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Neuron selection by relative importance for neural decoding of dexterous finger prosthesis control application

Hyoung-Nam Kim [a,b], Yong-Hee Kim [a], Hyun-Chool Shin [c], Vikram Aggarwal [b], Marc H. Schieber [d], Nitish V. Thakor [b,*]

[a] Department of Electronics Engineering, Pusan National University, Busan 609-735, Republic of Korea
[b] Department of Biomedical Engineering, Johns Hopkins School of Medicine, Baltimore, MD 21205, USA
[c] School of Electronics Engineering, Soongsil University, Seoul 156-734, Republic of Korea
[d] Department of Neurology, Neurobiology and Anatomy, Brain and Cognitive Sciences and Physical Medicine and Rehabilitation, University of Rochester Medical Center, Rochester, NY 14642, USA

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ABSTRACT

Future generations of upper limb prosthesis will have dexterous hand with individual fingers and will be controlled directly by neural signals. Neurons from the primary motor (M1) cortex code for finger movements and provide the source for neural control of dexterous prosthesis. Each neuron's activation can be quantified by the change in firing rate before and after finger movement, and the quantified value is then represented by the neural activity over each trial for the intended movement. Since this neural activity varies with the intended movement, we define the relative importance of each neuron independent of specific intended movements. The relative importance of each neuron is determined by the inter-movement variance of the neural activities for respective intended movements. Neurons are ranked by the relative importance and then a subpopulation of rank-ordered neurons is selected for the neural decoding. The use of the proposed neuron selection method in individual finger movements improved decoding accuracy by 21.5% in the case of decoding with only 5 neurons and by 9.2% in the case of decoding with only 10 neurons. With only 15 highly ranked neurons, a decoding accuracy of 99.5% was achieved. The performance improvement is still maintained when combined movements of two fingers were included though the decoding accuracy fell to 95.7%. Since the proposed neuron selection method can achieve the targeting accuracy of decoding algorithms with less number of input neurons, it can be significant for developing brain–machine interfaces for direct neural control of hand prostheses.
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1. Introduction

A brain–machine interface (BMI) is a methodology which enables a brain to communicate with an external device bypassing normal neuromuscular systems. Currently, a BMI has drawn much interest as an appropriate alternative for restoring both motor control [1–4] and sensory feedback to amputees so that they can again perceive heat, cold, pressure, and the position of a limb in space [1]. BMI systems collect neural activities from various cortical areas, such as the primary motor, premotor and posterior parietal cortex, and interpret the encoded motor-intent into control commands or kinematic parameters [2–4]. Up to now, many relevant studies have been exploited such as a closed-loop control of a computer cursor and target tracking, reaching and grasping task of a hand [5–7].

Presently dexterous, multi fingered prosthetic limbs are under development. Neural control of dexterous hands will require signals from a population of neurons coding for the hand and finger movements. Hence, an important problem in neural prosthesis control is to select, and preferably rank in terms of their relative importance, neurons coding for individual finger movements. Solution to this problem requires a trade-offs between achieving high decoding accuracy and low computational complexity. Since not all recorded neurons contribute equally to the all movements, since some neurons are related weakly or not at all to the specific movements, the use of as many neurons as possible does not guarantee high decoding accuracy and may even degrade the performance of the decoding algorithm. In addition, the increase in the number of input neurons puts a computational burden on finding an optimal solution especially when the goal is to implement such decoding algorithms in an experimental hardware [8,9]. Therefore, developing a metric for evaluating the contribution of neurons selected for BMI tasks is at the core of designing an efficient real-time BMI. Researchers have developed some techniques to evaluate the relative importance and select the best neurons coding for the information [9–12]. Sensitivity analysis and single neuron correlation analysis through a vector linear

* Corresponding author.
E-mail addresses: hnkim@pusan.ac.kr (H.-N. Kim), nitish@jhu.edu (N.V. Thakor).

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model were proposed to quantitatively rate the importance of neurons in neural to motor mapping [9,10]. These analyses depend on the decoding model and thus they are not easy to interpret from neurophysiologic points of view [10]. In another approach, a neuron's individual removal error was defined and then used for representing its importance in the population vector neural decoding method [11]. Recently, information theoretical analysis based on an instantaneous tuning model was applied to extract the important neuron subset for neural decoding on BMI [12]. However, these quantification methods of neurons' importance have been developed for predicting intended reach and cursor control and are not yet targeted toward achieving dexterous hand and finger control. Thus, a very active area of research currently is to develop neural control of dexterous hand prosthesis, i.e. provide realistic control strategies for actuation and control of individual and combined finger movements [13–23]. However, methods of neuron selection for complex finger movements, have not been well developed, and as such is the subject of this paper.

