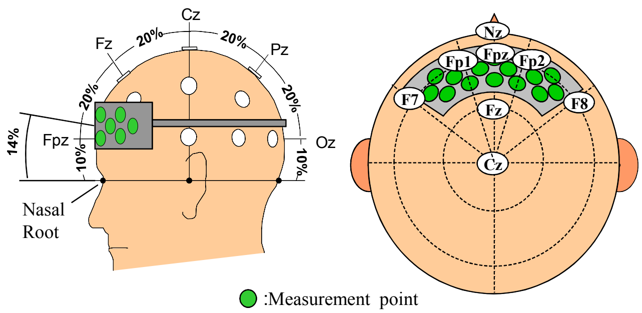
We consider the following cerebral state classification problems of subjects' mental imageries because the measurement area of OEG-16 is limited to the prefrontal cortex.

<u>Classification of Human Mental Motions</u>

When the human images his/her body parts movements, his/her brain becomes active and some transition pattern of cerebral blood flow appeared. So, we consider the online automatic classification of human motion images from his /her cerebral blood flow patterns. Motion images to be classified are following four states; 1) repetitive bending/extending of the right arm, 2) repetitive bending/extending of the left arm, 3) stepping of lower legs, and 4) relax.



(a)Optical probes and 16 measurement points



(b) Position setting based on 10-20 method

Fig.5 Experimental position setting of headset

Classification of Mental Commands to robot

Next, we consider the classification problem of mental commands to a robot in order to check whether the BMI can recognize human mental commands toward another object (not toward himself/herself). In the classification experiment, a robot image (Fig.4) is displayed on the laptop monitor in order to help a human subject imagine steady mental commands. The subject mentally commands a robot to 1) go forward, 2) go backward, 3) turn right, 4) turn left, and 5) stop. Then, BMI recognize the subject's mental command online based on the measured blood flow.

Classification of Evoking Emotions

Next, we consider the classification problem of human emotion in order to check whether the BMI can recognize human emotions from his/her cerebral blood flow patterns. Emotions to be classified here are following four types; 1) happy, 2) sad, 3) angry and 4) relax. The subjects were instructed to remember their specific "happy," "sad," "angry" situations that they had experienced in the past to evoke steady emotions.

Now we will explain the experimental setting in this paper. Each subject is fitted a headset with optical probes and directed to perform image evoking tasks. The probe is positioned so as to cover his/her prefrontal cortex. The probe position is decided based on the ten-twenty electrode system of the International Federation [16], as shown in Fig.5. Then, 14% from nasal root is selected as the central position of the probe. In each image evoking experiment, one trial consisted of multiple experimental tasks corresponding to the "actions (mental imageries)" to be classified. In a task, the subject performs only one action (imagery) at a time. The time span of each task was 60s. In the first and the last 20s, the subject does not perform any tasks but just wait and relax (no imagery). In the middle 20s, the subject performs a directed action. During the experiments, in order to avoid artifacts, we check that the subjects perform no body and head movement.

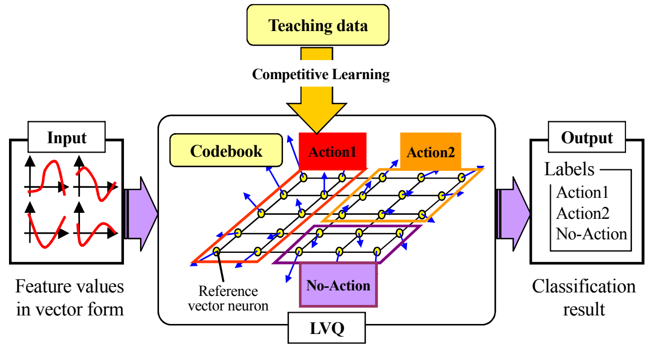


Fig.6 LVQ-based Classifier

III. CLASSIFIER FOR CEREBRAL BLOOD FLOW PATTERNS

The proposed cerebral state classifier consists of a preprocessing part and a LVQ-based classification part. We will explain them in following sections.

