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Motion Classification using Epidural Electrodes for Low-Invasive Brain-Machine Interface

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Abstract— **Brain-machine interfaces (BMIs) are expected to be used to assist seriously disabled persons' communications and reintegrate their motor functions. One of the difficult problems to realize practical BMI is how to record neural activity clearly and safely. Conventional invasive methods require electrodes inside the dura mater, and noninvasive methods do not involve surgery but have poor signal quality. Thus a low-invasive method of recording is important for safe and practical BMI. In this study, the authors used epidural electrodes placed between the skull and dura mater to record a rat's neural activity for low-invasive BMI. The signals were analyzed using a short-time Fourier transform, and the power spectra were classified into rat motions by a support vector machine. Classification accuracies were up to 96% in two-class discrimination, including that when the rat stopped, walked, and rested. The feasibility of a low-invasive BMI based on an epidural neural recording was shown in this study.**

I. Introduction

Brain-machine interface is a technique that links the brain to external devices via an informational connection. This technique is expected to be used to assist seriously disabled person to communicate and reintegrate their motor functions because it does not need the support of peripheral nerves and muscles.

BMI consists of two elemental technologies: brain activity measurement and information extraction. In other words, these technologies are physical and informational interfaces between living organisms and artifacts. An overview of the two technologies are given in the following sections.

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A. Brain activity measurements (physical interface)

Invasive and noninvasive methods of brain activity measurement are used for BMI systems. However, available information varies by electrode location, that is, the distances between the nerve and the electrode. The farther the electrodes are from the nerve, the less information they can record because the signals deteriorate by attenuation, spreading, and superimposing through biological tissues. Conventional electrical methods can be classified by electrode location: electroencephalographs (EEG) are recorded from the scalp, electrocorticographs (ECoG) are recorded from electrodes under the dura mater, and unit activity recording uses intracortical electrodes [1-3].

An EEG is a noninvasive, safe and convenient method; however, it offers less spatial resolution than invasive methods. The Literatures reports that the spatial resolution of an EEG is approximately 30–50 mm [4,5]. An EEG is also susceptible to noise because of weak signals.

In contrast, invasive methods, such as ECoG and intracortical electrodes, offer higher spatial resolution. These methods, though, require electrodes to be placed inside the dura mater, which affects the immune system of the central nerve. In particular, intracortical electrodes cause chronic inflammation, making long-term recording difficult [6].

Information is generally a trade-off with invasiveness. For daily and practical BMIs, the authors think an EEG is inadequate to control prosthetic devices because of noise susceptibility and the low availability of information. Conventional invasive methods, however, have the problems of foreign substance invasion into the brain system and the difficulty of long-term recording.

B. Information extraction (informational interface)

Information extraction is a process that transforms recorded signals into objective commands, such as moving a computer cursor. Neurophysiologic knowledge and mathematical approximation are used as extraction algorithms.

Raw signals are often transformed to firing rate, power spectra, and integration amplitude. Firing rate is a desirable feature for extraction, but can be obtained only in intracortical recording. Thus, power spectra and integration amplitude are used in EEGs and ECoGs.

In the case of using firing rate, the Population Vector Algorithm (PVA) method performed highly in a robot arm control [3]. Mathematical approximation also achieved control of a computer cursor and a prosthetic device in the research

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using intracortical recording, ECoGs and EEGs [1,2,7,8]. The researchers employed linear regression, artificial neural network, etc.

C. Approach of this study

As noted in section I A, conventional invasive methods of brain activity measurement are ECoG and intracortical recording which are suitable for daily and practical BMI but affect brain immunity. For BMI popularization, it is important that the method provides sufficient informational content and low-invasiveness.

In this study, epidural electrodes were used as a lower-invasive method than subdural and intracortical electrodes. The epidural electrode is located between the skull and dura mater and measures potentials (Fig. 1). It does not affect brain immunity because the surgery is restricted to outside the dura mater. Furthermore, the spatial resolution of the epidural electrode is thought to be a little less than that of the ECoG because of the attenuation and spreading of signals through the dura. If the epidural electrode can capture sufficient information for a practical BMI, it may be a good lower-invasive alternative method.

