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Prediction of arm trajectory from the neural activities of the primary motor cortex with modular connectionist architecture

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A R T I C L E I N F O

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A B S T R A C T

In our previous study [Koike, Y., Hirose, H., Sakurai, Y., Iijima T., (2006). Prediction of arm trajectory from a small number of neuron activities in the primary motor cortex. *Neuroscience Research*, 55, 146–153], we succeeded in reconstructing muscle activities from the offline combination of single neuron activities recorded in a serial manner in the primary motor cortex of a monkey and in reconstructing the joint angles from the reconstructed muscle activities during a movement condition using an artificial neural network. However, the joint angles during a static condition were not reconstructed. The difficulties of reconstruction under both static and movement conditions mainly arise due to muscle properties such as the velocity–tension relationship and the length–tension relationship. In this study, in order to overcome the limitations due to these muscle properties, we divided an artificial neural network into two networks: one for movement control and the other for posture control. We also trained the gating network to switch between the two neural networks. As a result, the gating network switched the modules properly, and the accuracy of the estimated angles improved compared to the case of using only one artificial neural network.

1. Introduction

Interest in the field of brain–machine interfaces has been increasing in recent years, and many papers on it have been published (Nicolelis, 2001; Serruya, Hatsopoulos, Paninski, Fellows, & Donoghue, 2002; Talylor, Tillery, & Schwartz, 2002; Wessberg, Stambaugh, Kralik, Beck, & Laubach, 2000). A brain–machine interface is a technology adopted for use by paralyzed people who cannot move their arms due to damage from an accident or a disease. The main goal is to allow paralyzed people to interact with society more freely by giving them control over an external device, such as a robot arm or a mouse cursor, from brain signals through a mathematical model.

Considerable research and development has been done in the field of invasive brain–machine interfaces since 1999, when Chapin, Moxon, Markowitz, and Miguel A L (1999) controlled the arm movement of a robot having one degree of freedom from the neural activity of the rat motor cortex. Carmena et al. (2003) succeeded in reconstructing the arm movement of a robot having three degrees of freedom, including grip force, from the neural activity of the premotor cortex, the primary motor cortex, and the posterior parietal cortical area of a monkey. In addition, Hochberg et al. (2006) succeeded in controlling a computer cursor on a two-dimensional display from the signal of the primary motor cortex of a human's brain.

In order to implement a brain–machine interface system similar to a human arm, it is essential to reconstruct the position and force information of the arm from the neural activity of the brain. For example, let us consider the case of a human picking up an object; the human first moves his arm to the position of the object from the original position of the arm and then grips the object with a proper force depending on the weight of the object. Therefore, the reconstruction of the force information is an important factor in the implementation of a brain–machine interface system. We used electromyography (EMG) signals to simultaneously reconstruct the position and force information. Since EMG signals reflect muscle tensions, we can precisely reconstruct the arm posture, joint torque, and stiffness from the EMG signals (Koike & Kawato, 1994, 1993, 1995).

Several hypotheses have been proposed to describe the relationship between the neural activities of the primary motor

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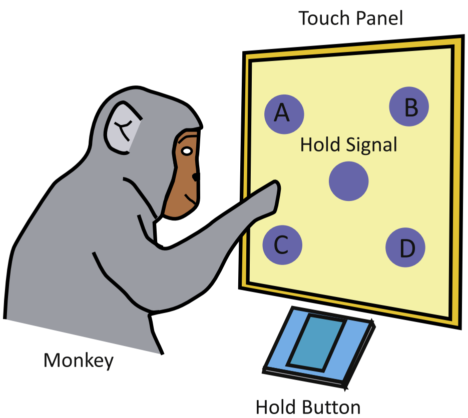

Fig. 1. Behavioral task. The monkey, trained to perform a continuous arm-reaching task, sat in a primate chair with its head fixed and facing a touch panel displaying five lights and five buttons.

cortex and motor control. Among these hypotheses, one states that the neural activities of the primary motor cortex encode the movement direction (Georgopoulos, Kalaska, Caminiti, & Massey, 1982), while another states that the neural activities encode the force (Fetz, Cheney, & German, 1976), and yet another states that the neural activities encode both the movement direction and the force (Kalaska, Cohen, Hyde, & Prud'homme, 1989). Despite these endeavors, the exact relationship between the neuron activities in the primary motor cortex (M1) and motor control remains unknown.