A. Data Preprocessing Part

In the proposed classifier [7], measured blood flow data are preprocessed by a frequency-based filter and a grouping /averaging method. The frequency filter is used to reduce biological fluctuations and noises in measured blood flow data. The biological fluctuations in relatively long time span are caused by human normal activities and measured as a drift behavior. And relatively high-frequency noises are caused by environmental factors such as the electric noise and the optical noise and so on. So, a numerical band-pass filter with cut-off frequencies of 0.005Hz and 0.05Hz is applied in the proposed portable NIRS-based BMI system. The grouping and averaging method is used to reduce the dimensions of the input vector space for the LVQ-based classifier and it is also effective against biological fluctuations and the uncertainties of the headset position etc. But, in this paper, we did not use the grouping/averaging method because the number of channels of the portable NIRS is relatively few. Measured data of all channels was used as an input vector for the classifier in this paper.

B. LVQ-based Classification Part

The classifier part is based on the learning vector quantization (LVQ[17]). LVQ is supervised learning method for clustering and quantizing the input vector space based on the affinity of input vector components as shown in Fig.6. It works as a vector classifier by tuning the reference vector neuron. In particular, LVQ learns the input-output relationships in the teaching data by using the competitive learning method. Then, it represents the relationships as a set of finite number of reference vector neurons which is called the "codebook." As a result of learning, each reference vector neuron acquires one of the output labels and produces the desired output defined in the teaching data. After learning, when it is used as a classifier, LVQ searches the best matched reference vector neuron that has the shortest Euclidean distance to a newly given input vector. Then, the output label, that the best-matched neuron has, is selected as an output. Because each reference vector neuron represents the feature of an input vector associated with its output label, we can analyze the classification process of the blood flow patterns.

In the proposed cerebral state classification, we define the feature values for LVQ learning in the vector form from the measured blood flow data. To classify the blood flow pattern effectively, we need to use not only raw measured data but also numerically processed data, such as the integrated and the differentiated and so on. In addition, effective classification requires data histories of the blood flow in the appropriate time window. So we searched appropriate feature values from various candidates through the learning experiment of LVQ. As a result, we selected the integrated data, the integrated data with basis, the maximum and minimum values of differentiated data, of the total hemoglobin concentration in the time window as feature values. The appropriate span of the time window was also searched and 15.6 s was selected. In Chapter V, a self-proliferating function of LVQ neurons will be added.

IV. Classification Experiments

A. Definition of the Evaluation Method

Now, we will define how to evaluate the results of the classification experiments. Fig.7 shows the definition of the evaluation method. For the purpose of definition of the performance indices, we assume that the subject did not perform any action ("No imagery") in the first and last 20 s and he/she executed "Imagery 1" in the middle 20 s in Fig.7. And we also assume that the classifier output the incorrect label "Imagery 1" in the first "No imagery" period, and that the output of the correct label "Imagery 1" was delayed, and that the incorrect label "Imagery 2" was output in the last "No imagery" period, as shown in Fig.7. The LVQ-based classifier can output the classification label in real time. Therefore, we adopted the time ratio of the correct output to the whole measurement span as the index of the classification performance. In addition, because the blood flow change had inevitable biological delays, we subdivided the classification error into several categories, as shown below.

Correct Output Rate
This is the total time rate when the classifier output was correct.

Incorrect Firing Rate
This is the total time rate when the classifier fired incorrect imagery labels. For example, this includes the cases that the classifier outputs some “Imagery” label in the "No imagery" period, and that some incorrect “Imagery” label is output in the "Imagery" period. These are most undesirable behaviors in a BMI system because these result in incorrect operations.

Delay Time Rate
This is the rate of the delay time between the beginning of the imagery and the time when the classifier recognizes it.

Persistent Time Rate
This is the time rate from the end of the subject's imagery to the time when the classifier recognizes it.