Some studies on brain activity conducted measurements by using epidural electrodes. These electrodes were used in clinical techniques and brain functional measurements that were auditory-evoked potentials and motor area activity [9,10]. For BMI use, [11] reported cursor control by epidural electrodes for one test subject in ECoG research, and external device control was also achieved in [12]. Nevertheless, more research is required about the feasibility of epidural electrodes for BMI.

The authors employed a pattern recognition method in this study. Specifically, a short-time fast Fourier transform (FFT) was used as the feature extraction for epidural potentials, and a support vector machine (SVM) was used for classification, which labels the epidural signals to the objective behavior.

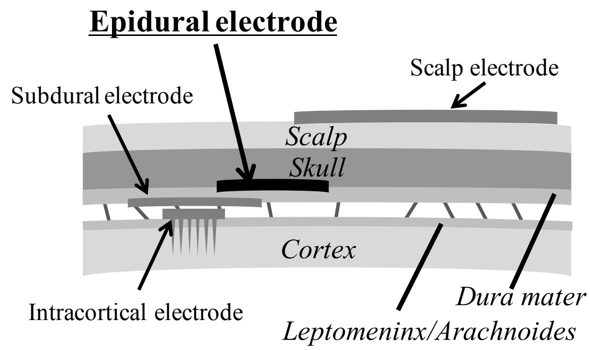

Fig. 1. Locations of an epidural electrode and conventional electrodes for recording cerebrum activities. Body tissue names are in italics.

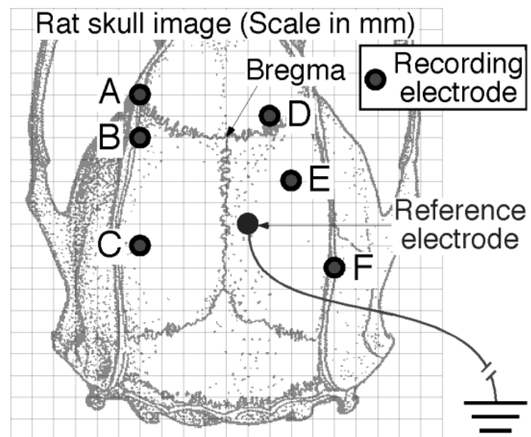

Fig. 2. Locations of the recording electrodes. The grid represents 1 mm^2. The locations were determined by relative distances from the bregma. "A-F" are the recording electrodes. The skull image is taken from [14]

II. METHODS

A. Measurement experiment on a rat

A rat experiment was used to confirm that the epidural electrode was available for motion classification. Brain activity was measured during movements.

A 14-week-old SD rat weighing 455 g was used. Six gold-plated pins were used as the epidural recording electrodes A–F, located as shown in Fig. 2. The locations were identified by the relative positions with the bregma. The part of the skull where the electrodes were to be seated was removed, taking care not to damage the dura mater. The electrodes were fixed on the skull by using dental cement. An anchor screw was used as the ground electrode and as the reference electrode.

The measurement experiment was conducted 5 days after the surgery. The rat was kept in a cage 450 mm long and its neural activity was recorded. The measurements were taken by a monopole between the reference electrode and the recording one. The difference between the recorded signals was calculated to remove in-phase noise (noted in section B). The cortical signal was amplified with a gain of 5000–10000 and recorded at a sampling rate of 20 kHz. The digitalization was 12-bit in ±10 V. In addition, a monochrome video camera recorded the movements of the rat from below (Fig. 3). The video data were synchronized with the logged data of the epidural electrodes. The frame rate of video recording was approximately 30 frames per second. The video data were used to confirm the rat motions in offline analysis. The luminance of the laboratory was set at 0.1 lux, and infrared LEDs were used as the light source for camera.

B. Analysis and classification

To investigate the relationship between the recorded signals and the motions, the signals were classified into the motions and the accuracy of the classification was calculated. Moreover, the appropriate electrode locations and the frequency bands in this study were investigated for accuracy.

