

Estimation of Locomotion Speed and Directions Changes to Control a Vehicle Using Neural Signals from the Motor Cortex of Rat

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Abstract—We have developed a brain-machine interface (BMI) in the form of a small vehicle, which we call the RatCar. In this system, we implanted wire electrodes in the motor cortices of rat's brain to continuously record neural signals. We applied a linear model to estimate the locomotion state (e.g., speed and directions) of a rat using a weighted summation model for the neural firing rates. With this information, we then determined the approximate movement of a rat. Although the estimation is still imprecise, results suggest that our model is able to control the system to some degree. In this paper, we give an overview of our system and describe the methods used, which include continuous neural recording, spike detection and a discrimination algorithm, and a locomotion estimation model minimizes the square error of the locomotion speed and changes in direction.

I. INTRODUCTION

Brain-machine interfaces (BMIs) are currently of interest because of their ability to provide a new modality for communication or device control. While many applications are tested on human beings using non-invasive measurements of brain activity such as the electroencephalogram (EEG), direct recording of the electrical activity from neurons is a promising technique for realizing a high-speed connection between a living body and artificial devices. Chapin et al [1], for example, developed a system to control the movement of a robotic arm using the neural signals from the primary motor cortex of a rat. More complex control of a robot arm through the neural signals of monkeys were reported by Wessberg et al. [2]. Moreover, Nicolelis has applied BMIs to therapeutic use for humans [3].

We have developed a BMI in the form of a small vehicle, which we call the 'RatCar'. A unique point of our RatCar system is that a neural signal source (i.e., a rat) is mounted on the vehicle body and the two components move around as a unit. The rat is therefore provided with somatosensory feedback as the vehicle moves. This enables the rat to realize that its desire to move has been satisfied through the vehicle movement. We expect this condition to increase the ability of the rat to adapt to the system. Our ultimate goal is to illude the rat into recognizing the vehicle as corresponding to its own original limbs, and this will enable use of the RatCar as a platform for future neuroscience research. In addition, the movement of the vehicle system causes electromagnetic noise and artifacts in the recorded signals, an inevitable problem for real applications in hospitals and day to day society. The development of the RatCar system will help us

investigate and solve these problems.

Here, we focus on basic control of the vehicle movements. We previously built a linear model based on a least squares error approach to estimate the locomotion speed [4]. We have expanded this model to estimate a more generalized locomotion state which includes the speed and changes of directions of a rat's movements. We compared these estimated values to the actual recorded ones, and attempted to control the vehicle.

II. METHODS

A flow diagram of the RatCar system is shown in Fig. 1. First, neural signals are recorded by neural electrodes implanted in the motor cortices of the rat's brain. These are amplified, filtered, and transferred to the A/D converter. Next, neural spikes are detected from the raw signals. A simple template matching technique is used to reduce noises and artifacts. In principle, this part of the system corresponds to the neurons which generated the spike waveform. Finally, the locomotion speed and changes in direction are estimated from the firing rates of spikes in each category.

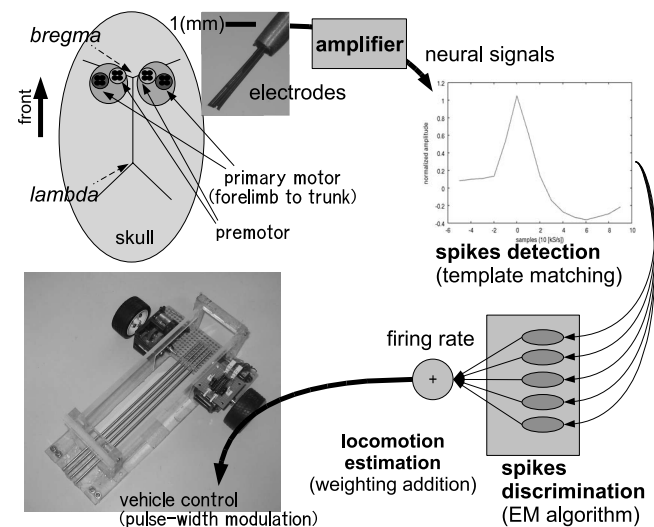


Fig. 1. Flow diagram of the RatCar system

A. Signals Recording

We determined the coordinates of the recording sites according to a stereotaxic atlas of the rat brain [5] and func-

tional localization maps [6], [7]. The areas corresponding to the forelimbs and the trunk in the primary motor cortices and the nearby premotor cortices were selected to represent the body movement during locomotion.

Next, we fabricated and implanted bundled electrodes consisting of tungsten wires to record signals in the areas described above. Each wire was 40 μm in diameter and coated with a parylene polymer. Its tip was cut off to gain 50 to 100 [k Ω] in impedance, which enabled us to simultaneously record the activities of several neurons around each electrode.

