Published in final edited form as:

IEEE Trans Neural Syst Rehabil Eng. 2018 December ; 26(12): 2240–2248. doi:10.1109/TNSRE.

2018.2875731

Single-finger Neural Basis Information-based Neural Decoder (nBINDER) for Multi-finger Movements

Hwayoung Choi,

Department of Electronic Engineering, College of Information Technology, Soongsil University, Seoul 06978, Korea

Kyung-Jin You,

Department of Electronic Engineering, College of Information Technology, Soongsil University, Seoul 06978, Korea

Nitish V. Thakor, Fellow, IEEE,

Department of Biomedical Engineering, Johns Hopkins University, Baltimore, MD 21218, USA

Marc H. Schieber, and

Department of Neurology, Neurobiology and Anatomy, Brain and Cognitive Sciences and Physical Medicine and Rehabilitation, University of Rochester Medical Center, Rochester, NY 14642, USA

Hyun-Chool Shin, Member, IEEE

Department of Electronic Engineering, College of Information Technology, Soongsil University, Seoul 06978, Korea

Abstract

In this paper, we investigate the relationship between single and multi-finger movements. By exploiting the neural correlation between the temporal firing patterns between movements, we show that the Pearson's correlation coefficient for the physically related movement pairs are greater than those of others; the firing rates of the neurons that are tuned to a single-finger movements also increases when the corresponding multi-finger movements are instructed. We also use a hierarchical cluster analysis to verify not only the relationship between the single and multi-finger movements, but also the relationship between the flexion and extension movements. Furthermore, we propose a novel decoding method of modeling neural firing patterns while omitting the training process of the multi-finger movements. For the decoding, the Skellam and Gaussian probability distributions are used as mathematical models. The probabilistic distribution model of the multi-finger movements was estimated using the neural activity that was acquired during single-finger movements. As a result, the proposed neural decoding accuracy comparable with that of the supervised neural decoding accuracy when all of the neurons were used for the multi-finger movements. These results suggest that only the neural activities of single-finger movements can be exploited for the control of dexterous multi-finger neuroprosthetics.

Keywords

neural decoding; finger decoding; multi-finger movement

I. INTRODUCTION

NEURAL signals of motor neurons can be acquired regardless of the loss of a muscle or the command function. Thus, by using neural decoding technology, it is possible to interface a number of machines directly or indirectly to the brain. Various neural decoding algorithms have been developed and demonstrated in terms of neural prosthetic control applications. One of them is the *population vector* (PV), which is a method of the estimation of the information that is represented by the whole neuron network through the assignment of different weights according to the vector components that correspond to the amount of each neural activity [1]–[6]. The *artificial neural networks* (ANN) is one of the popular neural decoding approaches that uses a learning algorithm based on the biological nervous system. The ANN is applied in neural decoding research and its superior performance has been confirmed [7], [8]. The Kalman filter-based neural decoding method is used to calculate the probability of neural activity showing a predefined state, and it is mainly used for the monitoring of the cursor control and three-dimensional (3D) arm trajectories [9], [10]. In addition, the *maximum likelihood* (ML) methods have provided promising results for the decoding of movements [11]–[13].

To make a bionic arm perform a function similar to a real human hand, the neural decoding technique should be able to discriminate between dexterous finger movements and simple ones. In [14], it was demonstrated that both hand translation and hand rotation can be decoded simultaneously from a population of motor cortical neurons. In [15], wherein the movements of the thumb, index and little fingers are shown to be more highly individuated than the movements of the middle or ring fingers through experiments with normal humans. Such a finding also matches the characteristics of actual finger movements. In [16], 27 degrees of freedom representing complete hand and arm kinematics were decoded using neural activities in M1 and F5. These findings triggered the development of brain-machine interface restoring hand and arm movements. [17]–[20] have provided promising researches on neuroprosthetic hand or arm interface. In [21], it is shown that the neurons in the primary motor cortex are usually associated with more than a single-finger movement, and that the wrist and finger movements can be divided into the following two types: flexion and extension. In [22], it is reported that the neurons that are tuned to one or more finger movements are close to 75% of the neurons in the hand area of the primary motor cortex. The paper also shows that there are neurons that are tuned to the multi-finger movements, and that these neurons are distributed throughout the hand region of the primary motor cortex. This is consistent with the finding that the neurons that are used in the single-finger movements are scattered throughout the hand area, rather than at specific locations subdivided within the primary motor cortex [14]. In [13], the probabilistic characteristics of a neural-firing pattern are modeled, and the finger movements are estimated using an ML estimator. In [23], the principal component analysis and eigenvector analysis are implemented on neuronal patterns to check whether the brain utilizes the principal component in the control of single-finger or wrist movements. In [9] and [24], Aggarwal *et al.* designed nonlinear filters to detect the onset of movements, and they defined several movement states to estimate the arm, hand, and finger movements. Although the mechanisms or network models have not been explicitly known, it has been suggested that