The authors selected objective motions: the state of stop, right forefoot lifting, left forefoot lifting, both forefeet lifting, and rest in the cage. Stop is the state of no motion but still standing on four limbs. Rest means no motion and lying flat. Right and left forefoot lifting occurred during walking. The

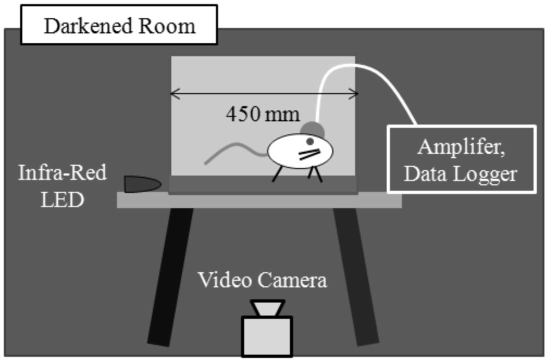

Fig. 3. Experimental settings. A monochrome video camera was used for recording the motions of the rat. The camera was below the cage and synchronized with the data logger.

classification of feet motions may be useful for intuitive external device control in the future.

The analytical process was conducted in three steps consisting of a difference calculation, a feature extraction, and a classification.

First, the signals recorded by the six electrodes were used to calculate the difference between each electrode to remove in-phase noise. Fifteen differential signals were calculated from the six electrodes.

Because epidural electrodes cannot detect neural firing spikes, power spectra were used as features. Neuron groups that have different functions are thought to be activated at different frequencies. A short-time Fourier transform was employed as the feature extraction method. Because the motions of walking change over a very short time, the window width of the Fourier transform was set at approximately 50 ms (1024 points). In this condition, the frequency resolution is constrained to be approximately 20 Hz. Hann window was used as a window function.

A feature vector was made of the 360 power spectra that consist of 24 frequency bands of 0–500 Hz per differential signal (The 40–60 Hz spectrum was removed to prevent hum noise of 50 Hz). For an investigation of effects in electrode locations and frequency bands, other feature vectors, consisting of five power spectra were also used in the classifications. These vectors were made of one difference of electrodes and 100 Hz band spectra.

We used nonlinear SVM as the classification method. To be more precise, LIBSVM which is an open source library of SVM was used in this study [13]. A radius basis function was employed as the kernel function.

The feature vectors were labeled with the states of motion using video data, and divided into learning data and test data. A classification test was conducted by five-fold cross validation. Groups of motions were set up to classify them at one time. The groups had 2–4 motions and each group was classified separately by SVM. The accuracy without any learning data was 1/(the number of motions in the group).

III. Results and Discussion

A. Measured signals

Fig. 4 shows time-line epidural signals that were measured during the motion change from stop to lifting both forefeet. Fig. 4 a) shows the differential potential between the electrodes A and E, and b,c) shows the power spectra of the differential signals. Fig. 4 d) shows the video data, and roman numerals of the pictures mean the time-line in a) and b). Fig. 4 indicates the epidural signal changes with the rat's motion.

The feature vectors are shown in Fig. 5. These were extracted from the differential potentials between electrode A and E during the motions of stop, right forefoot lifting, left forefoot lifting, both forefeet lifting, and rest. This indicates the difference among the feature vectors of the different motions. For instance, power spectra are weaker in rest than in stop.