The electrodes were tightly fixed on the skull using a resin adhesive and screws cut into the brain. Through the electrodes, the electrical potentials between any two wires were differentially recorded.

The signals obtained from the electrodes were amplified by 10,000 times voltage, filtered through 500 Hz to 3 kHz (*Nihon Koden MEG-6116*), and transmitted to an A/D converter (*National Instruments PCI-6071E*) installed in a computer. The acquisition rate was 10 kHz for each channel.

B. Spikes Detection and Discrimination

We applied template matching to the signals acquired in the computer to reduce noise and artifacts. We then detected spike waveforms at the peak amplitudes (i.e., a relative maximum or minimum).

We applied a Gaussian-mixture model (GMM) to the distribution of spike heights, assuming that spikes having similar peak amplitudes originated from the same neuron. The parameters for the Gaussian-mixture were estimated by the expectation-maximization (EM) algorithm[8] while a number of Gaussians were empirically determined.

C. Linear Model for Locomotion Estimation

The muscle activity of the body is expected to change during locomotion. This suggests that variation in the neuronal firing rate will be either positively or negatively correlated to the walking speed. Consequently, we assumed a model,

$$v(t) = \sum_{n=1}^N a_n x_n(t), \quad (1)$$

where the values of a_n are the contribution factors of neuron n having a firing rate of x_n at time t to the locomotion state v . This is the simplest representation describing the correspondence between neural activity and actual movements.

This linear model can be described in matrix form as,

$$X\vec{A} = \vec{V}, \quad (2)$$

where vector $\vec{A} = (a_1, a_2, \dots, a_i, \dots, a_n)^T$ for the contribution factors, matrix $X = (x_{k,i}) = (x_i(t = t_k))$ representing the firing rate of each neuron at each time t , and estimated speed vector $\vec{V} = (\tilde{v}(t = t_1), \dots, \tilde{v}(t = t_K))^T$ at each time t .

Therefore, vector \vec{A} can be estimated by minimizing the square error of the actual walking speed \vec{V} as follows:

$$\vec{A} = (X^T X)^{-1} X^T \vec{V}. \quad (3)$$

For all of these procedures, we used the same channels on the same rat for each trial, but the period of time for the estimation differed from that used to calculate weights (i.e., an open dataset).

1) *Forward Speed*: We used an animal exercising wheel (Fig. 2) to observe the locomotion speed of a rat as in our previous work [4]. The rat walked without interruption inside the wheel and an encoder attached to the wheel recorded its rotation speed. Neural signals were simultaneously recorded and a firing rate for each neuron was calculated every 100 ms.

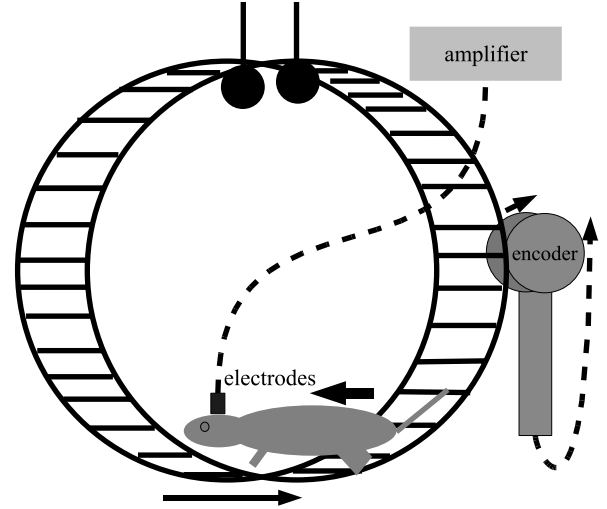


Fig. 2. A rat in exercise wheel. The wheel was supported by bearings that allowed it to rotate freely in both directions. The neural signal of the rat and the rotation speed of the wheel were simultaneously recorded while the rat walked inside of the wheel. Reprinted from [4]

2) *Changes in Direction*: To find the correspondence between neural spikes and changes in direction during locomotion, we built a Y-branch passage for a rat to walk through (Fig. 3).

While a rat was guided to walk through one of the branches (left or right), neural signals were recorded for 1 s before the rat stepped on the detector at the start of each branch. We then assigned a value of -1 or 1 to the locomotion state to specify the weights for a rat walking into either the left or right passage.

We attempted to discriminate which side (left or right) that a rat went to and calculated the sequence of locomotion state values every 100 ms to investigate their variation.

D. Vehicle Control

According to the estimated locomotion speed and changes in direction, the vehicle was controlled to trace the actual movement of a rat. The vehicle had two DC motors connected to the driving wheels. These were controlled by pulse-width modulated (PWM) signals generated by a D/A converter (*National Instruments PCI-6071E*) attached to the personal computer.

