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The analysis of the brain state measuring by NIRS-based BMI in answering yes-no questions

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Abstract

In recent years, Brain-Machine Interface (BMI) has been improved with the rapid development of the cerebral function measurement technologies. BMI is used for measuring the brain activity of the subjects and inferring his/her intention. These measuring results can control the devices such as the electric wheelchair or the electric arm directly. Previous studies have such problems that BMI device is not portable, and it takes much time to attach a lot of sensor nodes on the head of the subject. Therefore, we use portable NIRS, because it is easy for the subjects to mount it and their burden is low. This paper describes the analytical method for cerebral blood flow during imagining affirmative or negative answers to the questions. It was verified whether it is possible to use the NIRS as BMI to discriminate the yes answer or no without voice and gesture.

In our study, a subject keeps watching the display which shows a yes-no question, he/she imagines affirmative or negative answer to the questions. In the experiment, one test trial is in 30 seconds and it includes 10 seconds task between 10 seconds rests. Each test set consists of 10 trials. One subject has five test set. In our study, we used Wearable Optical Topography WOT-100 as measurement device of NIRS which has 10 channels (ch7-16) of prefrontal cortex. The NIRS data analysis procedure is as follows; in the first step, we used a band-pass filter to select the data of frequencies from 0.02Hz up to 0.1Hz. In the second step, measured NIRS data of each task set is divided into 10 blocks which are included 5 seconds data before the task and 10 seconds data after the task. In the third step, we calculated baseline of measured data from 5 seconds of the beginning and the end of the task blocks, and this baseline fitting is applied to the original data. In the last step, the neural network learned the important elements of the training data and classified the test data. Our method can discriminate between imagining affirmative or negative answers with 70% accuracy. At result, NIRS is useful to discriminate the yes-no answer of the questions.

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Keywords: brain-machine interface; near infra-red spectroscopy; imaging affirmative answer and negative one; neural network

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1. Introduction

In recent years, Brain-Machine Interface (BMI) has been improved with the rapid development of the cerebral function measurement technologies[1]. BMI is used for measuring the brain activity of the user and inferring his/her intention or command, and control the devices such as the electric wheelchair or the electric arm directly based on measured data. There are two major BMI types which are brain-waves analysis (Electro Encephalo-Graph: EEG) and cerebral blood flow measurement by far-infrared rays (Near Infra-Red Spectroscopy: NIRS). The EEG measures electric current at some electric probes on the scalp, and the electric current represents neuron activities. However, the minute signal electric voltage range is micro volt. Therefore, the EEG measurement equipment can amplify the difference of voltage between the signal of the reference point and the measuring point. NIRS is the method which is based on Beer-Lambert law that shows then relation of ray attenuation and density of an absorbing material. The density of the hemoglobin (Hb) in the blood is changed by brain activity. Local blood flow in the surface of the cerebrum can be observed by this blood oxygenation level which is dependent on brain activity. There are many previous studies of BMI that using EEG[2,3,4]. But, EEG is susceptible to noise as myoelectric, and it is difficult mounting. NIRS is although time resolution is low, has advantage is able to mount relatively easy, and it is less susceptible to noise as myoelectric. We considered that NIRS is suitable for BMI, because people are almost moving in their daily. Therefore, we were using the NIRS in this study.

In previous studies, determines the simple two-choice in a change in cerebral blood flow during reading silently by using multi-channel NIRS[5]. Several research fields such as neuro economics and neuro-marketing using brain measurement has been established[6]. In the field of neurological decoding, identify what the person is watching by cerebral blood flow[7]. These previous studies have such problems that subjects had to perform experiments in huge equipment, or to spend much time for attaching a lot of sensor nodes, therefore subjects had to be imposed burden. Therefore, we use portable NIRS, because it is easy for the subjects to mount it and their burden is low. This paper describes the analytical method for cerebral blood flow during imagining affirmative or negative answers to the questions. It was verified whether it is possible to use the portable NIRS as BMI to discriminate “yes” or “no” answer without voice or gesture.

2. The analysis of the brain state in answering yes-no questions

We constructed a BMI system which discriminates affirmative or negative in subject's mind by a simple 10ch NIRS. We were examined from the experiment that it is possible to execute such task for BMI by a simplified NIRS.

2.1. Experiment

In this paper, we investigate the brain state in answering yes-no question by measured NIRS data. We have 10 subjects who are young men in their twenties, 9 right-handed subjects and a left-handed subject. They have all normal vision or forced vision.