Others
This is the time rate that does not belong to any of the above categories, for example, when the classifier output "No imagery" before the end of the subject's imagery. This category is revised in Chapter V in order to indicate the stability in the daily living environment.

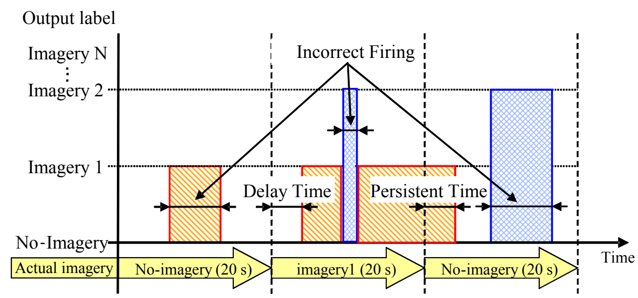


Fig.7 Definition of performance indices

TABLE I. Experimental Results

Human mental motions	Subject A	Subject B	Subject C
Correct output rate[%]	79.8	87.0	82.4
Incorrect firing rate[%]	2.3	2.7	4.1
Delay time rate[%] (Avg. delay time [s])	3.3 (1.98)	1.9 (1.14)	4.0 (2.4)
Persistent time rate[%] (Avg. Persistent time [s])	1.0 (0.6)	1.0 (0.6)	0.9 (0.54)
Others[%]	13.7	7.5	8.6
Mental commands to robot	Subject A	Subject B	Subject C
Correct output rate [%]	77.5	79.2	77.8
Incorrect firing rate [%]	3.0	2.7	3.4
Delay time rate[%] (Avg. delay time [s])	5.7 (3.42)	4.2 (2.52)	3.1 (1.86)
Persistent time rate[%] (Avg. Persistent time [s])	0.5 (0.3)	0.6 (0.36)	1.6 (0.96)
Others[%]	13.3	13.2	14.0
Evoking Emotions	Subject A	Subject B	Subject C
Correct output rate [%]	80.3	79.0	84.1
Incorrect firing rate [%]	4.2	3.7	3.2
Delay time rate[%] (Avg. delay time [s])	6.0 (3.6)	5.4 (3.24)	6.5 (3.72)
Persistent time rate[%] (Avg. Persistent time [s])	0.8 (0.48)	0.9 (0.54)	0.3 (0.18)
Others[%]	8.7	11.0	5.9

B. *Classification Experiments*

Imagery classification experiments were conducted. The results were shown in Table I. The categories of the performed imagery classification tasks were "Mental motions," the "Mental commands to a robot" and "Emotions" as described in Chapter II. Three male subjects were engaged in the experimental tasks. They were students belonging to our laboratory and had no experience of portable NIRS measurement experiments. The average performance indices of ten trials for each subject were shown in the table I.

In the category of human mental motion classification, the correct output rate scored about 80 to 87%. And in the mental command classification experiment and the emotion classification experiment, the scores were 77~79% and 79~84% respectively. The scores of the incorrect firing rate were 2%~4% in each category. Although the incorrect firing rate is most undesired factor, they were low in all categories. The delay time rate was mainly caused by inevitable biological delay and scored about 2%~7% (1 ~ 4 seconds). Thus, the total performance of the proposed cerebral state classifier is considered to be sufficiently high. However, the rate of the others scored 6~14% in the experiments. This was caused by various influences of the biological fluctuation, the variation and uncertainty of the probe position in taking off and putting on the headset, the condition of the living environment, etc. So, we need to improve the classification performance in the daily living environment. Therefore, in the next chapter, we revise the evaluation method of "others" category and will discuss the improving method in practical use of BMI.

V. Improvement of Classification Performance in Living Environment

In this chapter, we will discuss the improving method of classification performance in the daily living environment. At first, we subdivide the "Others" category and define the stability of the classification. Then, we will discuss the influence of daily living activities and make an attempt to eliminate the disturbance caused by human breathing as an example. Finally, we add a self-proliferating function to the LVQ classifier and conduct additional learning experiments in order to reduce the influence of measuring conditions.