We present a new simple metric for quantifying the relative contribution of a neuron toward finger movements. Based on the change in firing rate before and after the starting moment of each instructed finger movement, we define a random variable for the change in firing rate. Then, finding the means of each random variable over six trials for each movement, we finally compute the variance of the means over whole movements for each neuron. A larger variance of neural activations over each finger movement means that the corresponding neuron is activated distinguishably for each finger movement, and it can contribute to accurate decoding performance of all finger movements. Thus, we use these variances as a new metric for ordering neurons. With the ordered neurons we performed maximum-likelihood (ML) neural decoding [20] and then compared the performance with that of randomly selected neurons. Our objective is to demonstrate an improvement in decoding accuracy.

The remainder of the paper is organized as follows: In Section 2, neuron selection based on neural activity is developed and ML neural decoding with the selected neurons is introduced. Section 3 shows the performance improvements with the selected neurons by comparing ML decoding performances with and without selected neurons. We analyze the decoding performance when both individual and combined finger movements are included. Section 4 presents the conclusion.

2. Neural decoding based on neuron selection of M1 neurons

2.1. Neuronal recordings from motor (M1) cortex

Three male rhesus (*Macaca mulatta*) monkeys—K, G, C—were trained to perform visually cued movements of individual fingers and the wrist movements. In addition, the monkey K was trained to perform combined finger movements involving two digits in order to test the decoding accuracy of more dexterous and complex movements. The monkeys were prepared for single-unit recording by surgically implanting both a head-holding device and a rectangular Lucite recording chamber that permitted access to the area encompassing M1 contralateral to the trained hand [18]. These recording were obtained using self-made, glass-coated, Pt–Ir, microelectrodes. Recording tips were etched to be parabolic in shape and approximately 10 μm wide 20 μm back from the tip [21]. There were 12 distinct individual movements: flexion (*f*) and extension (*e*) of each of the fingers (1 = thumb,. . ., 5 = little), the wrist (*w*) of the right hand, and six combined two-finger movements: $f_{12}, f_{23}, f_{45}, e_{12}, e_{23}, e_{45}$. The monkeys placed their right hand in a pistol-grip manipulandum; this grip separated each finger into a different slot. The pistol grip manipulandum was also mounted on an axis allowing flexion and extension of the wrist. The monkeys were instructed to flex or extend a single digit until a microswitch was closed. The duration of each trial was approximately 2 s, and for analysis all trials were aligned such that switch closure occurred at 1 s [18]. Throughout these investigations, the monkeys were cared for according to the "Guiding Principles for Research Involving Animals and Human Beings" accepted by the American Physiological Society [13]. A detailed description of the methods used to train the monkey and the actual experimental protocols can be found in [12,13]. Single-unit activities were recorded from 115 task-related neurons in the M1 cortex of the monkey. Independent trials of each type of movements were recorded six times.

2.2. Ordering of neurons by relative importance

To define the neural activity, we need a random variable representing firing rate of a neuron for each finger movement. Let $r_n(m)$ be a random variable of firing rate of a neuron n for a movement type of m. Specifically, $r_n(0_m)$ denotes the baseline activity of the neuron n before the movement of m. Then, we can define the neural activity considering only movement by introducing the following random variable [20]:

$$x_n(m) = r_n(m) - r_n(0_m). \tag{1}$$

Since the random variable of $x_n(m)$ represents the change in firing rate before and after the starting moment of instructed finger movement, it can be used as a metric of neuron's activation for respective movements. Considering the randomness of neural activity, we can determine the neuron's sensitivity to a particular finger movement m by obtaining the ensemble average of $x_n(m)$, *i.e.*, $E[x_n(m)]$. The estimate of $E[x_n(m)]$ is usually computed by averaging the recorded neural activation, $x_n(m, k)$, for possible training sets, that is

$$\mu_n(m) = \frac{1}{P}\sum_{p=1}^{P} x_n(m, p) \tag{2}$$

where P is the number of independent training sets. As P increases, the reliability of the metric can be also improved. However, the increase of P means that more training data are needed and thus there is a trade-off between the data size and the metric reliability. Letting M be the total number of tested movement types, then the neuron n has M $\mu_n(m)$s and each $\mu_n(m)$ represents the estimate of the neuron's activity corresponding to the movement of m. As a result, the value of $\mu_n(m)$ can be considered a straightforward metric for the absolute degree of neural activation ascertaining how much the neuron n contributes to a particular movement of m independent of other movements. This metric, however, cannot be directly applied for selecting the input neurons because the goal of neural decoding is to find the unknown movement from recorded spike signals. For any metric to be available for ascertaining the importance of a neuron when selecting an appropriate input neuron set for neural decoding, it should reflect the relative difference of activations among all the tested movements, not the absolute magnitude of activation for a particular movement. To achieve this goal, we define a relative importance of a neuron n with the inter-movement variance of neural activities as the following equation:

$$V_n = \frac{1}{M}\sum_{m=1}^{M} (\mu_n(m) - \bar{\mu}_n)^2 \tag{3}$$

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