In our experiment, a subject keep watching the display which shows a question, he/she imagined affirmative or negative answers to the questions. All of the questions are different. In the experiment, one test trial is in 30 seconds and it includes 10 seconds task between 10 seconds rests (Fig. 1). Each test set consists of 10 trials. One subject has five test set. In our study, we used Wearable Optical Topography (WOT-100) (Fig. 2) as measurement device of NIRS which has 10 channels (ch7-16 shown in Fig.3) of prefrontal cortex.

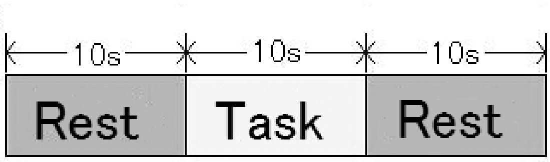


Fig. 1. Experimental procedure

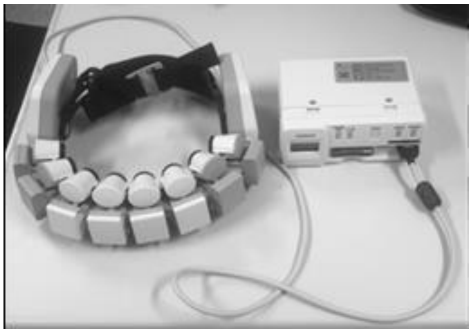


Fig. 2. WOT-100

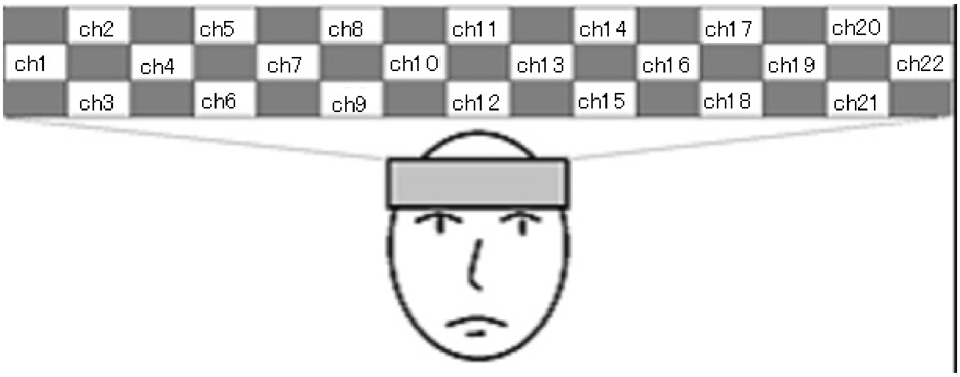


Fig. 3. Measurement channels

2.2. NIRS data analysis

We analyzed the NIRS data, according to the processes show in Fig. 4. The NIRS data phase is as follows. In the first step, we used a band-pass filter to select the data of frequencies from 0.02Hz up to 0.1Hz. In the second step, measured NIRS data of each task set is divided into 10 blocks which are included 5 seconds data before the task and 10 seconds data after the task. In the third step, we calculated baseline of measured data from 5 seconds of the beginning and the end of the task blocks, and this baseline fitting is applied to the original data. In the last step, the neural network learned the average value between task blocks of the training data and classified the test data. The data that was used in this analysis is the total amount of hemoglobin.

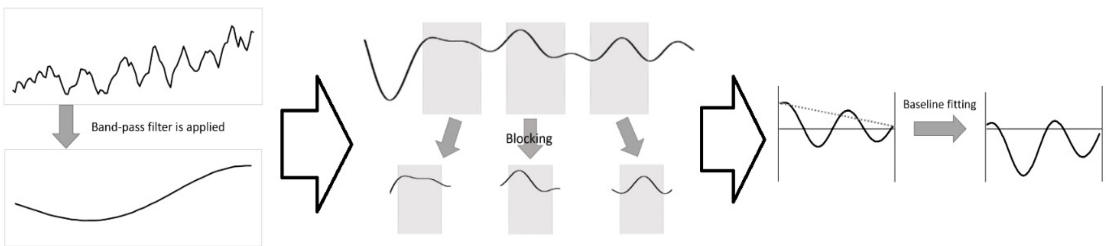


Fig. 4. Process of NIRS data analysis

2.3. Discrimination of NIRS data by neural network

We used the three-layer neural networks to classify NIRS data (Fig. 5). The three-layer neural networks is effective to classify NIRS data in previous study[8]. We used a statistical analysis tool R in this analysis.