A. *Revision of Evaluation Method*

"Others" category in the performance indices includes the cases of that 1) the classifier outputs "No imagery" before the end of the subject's imagery and that 2) the classifier outputs "No imagery" in the whole period of a trial. So, we define the former as "No reaction time" and the latter as "No reaction data". "No reaction time" is useful for defining the "Stability of classification" by calculating the ratio of the maintained time of correct imagery output (See Fig.8). "Stability = 1.0" indicates the most ideal classifier. On the other hand, the number of "No reaction data" provides clues about the classification failures caused by changing conditions, e.g. the human mental and physical condition, the environmental condition, the probe setting position, etc. So, it implies the robustness of the classification in the living environment.

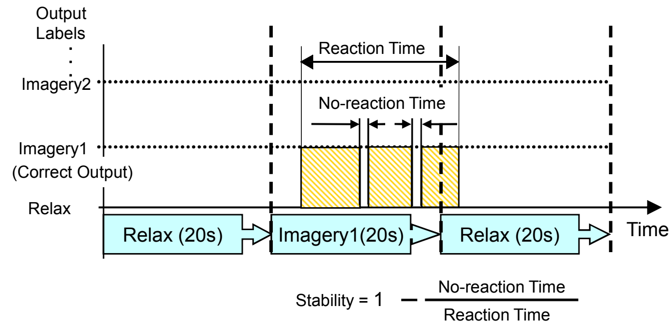
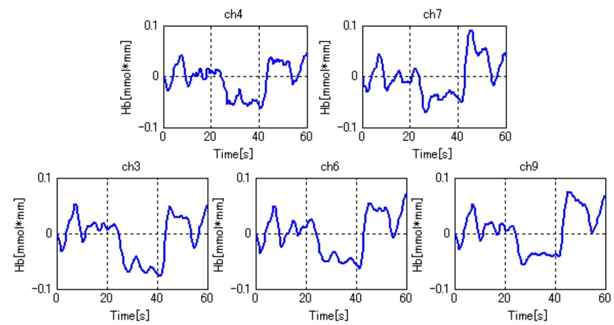
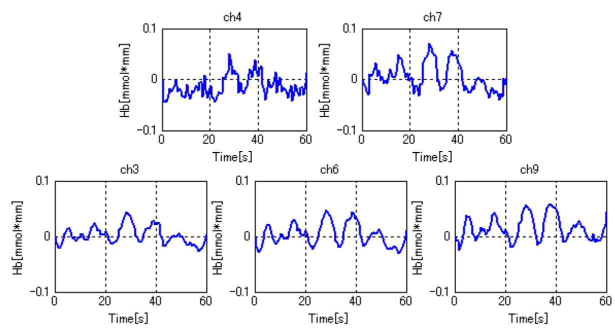


Fig.8 Modified Definition of Classification Stability



(a) Breath hold



(b) Deep breathing

Fig.9 Blood flow change of daily performance

B. *Influence of Daily Living Activity to Blood flow pattern*

In the practical use of BMI, the cerebral blood flow suffers from the influences of daily living activities and environmental conditions. In this paper, we tried to design a disturbance removal method and remove the influence of human breathing experimentally as an example. Fig.9(a) shows a subject's blood flow data in which he performed "breath hold" during the middle 20 seconds. Similarly, Fig.9(b) shows a blood flow data in which the subject performed "deep breathing in cycles of 5 seconds" during the middle 20 seconds. In the first and last 20 seconds, he just relaxed with normal breathing. We can find the facts that the breath hold decreases the hemoglobin concentration in the blood flow and that the deep breathing causes cyclic fluctuations. They may be the non-negligible disturbance in BMI classification.

