NEURAL SELECTION METHOD BY RELATIVE NEURONAL IMPORTANCE FOR NEURAL DECODING

Yong-Hee Kim,Yu-Ri Lee*, Hyun-Chool Shin**, Nitish. V. Thakor***, Hyoung-Nam Kim**

*School of Electrical Engineering, Pusan National University, Busan Korea
**School of Electronic Engineering, Soongsil University, Seoul Korea
***Department of Biomedical Engineering, Johns Hopkins Univ. School of Medicine, Baltimore USA

ABSTRACT

In a Brain-Machine Interface (BMI) system based on neural spike signals, the increased number of involved neurons does not always guarantee the higher decoding performance. The inclusion of lowly-tuned input neurons to the intended movement can aggravate a computational burden, and even degrade the decoding accuracy of the BMI system. In this paper, to find highly-tuned neurons, we present a new metric for evaluating the information content of neurons recorded in primary motor cortex (M1) area of non-human primate during complex finger movements. Selecting a subpopulation of rank-ordered neurons improves decoding accuracy irrespective of the decoding algorithm. In the maximum-likelihood (ML) neural decoding of finger movements, each neuron's activation is quantified by the change in firing rate before and after finger movement, and the quantified value is then represented by the absolute importance indicating the contributions of each neuron to the intended movement. Since this absolute importance 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 variance of absolute importance values corresponding to each intended movement.

Index Terms— Brain-machine interface (BMI), neural decoding, neuron selection.

1. INTRODUCTION

A Brain-Machine Interface (BMI) is a communication pathway between a brain and an external device to provide a relevant alternative for people with damaged cognitive or sensory-motor functions [1]. To achieve this goal, a BMI system interprets a motor intent encoded in the recorded neural activities into control commands for its application. Up to now, many studies have been exploited such as a 2D target tracking task, closed-loop control of a computer cursor and 3D food reaching task [2-7]. In these fields, it is a significant problem to accomplish high decoding accuracy with low computational complexity to implement potable and practical BMI systems. Generally, the computational burden of BMI systems is increased dramatically as the number of input neurons and even extra input neurons degrade the decoding accuracy due to model overfitting. So, the efforts to ascertain the contribution level of each input neuron have been continued simultaneously [9-12]. Recently, more dexterous and realistic control strategies of actions such as individuated, combined finger movements are a matter of the utmost concern in this field [13-20]. Therefore, developing an appropriate metric for ascertaining the contribution of neurons is needed for neural decoding of dexterous finger movements.

In this paper, we present a new simple metric for selecting highly-tuned neurons. With the highly ranked neurons we performed ML neural decoding and then compared the performance of the ML decoding using randomly selected neurons. The remainder of the paper is organized as follows: In Section 2, the proposed neuron selection method is described. Section 3 shows the simulation results of ML neural decoding using the selected neurons. Section 4 concludes this paper.

2. NEURAL DECODING BASED ON THE PROPOSED NEURON SELECTION METHOD

2.1. Neuronal Recordings from Motor (M1) Cortex

A male rhesus monkey (*Macaca mulatta*) was trained to perform visually-cued movements of individual fingers, the wrist, combined fingers. There were 12 distinct individuated movements: flexion (f) and extension (e) of each of the fingers (1=thumb,…,5=little) and of the wrist (w) of the right hand and six combined two-finger movements: f12, f23, f45, e12, e23, e45. The monkey placed its right hand in a pistol-grip manipulandum which separated each finger into a different slot. The pistol grip manipulandum was also mounted on an axis allowing

This research was supported by the Korea Research Foundation Grant (KRF-2009-013-D00090).