In order to train neural networks by 5-fold validation (Fig. 6), we divided brain data into five classes (Class A-E). In each trial, the training data are made from the data of Class B-E, and the data of Class A is used for the classification validation. Each of neural networks has learned by these training data, and has classified the test data for five times. After these processes, we calculated the average of the results. We used a quasi- Newton method for learning of neural networks, which is an algorithm that extends Newton method. To keep the convergence in the vicinity of the solution at Newton method, and to obtain more reliably converged solutions, the approximating the hessian is used.

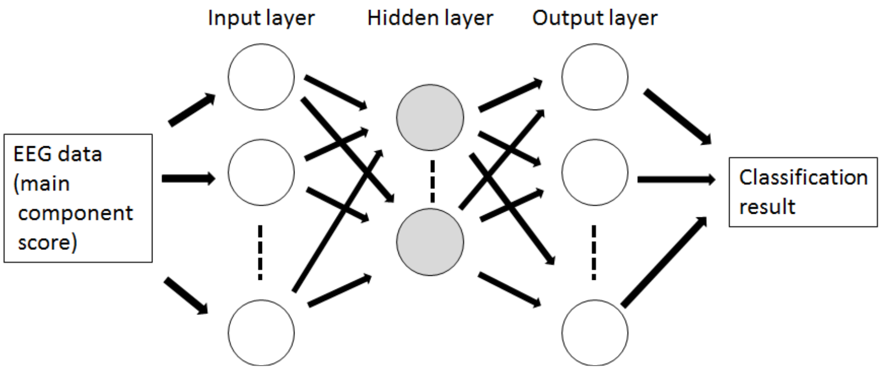


Fig. 5. Three-layer neural networks

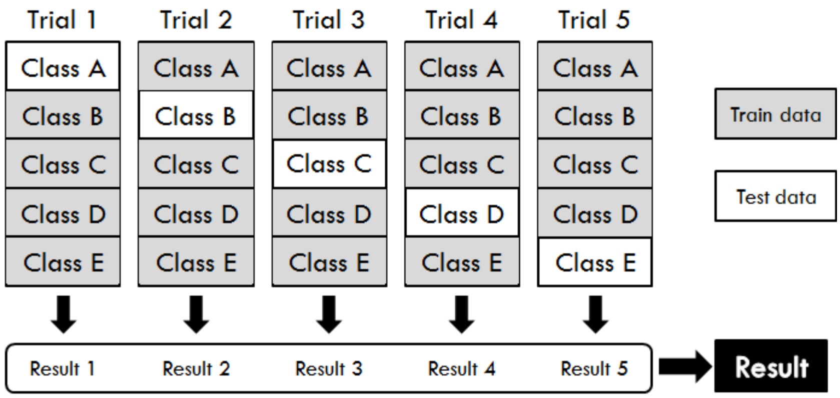
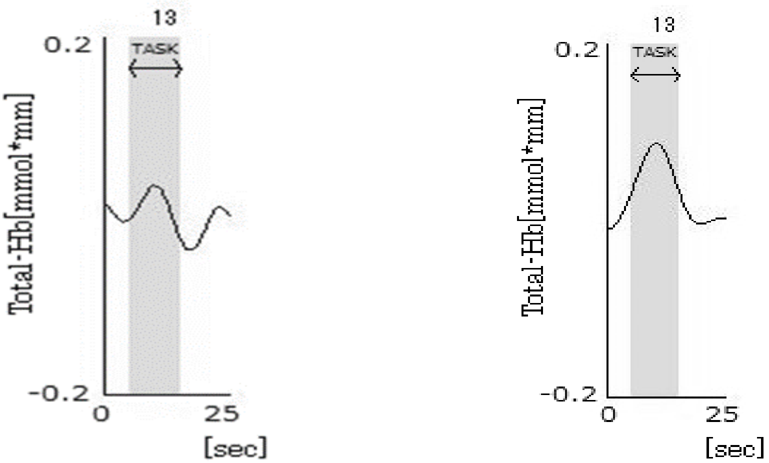