the dexterous movements that are completed through the combination of individual muscular movement may be controlled by a new network of multiple types of multiple neurons [25]. Even if a multi-finger movement is anatomically a direct combination of single-finger movements, it is not clearly known whether a neurological relationship exists between the neural network of the multi-finger movements and that of the single-finger movements.

Considering only the flexion and the extension of the finger, 10 kinds of single-finger movements and 40 kinds of two-finger movements exist. If the elements of the finger movements, such as the angle of joints, the velocity of movements, or the muscle forces, are additionally considered, then the number of movement combinations would increase exponentially. Since the experiments require multiple training data to ensure the discrimination accuracy in all of the machinelearning techniques, it is difficult to implement prosthesis devices that support multi-finger movements. To address this problem, the training process of multi-finger movements need to be minimized.

This paper identifies whether the motor neurons that are involved in the single-finger movements show neural activation during multi-finger movements. Inspired by this observation, a method of modeling the neural-firing patterns of multi-finger movements is proposed only using single-finger movements. A neural information related to single-finger movements is used as a neural basis for multi-finger decoding; i.e., the neural basis informs a neural decoder (nBINDER) of building neural activation models of multi-finger movements. The proposed nBINDER is verified by comparing the accuracy of neural decoding with that of the conventional method [13], which requires supervised models using training data of multi-finger movements. The proposed nBINDER is highly innovative in that it can overcome the limitations of the existing methods, which requires the training data.

II. MATERIAL AND METHODS

A. Experimental Protocol

A detailed description of the data recording from the M1 neurons and the previously used ML decoding method can be found in [13]. All care and use of these monkeys was approved by the University Committee on Animal Resources at the University of Rochester. In this subsection, a brief summary of the experimental protocol is provided. Each monkey (*Macaca Mulatta*) was trained to perform visually cued individuated flexion and extension movements of the right hand fingers. Monkeys K and S each performed all 10 single-finger movements involving flexion or extension of a single digit. In addition, each monkey performed movements involving concurrent flexion or extension of two digits. Monkey K performed six multi-finger movements and monkey S performed two. We abbreviate each instructed movement using the number of the instructed digit (1=thumb through 5=little finger), and the second letter of the instructed direction (f=flexion and e=extension). For example, 4e indicates the extension of the ring finger and (1+2)f indicates the simultaneous flexion of the thumb and index finger. Sitting in a primate chair, the monkey placed the right hand in a pistol-grip manipulandum that separates each finger into a different slot. At the end of each slot, each fingertip laid between two micro-switches. By flexing or extending the fingers a few millimeters, the monkey closed the ventral and dorsal switches, respectively. This pistol-grip manipulandum was mounted, in turn, for axis-permitting

flexion and extension wrist movements. The monkey viewed a display on which each digit (or the wrist) was represented by a row of five light emitting diodes (LEDs). When the monkey flexed or extended a digit, thereby closing a micro-switch, the central yellow LED was deactivated and the green LED to the left or right, respectively, was activated. Therefore, the yellow and green LEDs informed the monkey of the switches that were open and those that were closed. The red LEDs at either end of the row were illuminated as cues that instructed the monkey to close either the flexion or the extension switch. The trained monkey was prepared for single-unit recording owing to the surgical implantation of both a head-holding device and a rectangular Lucite recording chamber that permitted access to an area encompassing the M1 that is contralateral to the trained hand. A few days after this procedure, daily recording session of 2–3 hours began. The data were recorded from 115 and 107 of the task-related neurons of the monkey K's and the monkey S's M1 neurons, respectively. The monkey performed all the 16 possible movements involving the flexion and extension of the fingers. The neurons have been recorded for at least six trials of each type of finger movement. A detailed description of the experimental protocol can be found in [14].