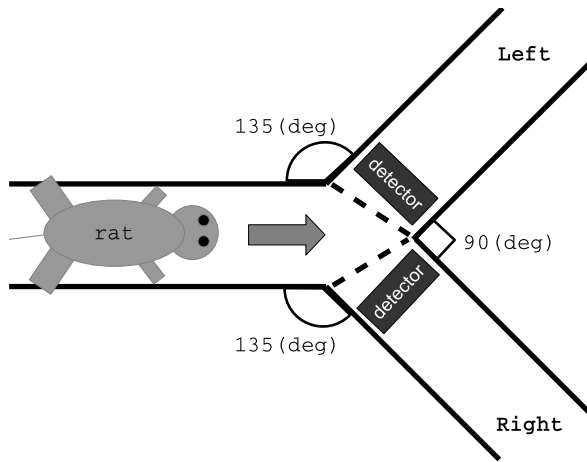


Fig. 3. A rat in a Y-branch passage. A rat was released at one end of the passage (left side of the figure) and guided to walk through one of the branches. Neural signals were recorded for 1 s before a rat passed over the detector installed at the entrance of each branch.

III. RESULTS

A. Forward Speed

Fig. 4 shows the estimated locomotion speed (gray) and the actually recorded locomotion speed (black) during a trial. These were coincident with each other. The mean square error for this trial was 0.032 and the correlation coefficient was 0.965.

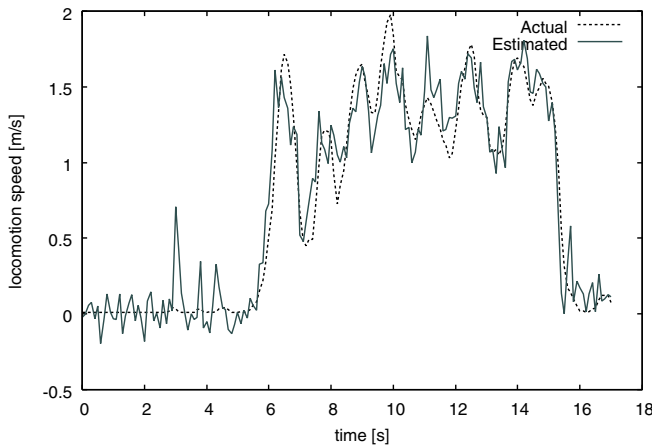


Fig. 4. Actual (black) and estimated (gray) walking speed of a rat

B. Changes in Direction

Fig. 5 shows the estimated locomotion state values for left-turning and right-turning. Although these values are far from the desired values (1 or -1) especially for left-turning, the values tended to be discriminated for most trials.

Fig. 6 shows the estimated locomotion state values for every 100 ms. These values differed remarkably between trials. Some trials showed large shifts towards extreme values, although the overall value tended to be localized around zero.

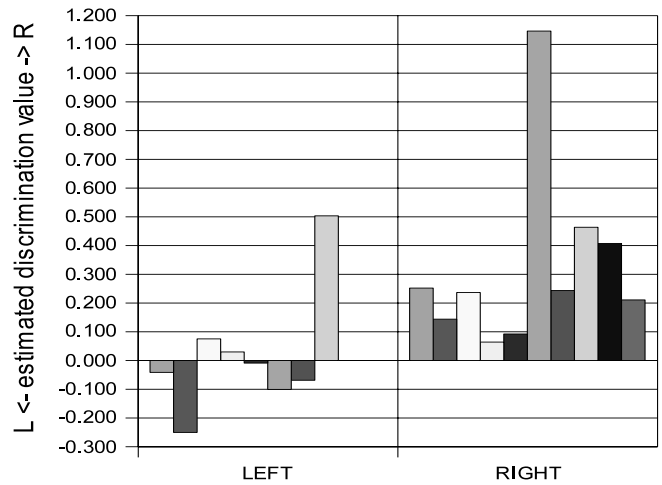


Fig. 5. Estimated direction values, which should be -1 for left and 1 for right

IV. DISCUSSION

A. Neural Measurement

Our electrodes were redesigned to have a smaller diameter (50 μm) than in previous experiments [4] to reduce invasiveness when they penetrated the brain. The possibility of recording from more channels was increased to the degree that some neurons could be clearly recorded even after several months. However, many channels became disabled soon after the implant. The reasons for this are still unclear and histological investigation around the electrodes will be needed.

We implanted electrodes in the primary motor and premotor cortices to read the intention of a rat regarding locomotion. The implanted areas were determined based on previous studies [5], [6], [7], but the position control was not accurate because of individual differences and obstacles such as blood vessels. In addition, we could record obvious neural signals from all recording regions for only a few of the rats. These problems prevented us from comparing the properties of each area and from finding the busy recording sites to estimate the locomotion states. We need to develop a system which is more robust with regard to individual differences and recording sites, and we may have to increase the number of trials.