Fig. 6. 5-fold validation

3. Experimental results

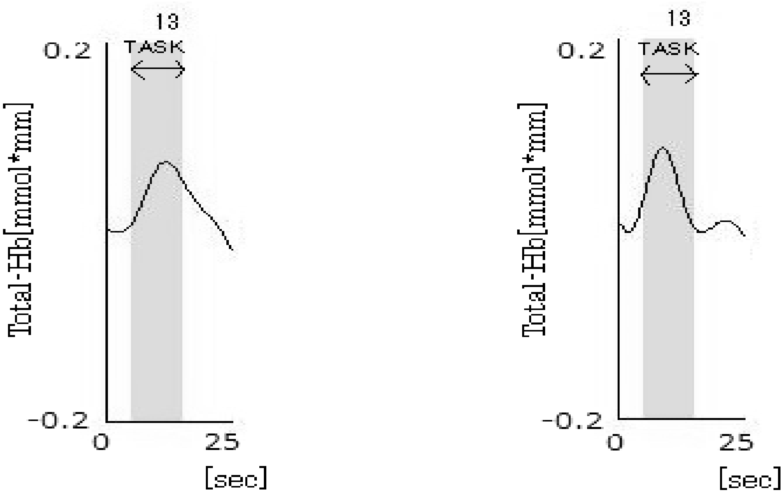
3.1. Analyzed data

We averaged the synchronized signals with the task for each subject. As a results, Fig. 7 shows the activities of the subject B. Fig. 8 shows the activities of the subject A of the first experiment and the second experiment. The cerebral blood flow of frontal lobe is increasing during imagining affirmative or negative answers to the questions. The cerebral blood flow change is bigger during negative imagining than affirmative answers. It was possible to extract the characteristics of the activity, because the cerebral blood flow tended to converge to 0 at rest. We compared the first experiment and the second experiment. They were very different during imagining affirmative. This result shows the different cerebral blood flow caused by the physical condition of the subjects.



(a) Imagined affirmative (b) Imagined negative

Fig. 7. Experimental results (ch13 of the subject B)



(a) Imagined negative at first experiment (b) Imagined negative at second experiment

Fig. 8. Experimental results (ch13 of the subject A)

3.2. Classification result

Table 1 shows the clustering results and the classification accuracy. The result of classification by the neural network show that the accuracy rate on average during imagining affirmative, on average during imagining negative and on overall average are 72.7%, 65.7% and 72.7%, respectively. The classification rate of the subject A during imagining negative is less than 50%. This is because the subject A hesitated to answer the questionnaire. From this fact, this hesitation should be excluded from our analysis, or extend the identified for "negative" and "positive" and "do not say either way".

From these results, NIRS is useful to discriminate the yes-no answer of the questions. But it is not enough to implement this method in the real world. Our next target is to create more efficient classification method. In this study, we have used total hemoglobin (Total Hb) the feature amount for identification. To use the oxy hemoglobin (Oxy-Hb) and the deoxy hemoglobin (Deoxy-Hb) instead of total hemoglobin (Total Hb), we can create more efficient classification. We have to increase the number of experiments and improve the learning efficiency of neural networks in the study to improve classification accuracy.

Table 1. Identification result

	affirmative	negative	average
Subject A	92.3%	41.7%	67.0%
Subject B	82.4%	62.5%	72.5%
Subject C	73.3%	70.0%	71.7%
Subject D	61.5%	83.3%	72.4%
Subject E	61.5%	66.7%	64.1%
Subject F	68.8%	66.7%	67.8%
Subject G	70.6%	62.5%	66.6%
Subject H	73.3%	70.0%	71.7%
Subject I	66.7%	71.4%	69.1%
Subject J	76.5%	62.5%	69.5%
Average	72.7%	65.7%	69.2%

4. Conclusion

In this paper, we have described the analytical method for cerebral blood flow during imagining affirmative or negative answers to the questions. It was verified whether it is possible to use the portable NIRS as BMI to discriminate the yes answer or no without voice and gesture. Our method consists of a band-pass filter, blocking, baseline fitting and neural networks. Furthermore, the neural networks have been trained by 5-fold validation. The subjects keep watching the display which shows a question, he/she imagined affirmative or negative answers to the questions. The result of classification by the neural network show that the accuracy rate on average during imagining affirmative, on average during imagining negative and on overall average are 72.7%, 65.7% and 72.7%, respectively.

In the future, we will try to improve the identification rate. In order to achieve this purpose, we have to increase the number of experiments and improve the learning efficiency of neural networks in the study to improve classification accuracy.

Acknowledgements

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