Previous studies to determine the relationship between the neural activities of the primary motor cortex and motor control analyzed the correlation between the neural activities of M1 and the magnitude and direction of movement or force. However, the actuator that generates the movement and force is a muscle. We have proposed computational models (Koike & Kawato, 1994, 1993; Kyuwan, Hideaki, Toshio, & Yasuharu, 2005; Yagishita, Domen, Sato, & Koike, 2003) to estimate the joint torque, joint angle, impedance, and so on from the activity of muscles. By using these models, we can estimate the movement direction and the force from the activity of muscles. Some studies have used these results to devise a model to determine the relationship between the neural activities of the primary motor cortex and movement; this relationship cannot be determined by the conventional method of calculating the correlation between the neural activities and movement. For example, Todorov (Emanuel, 2000) has proposed a model that generates movement. In this model, since the activity of muscles is made by inserting a time-delay term into the neural activities of the primary motor cortex, muscle activity simply becomes a linearization of neural activities. The force generated in the muscles was estimated by using a first-order model from two parameters: the length of the muscles and the contraction velocity.

We considered the model of the muscle as a second-order low-pass filter and thus designed it to have the characteristics of smoothness and time delay. The low-pass filter was designed from the relationship between human muscles and force (Koike & Kawato, 1995). We implemented the nonlinear characteristics of muscles related to the joint angle and contraction velocity of muscles by using two different artificial neural network models. In this way, by incorporating the smoothness and nonlinearity of a musculoskeletal system in the model, we can precisely reconstruct the actual movement, even when using a linear model between the neural activities of the primary motor cortex and muscle activities.

In this study, we first reconstructed nine muscle tensions (filtered EMG signals) from the neural activity of 105 neurons in M1 by using a linear regression method. We then estimated the joint angles in four degrees of freedom related to the shoulder and the elbow from the reconstructed muscle tensions by using a modular artificial neural network model.

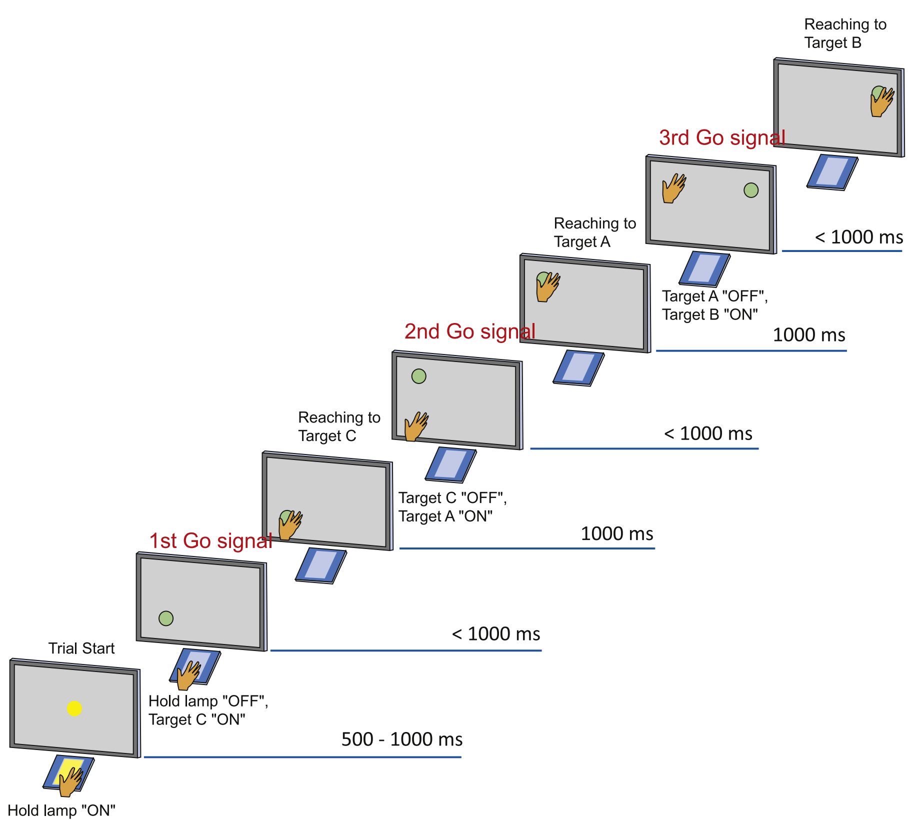

Fig. 2. Sequential arm-reaching task (Hold–C–A–B sequence).