B. Signal Processing and Estimation

In this work, we implemented an automatic spike discrimination method based on GMM and the EM algorithm. This method suppressed the influence of the manual configuration of parameters, and increased the reliability of the results. However, there are some parameters that an experimenter still has to set empirically: the initial GMM condition, the selection of reliable neurons, etc. In the future, these should also be automatically determined to enable more reliable results.

While the results from estimation of the locomotion speeds showed the ability of the simplified linear model to work as

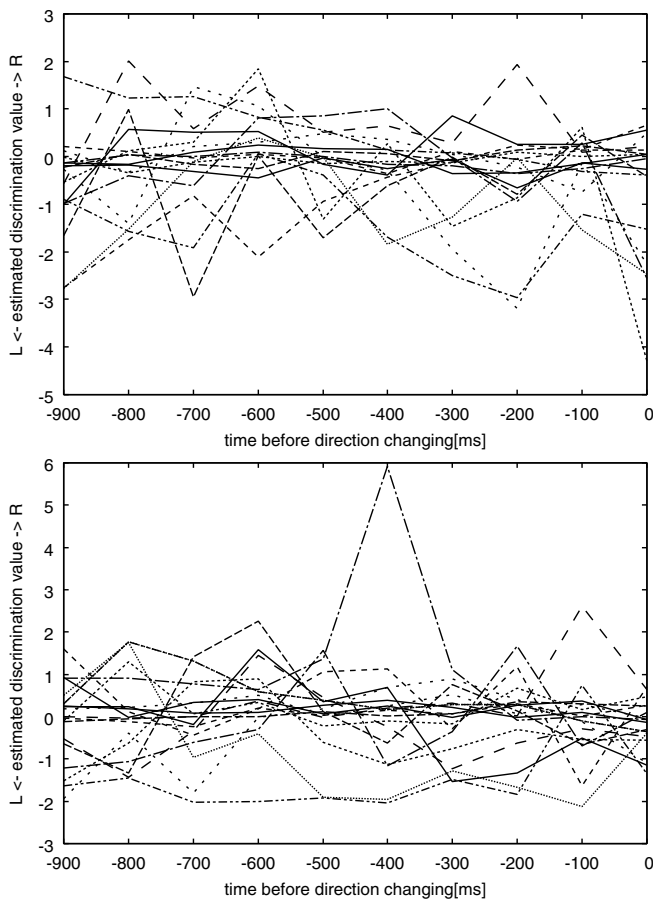


Fig. 6. Estimated direction values for each 100 (ms) as a rat walked toward the detectors. The upper and lower figures are for trials where a rat walked respectively to the left or to the right. The times on the x-axis indicate the remaining time until a rat stepped on either detector.

an intention translator, the results for changes in direction included large errors and variances. Some large errors were caused by calculation inaccuracy due to attempts to divide by zero or to zero determinants of matrices. The introduction of a more reliable calculation technique and the automatic elimination of ill-natured signals (e.g., those having no correlation to the locomotion or that are too uniform) in advance will be effective measures to prevent such errors.

Our current locomotion state estimator depends only on the adjacent firing rates. The use of temporal changes in the firing rates may increase the estimation accuracy. In particular, we need to reduce the excessive variation in the estimated values which was caused by neural activity unrelated to locomotion. This can be done by using a finite impulse response (FIR) filter (e.g., the AR model) or infinite impulse response (IIR) filters (e.g., Kalman filters).

C. Vehicle Control

Some rats tended to stop moving when left in the wheel or on the Y-branch passages used to record the locomotion states. This reduced the number of samples and the recorded neural firings were useless in these cases. Advance selection of rats more likely to move or the application of methods to

motivate a rat to walk are needed. Possible methods include stimulation methods using electrical stimulus, flashing lights, or sounds, and feeding techniques.

So far, we have developed methods for independently estimating locomotion speed and changes in direction. Therefore, although the rat's intention was unconfirmed when we attempted to move vehicle using the neural signals of a rat mounted on it, the vehicle did actually move. In future, we will apply an event recorder system using video cameras to monitor the intention while a rat is freely moving.

V. CONCLUSION

The RatCar system consist of a vehicle controlled by the neural signals from the motor cortices of a rat, and we have estimated the rat's walking speed and changes in direction from these signals. Stronger correlation than in previous experiments was achieved between the actual and the estimated walking speeds. In addition, an approximate discrimination of changes in direction was achieved. Those results made it possible to realize some control of the vehicle.

A relatively large degree of error still remains, though, especially in the estimation of changes in direction. An improved method to determine the implanting positions ad a better model for estimating locomotion states will need to reduce errors.

ACKNOWLEDGMENT

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