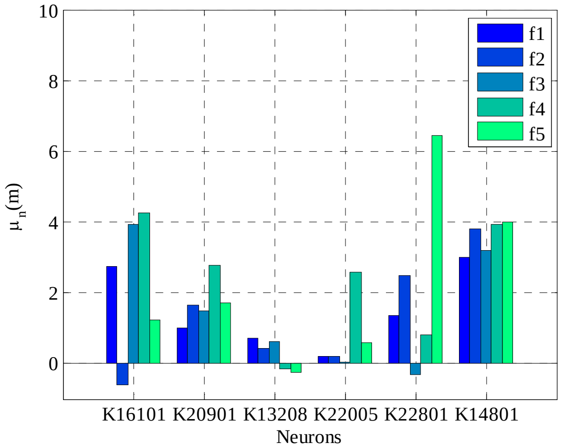

Fig. 1. Absolute importance of six randomly-selected neurons for each of the five individuated-finger movements.

flexion and extension of the wrist. The monkey was instructed to flex or extend a single digit until a microswitch was closed. A detailed description of the methods used to train the monkey and the actual experimental protocols can be found in [12] and [13]. Single-unit activities were recorded from 115 task-related neurons in the M1 neurons of the monkey. Independent trials of each type of movements were recorded six times.

2.2. Absolute importance of neurons

Let $r_n(m)$ be a random variable of firing rate of a neuron n after the movement of m. Specifically, $r_n(0_m)$ denotes the baseline activity of the neuron n before the movement of m. Then, the neural activity can be defined as a change of the firing rate between before and after finger movement [20].

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

The random variable of $x_n(m)$ represents that a degree of the activation of the neuron n for the finger movement m. So, the expectation of $x_n(m)$ can be used as a metric of neuron's importance determining how much it contributes to respective movements. This can be attained by computing the average of $x_n(m)$ for possible training sets, that is,

$$\mu_n(m) = \frac{1}{K}\sum_{k=1}^{K}(x_n(m) \text{ in } k\text{-th trials}), \tag{2}$$

where K is the number of independent training sets. This metric shows the absolute importance of each neuron for a given movement. Fig. 1 shows that each neuron has various values of $\mu_n(m)$ for some different movement type of m. The absolute importance, however, cannot be directly used for neural decoding because the neural decoding is to find the movement corresponding to given spike signals.

2.2. Ordering of neurons by relative importance

The good candidate as an input neuron is a highly-tuned one that a trend of neural activities of the corresponding neuron is very diverse for the each finger movement. A statistical point of view, the probability density functions of each random variable $x_n(m)$ are distinguishable for each finger movement. With this respect, we define a relative importance of neurons which measures a degree of difference of neural activity for each movement. With this respect, we consider the variance of the absolute importance of each neuron for the tested movements. This is computed by

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

where M denotes the number of the tested movements and $\bar{\mu}_n$ is the mean of the absolute importance, $\mu_n(m)$ for the tested movements given by

$$\bar{\mu}_n = \frac{1}{M}\sum_{m=1}^{M}\mu_n(m). \tag{4}$$

After computing the relative importance of each neuron, we can rank neurons by their impact factors of relative importance.

3. RESULTS AND DISCUSSION

Neuron selection is crucial for the future applications of neuroprosthetic control because we need to reduce computational complexity and thus implement BMIs with low cost and low power. The proposed method for neuron selection was examined by comparing the performance of the ML decoding with Skellam and Gaussian distribution, but using the randomly selected neurons and the highly-ranked neurons ordered by the proposed method. The observation interval of Δt was 100ms and the firing rate of $r_n(m)$ was obtained by averaging the number of spikes for 300ms after the movement of m. The baseline activity of $r_n(0_m)$ was obtained by averaging the number of spikes for 800ms before the movement of m. Six independent trials were recorded for each movement, the five trials of which were used for training, i.e., K=5 and the rest trial was used for testing. Thus, six different combinations can be used for training and testing. The ML decoding without ordering was performed with randomly chosen N neurons. To raise the reliability of the decoding performance, the random selection was repeated 400 times. On the other hand, for the rank-ordered neurons, if N neurons are used for ML