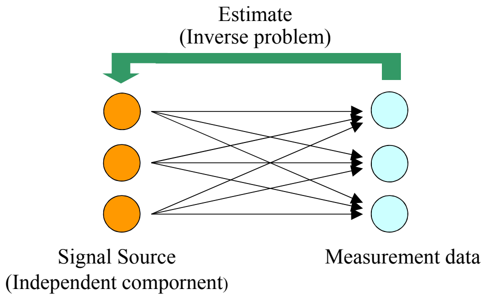


Fig.10 Independent component analysis (ICA)

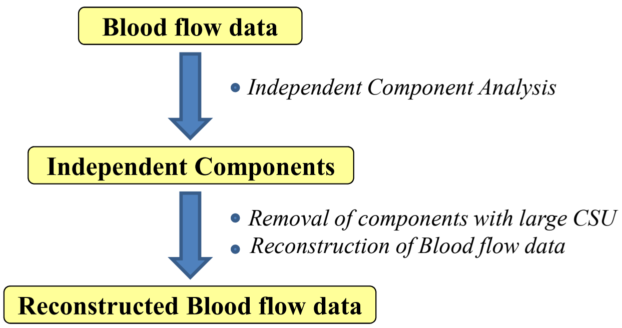


Fig.11 Removal procedure of breathing

So, we considered to remove the influence of the breath by using the independent component analysis (ICA) because the fluctuations caused by breathing tend to give the influence widely and uniformly to whole NIRS channels. ICA [18] is an algorithm which enables to find the independent sources from the measured data, as shown in Fig.10. By removing some components from the estimated independent sources, the measurement data can be reconstructed and revised based on the rest of components of independent sources. Fig.11 shows the procedure for the removal of breathing influences. At first, by using ICA analysis, we decompose the time-series blood flow data of all channels to independent components. Then, the uniformly-influenced components are deleted and finally, we reconstruct the time-series blood flow data from the remaining independent components. We used the coefficient of spatial uniformity (CSU) proposed by S.Kohno [19] to identify the uniformly-influenced component. As a result of experimental considerations, independent components with large CSU values indicated breathing, the high-frequency noise, the drift effect, etc. So, we removed independent components with the top 3 CSU values in the following classification experiments.

To confirm the effectiveness of the proposed removal method, we conducted classification experiments for mental motions and emotions. In the experiments, a subject (Subject A in Table I) executed the above-mentioned mental motion evoking task and the emotion evoking task "with his breath held in the middle 20s." The number of trials in each task was 10. Table II and III show experimental results of classification of the mental motion evoking task and the emotion evoking task with and without ICA-based disturbance removal. In tables, we summarized the average performance of 5 different LVQ codebooks to indicate the performance in the practical use. It should be noted that the correct output rate and the incorrect firing rate were greatly improved by ICA-based removal method. This is because the disturbance caused by the breath hold, the high-frequency noise and the drift was removed effectively. The classification stability also increased significantly from 0.55 to 0.77 in the mental motion classification and from 0.56 to 0.77 in emotion classification. On the other hand, the number of no-reaction data increased from 0.5/10 to 1.5/10 in Table II and from 0.4/10 to 1.4/10 in Table III. This also contributed to the improvement of the incorrect firing rate. These results show the effectiveness of the disturbance removal.

TABLE II. RESULTS OF ICA-BASED DISTURBANCE REMOVAL (MENTAL MOTION CLASSIFICATION)

Mental Motions	Without ICA	With ICA
Correct output rate [%]	74.0	85.7
Incorrect firing rate [%]	8.1	3.1
Delay time rate[%] (Avg. delay time [s])	6.3 (3.8)	2.7 (1.6)
Persistent time rate[%] (Avg. Persistent time [s])	1.0 (0.6)	1.2 (0.7)
No reaction time rate[%]	11.8	7.6
Stability	0.58	0.76
Avg. number of no reaction data	0.5	1.5

TABLE III. RESULTS OF ICA-BASED DISTURBANCE REMOVAL (EMOTION CLASSIFICATION)

Evoking Emotions	Without ICA	With ICA
Correct output rate [%]	70.8	86.2
Incorrect firing rate [%]	15.3	3.2
Delay time rate[%] (Avg. delay time [s])	3.3 (2.0)	3.3 (2.0)
Persistent time rate[%] (Avg. Persistent time [s])	0.9 (0.53)	2.2 (1.3)
No reaction time rate[%]	11.2	5.4
Stability	0.55	0.77
Avg. number of no reaction data	0.4	1.4