B. Classification accuracies

Table 1 shows the accuracies in the classification using a

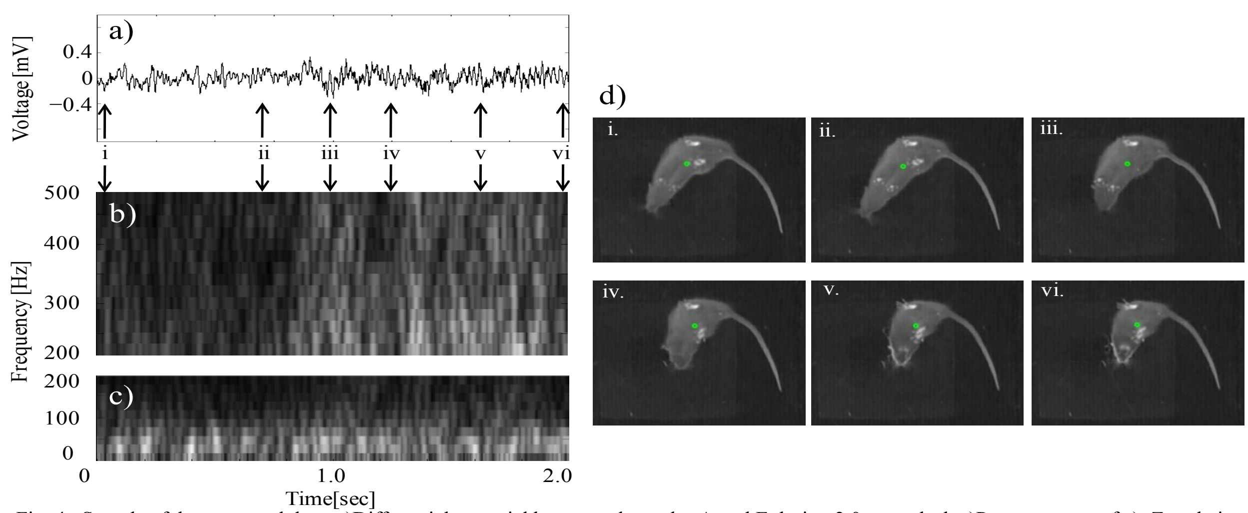

Fig. 4. Sample of the measured data. a)Differential potential between electrodes A and E during 2.0 seconds. b,c)Power spectra of a). Z scale is different between b) and c). d)Pictures of the rat recorded below the cage. Roman numbers at the upper left of the pictures indicate a time-line marked between a) and b). The rat set forefeet on ground during i–iii, and lifted them during iv–vi.

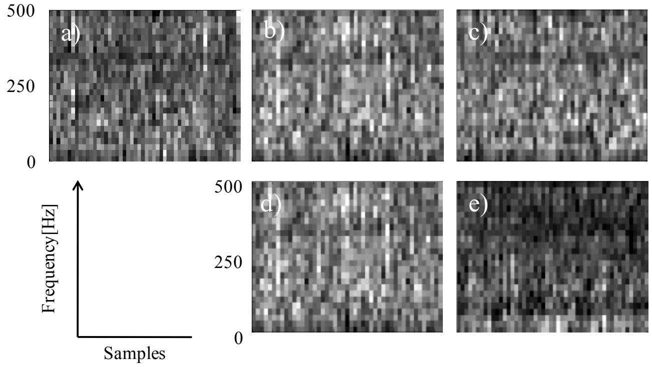

Fig. 5. Feature vectors that were extracted from the epidural potentials. The values of the vectors were scaled in every frequency band. a)Stop. b)Right forefoot lifting. c)Left forefoot lifting. d)Both forefeet lifting. e)Rest.

360-dimension feature vector. In the section of "Motion," RF, LF, and BF mean right forefoot lifting, left forefoot lifting, and both forefeet lifting, respectively. The accuracies varied with the objective motions. The classification of RFF and LFF showed the lowest accuracy. This means the measured epidural potentials of RFF were similar to be ones of LFF. RFF-LFF classification is thought to be difficult by the conditions of this paper because the accuracy was nearly random selection. In contrast, stop-rest classification showed the highest accuracy, and it is thought that the epidural potentials of these states were clearly different from each other. Excluding the RFF-LFF classification, the accuracies exceeded one of random selection.

In the classification using five-dimensional feature vectors, the accuracies were various with electrode locations and frequency bands (data not shown). Suitable electrode location and frequency band were different in objective motions. This is viewed as the effect of the difference of the activated location in each motion.

In addition, we used artificial neural network (ANN) for classification instead of SVM. However, accuracies in ANN use were approximately 5% lower than in SVM use (data not shown).

IV. Conclusion

In this study, epidural electrodes were used for brain activity measurement of the rat as a low-invasive BMI method and the recorded signals were analyzed and classified using short-time Fourier transform and support vector machine. The rat motions, which were the state of stop, right forefoot lifting, left forefoot lifting, both forefoot lifting, and rest in the cage, were classified from epidural potentials.

The accuracies were up to 96% in two-motion classifications. Excluding RFF-LFF classification, the accuracies exceeded random selection.

This study showed the feasibility of low-invasive BMI based on epidural neural recording. However, more research about other electrode locations and suitable methods are required in the future.

Table 1. Classification results of the motions. In the Motion section, RF, LF, and BF mean right forefoot lifting, left forefoot lifting, and both forefeet lifting, respectively.

Num. of Classes	Motion	Accuracy [%]
2-class	Stop-BFF	75.8
	Stop-RFF	89.0
	Stop-LFF	80.5
	Stop-Rest	96.1
	RFF-LFF	46.5
	RFF-BFF	70.8
3-class	Stop-RFF-BFF	66.3
4-class	Stop-RFF-BFF-Rest	73.2

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