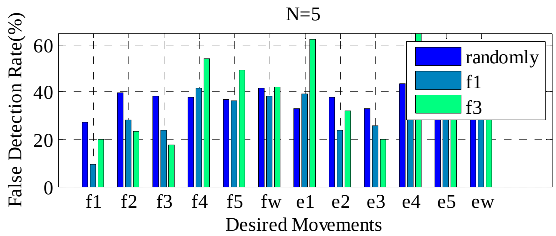

Fig. 2. False-detection rate for each given movement with the ordered neurons by $\mu_n(1)$, $\mu_n(3)$ and randomly-selected neurons. The number of neurons involved in decoding is 5.

decoding we can choose top (N+L) ranked neurons from the list in descending order. Then, N neurons are randomly selected in order to raise the reliability for the results of decoding accuracy by increasing the possible neuron groups. So, the possible number of selections is, ${}_{N+L}C_N$ this results in the total number of movements for decoding of $12 \times 6 \times {}_{N+L}C_N$. Among the recorded six trials data, the neural activities are averaged over five independent trials to train the ML model and the one trial data is used for testing.

3.1. Absolute importance of neurons

We first computed $\mu_n(m)$, the absolute contribution impact of each neuron for the 12 individuated movements to verify the metric for determining neurons' importance. Fig. 1 shows that each neuron has various values of $\mu_n(m)$ for some different movement type of m. To clearly show the effectiveness of $\mu_n(m)$, we ordered neurons according to $\mu_n(m)$ and chose the one of 12 ranked neuron lists. We used the highly ranked neurons for ML neural decoding and computed the false detection rates for each desired movement m. Since $\mu_n(m)$ is most highly related to the movement of m, the use of the ordered neurons by $\mu_n(m)$ yields the lowest false detection rate (FDR) when the desired movement is compared to others. Figs. 2 show the FDRs for each desired movement with the 5 neurons ordered by $\mu_n(1)$ and $\mu_n(3)$, the "1" and "3" denote the finger movement f1 and f3. In both cases, the FDR for the desired movement of m=1 had the lowest value but the difference between the FDR of m=1. This means that each movement has its own pattern of neural activation.

The ordered result by $\mu_n(m)$ only shows the activity level of each neuron involved in the movement of m, so it does not assure the accurate neural decoding for the remaining 11 movements. Because the desired movement is not revealed in real environments, the absolute importance is not appropriate as a metric for ascertaining the importance of neurons.

3.2. Selection of Neurons

Since the goal of neural decoding is to find the intended movement corresponding to given neural activity, the use of ordered neurons by $\mu_n(m)$ may not provide the best

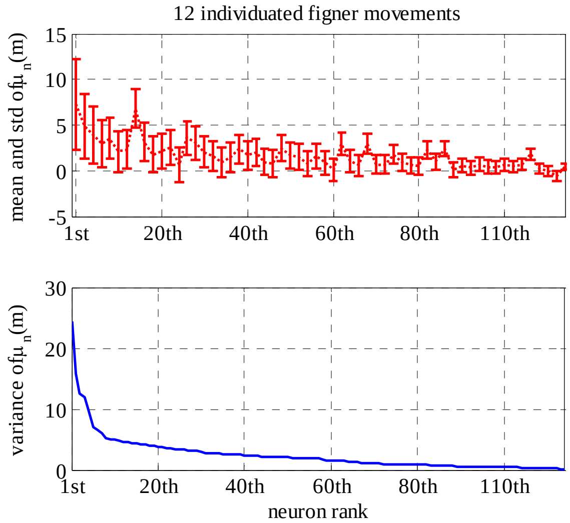

Fig. 3. Variance and mean of averaged absolute importance of each neuron for 12 individuated movements.