C. *Effect of LVQ-based Classifier with Self-proliferating Neurons and Additional Learning Experiments*

LVQ-based Classifier with Self-proliferating Neurons

In the practical use of BMI, human blood flow patterns tend to fluctuate according to the changes of conditions such as the human mental and physical condition, the environmental condition, the variation and the uncertainty of the fitted probe position in taking off and putting on the headset and so on. Therefore, the classifier needs to learn various blood flow patterns in many conditions. But the learning capacity of a normal LVQ with the fixed number of neurons is limited and we cannot decide an optimal number of neurons for the given problem to be learned in advance.

So, we added the self-proliferating function of neurons to the LVQ classifier. In a normal LVQ learning algorithm (i.e.

the competitive learning algorithm), the best matched reference neuron (i.e. the winning neuron) that has the shortest Euclidean distance to each teaching input vector is selected and tuned so as to represent the input-output relationship appropriately. Then, the learning coefficient of the selected winning neuron is reduced gradually and the neuron tuning converges finally. Therefore, in the modified LVQ classifier, we add a new reference neuron to the codebook when the Euclidean distance between the winning neuron and a given teaching input vector is long and the learning coefficient of the winning neuron is too small.

$$D_{win\_neuron} > D_{threshold} \tag{1}$$

$$\alpha_{win\_neuron} < \alpha_{threshold} \tag{2}$$

D_{win_neuron} and α_{win_neuron} represent the Euclidean distance and the learning coefficient of the winning neuron respectively. $D_{threshold}$ and $\alpha_{threshold}$ are thresholds that represent the criteria of adding a new neuron. In an adding process, a new neuron is placed in an intermediate position of the codebook's vector space between the winning neuron and a teaching input vector.

Additional Learning Experiments

In order to confirm the validity of the additional learning with self-proliferating neurons, we performed two types of experiments.

At first, the additional learning was applied to the on-site calibration of the LVQ codebook. In the experiment, we prepared codebooks for two subjects, which were learned by the LVQ classifier over half a year ago. Because the cerebral blood flow tends to changes according to human metal and physical condition and the environmental condition, the performance of the old codebook will not be sufficient to use. So, we measured an additional teaching data (only 1 trial) for each subject on site and performed the additional learning to calibrate the codebook. Then, we compared the classification performance of old and new codebooks. TABLE IV shows performance indices of the mental motion classification against newly measured blood flow data (not teaching data). After the additional learning, the number of LVQ neurons in the codebook increased from 35 to 39 for Subject A and from 35 to 40 for Subject B. It should be noted that the correct output rate and stability were improved by on-site calibration.

Secondly, we performed the additional learning experiments in order to confirm whether the "day-by-day additional learning (repetitive tuning)" can improve the classification performance of the imperfect codebook gained from the initial few teaching data. Three male subjects engaged in this experiment. Subject A and B were the same as in Table I. Subject D is a new person who had no experience of the NIRS experiment. The subjects engaged in the mental motion classification experiment repetitively for 5 days and the codebook was learned additionally by using newly measured data. The "day-by-day repetitive tuning" is considered to improve the generalization ability of the classifier by using various teaching data measured in daily different conditions (e.g., environmental conditions, human mental and physical conditions, the probe position).