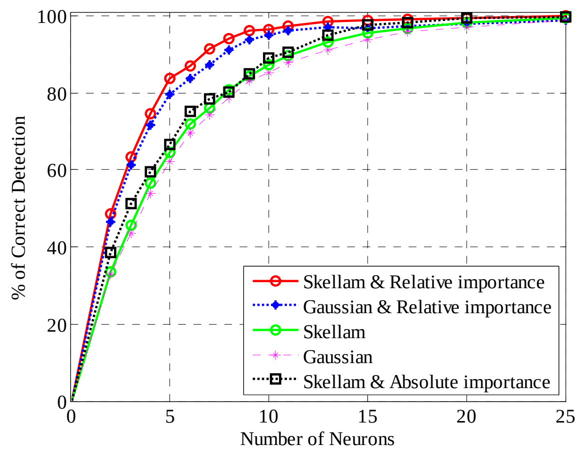

Fig. 4. Performance of the ML decoding methods in individuated finger movements based on Skellam and Gaussian distributions with ordered neurons by the absolute importance (when m=1), the variance of the individuated movement activity and without any ordering.

performance. The absolute importance for the specific movement gives the information mainly related to the specific movement and thus we need to obtain relative importance by computing the variance of the absolute importance values, V_n. For the 12 individuated movements, we computed V_n for each neuron and arranged them in the decreasing order. Fig. 3 shows V_n and for the ordered neurons, where we can find that some neurons have larger values of $\bar{\mu}_n$ than others. Since $\bar{\mu}_n$ is the mean value of $\mu_n(m)$ for all movements, it represents the mean of absolute importance of the neuron n. This means that some neurons with the high absolute importance may have low relative importance if they have the similar contributions to all movements. Also, from the plot of V_n we can find that a

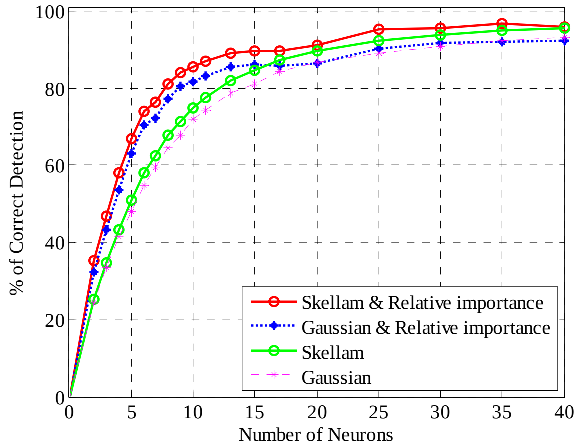

Fig. 5. Total movements performance of the Skellam and Gaussian distribution based ML decoding methods with ordered neurons by the variance of the combined-finger activity, and without any ordering.

knee occurs near the 10th neuron, which makes us expect that neural decoding performance would saturate around 10th neurons.

In the fig. 4, the use of the proposed neuron selection method in individuated movements improved decoding accuracy by about 23.30 % in the case of 5 neurons and about 9.23 % in the case of 10 neurons. With only 15 highly-ranked neurons, the decoding accuracy of almost 99.48% was achieved. As shown in the fig. 5, the performance improvement is still maintained when combined movements of two fingers were added though the decoding accuracy was about 95.66%.

4. CONCLUSION

We have presented a neuron selection method based on the neural activity by defining the relative importance of each neuron contributing to motor movements. The proposed neuron selection method improved the neural decoding performance remarkably due to the use of highly tuned neurons. In other respect, neuron selection may decrease the required number of neurons for neural decoding. This is very meaningful for implementation of low-power and potable BMI devices.

5. REFERENCES

[1] P. R. Kennedy, R. A. Bakay, M. M. Moore, K. Adams, J. Goldwaithe, “Direct control of a computer form the human central nervous system,” IEEE Trans. Rehab. Eng., vol. 8, pp. 198-202, June 2000.

[2] Wessberg, J., Stambaugh, C. R., Kralik, J. D.,Beck, P. D.,Laubach, M., Cahpin, J. K., et al. "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," *Nature*, vol. 408, no. 6810, pp. 361-365, 2000.

[3] D. W. Moran, A. B. Schwartz, "Motor cortical activity during drawing movements: Population representation during spiral tracing," J. Neurophysiol., vol. 82. pp.2693-2704, 1999.

[4] D. M. Taylor, S. I. H. Tillery, A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," Science, vol. 296, pp. 1829-1832, 2002.

[5] M. D. Serruya, N. G. Hatsopoulos, L. Paninski, M. R. Fellows, and J. P. Donoghue, "Instant neural control of a movement signal," *Nature*, vol. 416, no. 6877, pp. 141-142, 2002.

[6] J. M. Carmena, M. A. Lebedev, R. E. Crist, et al., "Learning to control a brain-machine interface for reaching and grasping by primates," PLoS Biology, vol. 1, no. 2, article E42, 2003.

[7] A. Georgopopoulous. J. Kalaska, R. Caminiti, j. Massey, "On the ralations betweeen the direction of two-dimensional arm movements and cell discharge in primate motor cortec," J. Nerurosci., vol. 2, pp1527-1537, 1982.

[8] D. T. Westwick, E. A. Pohlmeyr, S. A. Solla, L. E. Miller, E. J. Perreault, "Identification of multiple-input systems with highly coupled inputs: application to EMG prediction from multiple intracortical electrodes," Nerual Computation, vol. 18, no. 2, pp. 329-355, 2006.

[9] G. Singhal, V. Aggarwal, S. Acharya, J. Aguayo, J. He, N. Tahkor, "Ensemble Fractional Sensitivity : A Quantitative Approach to Neuron Selection for Decoding Motor Tasks," *Comput. Intell. Neurosci*., Feb 2010.

[10] J. C. Sanchez*, et al.*, "Ascertaining the importance of neurons to develop better brain-machine interfaces," *IEEE Trans Biomed Eng,* vol. 51, pp. 943-53, Jun 2004.

[11] Y. Wang*, et al.*, "Ascertaining neuron importance by information theoretical analysis in motor Brain-Machine Interfaces," *Neural Netw,* vol. 22, pp. 781-90, Jul-Aug 2009.

[12] R. Wahnoun*, et al.*, "Selection and parameterization of cortical neurons for neuroprosthetic control," *J Neural Eng,* vol. 3, pp. 162-71, Jun 2006.

[13] M. H. Schieber. "Individuated finger movements of rhesus monkeys: a means of quantifying the independence of the digits," J. Neurophysiol. vol. 65, no. 6, pp. 1381-1391, June 1991.

[14] M. H. Shieber. L. S. Hibbard, "How somatotopic is the motor cortex hand area?," Science, vol, 261, pp. 489-492, July 1993.

[15] A. V. Poliakov, M. H. Schieber, "Limted fucntional grouping of neurons in the motor cortex and area during in inviduated finger movements: A cluster analysis," J. Neurophysiol., vol. 82, pp. 3488-55, Dec. 1999.

[16] A. P. Georgopoulos, G. Pellizzer, A. V. Poliakov, M. H. Scheiber, "Neural coding of finger and wrist moevments," J. Comput. Neurosci., col. 6, pp. 279-88, May-jun. 1999.

[17] M. H. Scheiber, "Motor cortex and the distributed anatomy of fonger movements," Adv. Exp. Med. Biol., vol. 508, pp. 411-6, 2002.

[18] V. Aggarwal*, et al.*, "Asynchronous decoding of dexterous finger movements using M1 neurons," *IEEE Trans Neural Syst Rehabil Eng,* vol. 16, pp. 3-14, Feb 2008.

[19] S. Acharya*, et al.*, "Decoding individuated finger movements using volume-constrained neuronal ensembles in the M1 hand area," *IEEE Trans Neural Syst Rehabil Eng,* vol. 16, pp. 15-23, Feb 2008.

[20] H.-C. Shin*, et al.*, "Neural Decoding of Finger Movements Using Skellam Based Maximum Likelihood Decoding," *IEEE Trans Biomed Eng,* Apr 28 2009.

[21] M. Jazayeri and J. A. Movshon, "Optimal representation of sensory information by neural populations," *Nat Neurosci,* vol. 9, pp. 690-6, May 2006.