TABLE IV. ON-SITE CALIBRATION EXPERIMENT

	Subject A	
	Old codebook	New codebook
Number of neurons	35	39
Correct output rate [%]	63.0	70.6
Incorrect firing rate [%]	18.2	12.0
Delay time rate[%] (Avg. delay time [s])	5.8 (3.5)	6.0 (3.6)
Persistent time rate[%] (Avg. Persistent time [s])	10.2 (6.1)	2.6 (1.6)
No reaction time rate[%]	3.3	8.8
Stability	0.50	0.58
Avg. number of no reaction data	0.5	0.2
	Subject B	
	Old codebook	New codebook
Number of neurons	35	40
Correct output rate [%]	67.3	76.6
Incorrect firing rate [%]	6.2	10.8
Delay time rate[%] (Avg. delay time [s])	0.7 (0.4)	3.5 (2.1)
Persistent time rate[%] (Avg. Persistent time [s])	0.0 (0.0)	1.0 (0.6)
No reaction time rate[%]	25.9	8.5
Stability	0.33	0.53
Avg. number of no reaction data	0.5	0.0

The detailed step of the experiment was as follows. At first, we prepared the initial codebook for each subject by learning the subject's blood flow patterns of 5 trials in advance. On a different day, each subject engaged in the classification experiment and the blood flow data of 3 trials were measured and utilized for the additional learning of LVQ codebook with self-proliferating neurons. This was defined as "a section". Every time the subject performed a trial, the headset was taken off and put on again in order to simulate the daily use of BMI in severe conditions. Each subject engaged 2 sections per day (in the morning and in the early evening) to simulate the change of environmental and human mental/physical conditions. The sections were carried out repetitively for total 5days.

TABLE V shows the change of the number of LVQ neurons during "day-by-day additional learning". The number of neurons gradually increased and it was different with each subject. The result is considered to indicate the variations of blood flow data. TABLE VI and VII show the changes of the correct output rate and the incorrect firing rate. Both indices were improved gradually by "day-by-day repetitive tuning" in spite of severe experimental conditions. TABLE VIII and VIX show the changes of the classification stability and the number of no reaction data, respectively. We can also see the gradual improvement. Thus, it was found out that the additional learning had a possibility to improve the classification performance in the daily living environment. To develop more efficient learning and classifying method with a better performance is our future work.

VI. CONCLUSIONS

In this paper, we developed a portable NIRS-based BMI system and performed the classification experiments for human mental motions, mental commands to a robot and emotions. The experimental results show the effectiveness of the ICA-based disturbance and LVQ-based classifier with the self-proliferating function. To develop more efficient learning and classifying method with a better performance is our future work.

TABLE V. NUMBER OF LVQ NEURONS (DAY-BY-DAY ADDITIONAL LEARNING)

	Number of LVQ neurons		
	Initial	Final	Inclement
Subject A	35	68	33
Subject B	35	72	37
Subject D	35	79	44

TABLE VI. CORRECT OUTPUT RATE (DAY-BY-DAY ADDITIONAL LEARNING)

	Correct output rate [%]				
	Day 1	Day 2	Day 3	Day 4	Day 5
Subject A	64.4	69.9	69.0	71.6	70.9
Subject B	54.7	76.7	66.3	60.2	70.1
Subject D	64.3	64.3	65.3	71.1	69.7

TABLE VII. INCORRECT FIRING RATE (DAY-BY-DAY ADDITIONAL LEARNING)

	Incorrect firing rate [%]				
	Day 1	Day 2	Day 3	Day 4	Day 5
Subject A	19.0	15.6	7.9	13.7	12.7
Subject B	16.6	3.5	19.1	18.0	12.8
Subject D	23.8	13.1	13.6	9.0	8.5

TABLE VIII. CLASSIFICATION STABILITY (DAY-BY-DAY ADDITIONAL LEARNING)

	Classification stability				
	Day 1	Day 2	Day 3	Day 4	Day 5
Subject A	0.34	0.55	0.22	0.47	0.40
Subject B	0.18	0.66	0.35	0.33	0.42
Subject D	0.44	0.25	0.45	0.50	0.64

TABLE IX. NO REACTION DATA (DAY-BY-DAY ADDITIONAL LEARNING)

	Number of no reaction data				
	Day 1	Day 2	Day 3	Day 4	Day 5
Subject A	0.5	0.3	0.5	0.0	0.0
Subject B	0.8	0.8	0.5	0.3	0.2
Subject D	0.2	1.0	0.2	0.5	0.3

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