B. Neural Activations of Finger Movements

The *perievent time histogram* (PETH) shows the modulations of the temporal firing pattern in an event-dependent manner. Each subplot of Fig. 1 shows examples of the PETH (top) and the corresponding six spike-raster plots (bottom) of the M1 neuron during the 16 instructed finger movements. Parallel spike rasters from the six independent trials of each type of finger movement for each neuron were aligned at the time of the switch closure (1:0 s) of each 2:0 s display. The blue circle and the red triangle that are beneath each raster line indicate the times of the cue LED sign and the switch closure in each of the trials, respectively.

The K22404 neuron is active during the 4f and 5f movements. Interestingly, this neuron is also active during the finger 4 and 5 flexion, (4+5)f. The K13409 that is highly tuned for 2e is active for the (1+2)e and (2+3)e finger movements that are combinations of 2e and the other fingers. These two examples indicate that some neurons that are responsive to the single-finger movements are also participate in the corresponding multi-finger movements.

C. Neural correlation Between Multi-Finger Movements and Single-Finger Movements

1) Neural Correlation: To quantitatively analyze the neuronal correlation between the single and multi-finger movements, a calculation of the time-domain correlation in terms of the Pearson's correlation coefficients was performed. For the analysis, the 2:0 s recording interval was divided into three non-overlapping windows. 'Base' indicates the interval from 0:0 s to 0:7 s, which corresponds to the period before the finger movements, 'Onset' indicates the interval from 0:7 s to 1:4 s during the finger movements, and 'After' is the interval from 1:4 s to 2:0 s.

Let the vector $\mathbf{c}_m = [c_m(1) \ c_m(2) \ \cdots]$, and the corresponding PETH comprises the 20ms neuronal bin size for the finger movement m among the 16 possible choices. The relation

between the two corresponding PETH movements i and j of the given neuron was then measured using the Pearson's correlation coefficient.

$$\rho_{i,j} = \frac{\sum_t (c_i(t) - \bar{c}_i)(c_j(t) - \bar{c}_j)}{\sqrt{\sum_t (c_i(t) - \bar{c}_i)^2} \sqrt{\sum_t (c_j(t) - \bar{c}_j)^2}} \quad (1)$$

where $\bar{c}_m$ represents the time-averaged spike counts over the cm .

Fig. 2(a) shows the neuron-averaged correlation of all of the 115 neuronal movements during the onset period. Each dot represents the correlation, and the size and intensity of the circle is proportional to the correlation coefficient. It is evident that a strong neural correlation exists in the diagonal elements; this result represents the correlation between single-finger and related multi-finger movements. Not all of the neurons equally contribute to the finger movements; some of the neurons in fact are responsive to certain finger movements whereas some are not. Thus, 10 high-responding neurons were selected and grouped. This grouping was performed using a t -test ($p < 0.05$) for the PETHs on base and onset periods. Fig. 2(b) shows the results from the 10 high-responding neuron group for each single-finger movement. For the physically related single and combined-finger pairs, the correlation-coefficient values are as high as 0.7, and for uncorrelated pairs, the correlation-coefficient values are as low as 0.3 or less.

2) Hierarchical Cluster Analysis: Ward's minimum variance algorithm [26] is one of the bottom-up hierarchical cluster analysis methods, and it was used here to find the clusters or nodes with a minimal variance.

Let $r_n(m)$ be the neural activity (i.e., neuronal-spike counts over a (=700ms) temporal window) of neuron n for a finger movement m among the possible choices. The neural activation that is related to the m movement is defined by

$$x_n(m) = r_n(m) - r_n(0) \quad (2)$$

where $r_n(0)$ is the baseline activity of the neuron n before the finger movement, and $r_n(m)$ is the onset of the specific movement m .

The hierarchical-cluster analysis was used for this neural activation to confirm the inter-movement relationships. The dissimilarity of any two movements constitutes those hierarchical clusters with a Euclidean distance between $x_n(i)$ and $x_n(j)$. Through the completed cluster-tree structure, it is possible to confirm the movement that is most similar to the other movements; that is, the most suitable movement for the configuration of the cluster. It also verifies the number of merge levels that are required for the same cluster regarding a particular movement.

In Fig. 3, the left half of the circular movement shows the flexion movements and the right half shows the extension movements. An arc connects the two movements (or clusters)

represents a *merge*. The distance to the arc also indicates the dissimilarity of the two movements. As expected from the neural correlation analysis of Fig. 2, (1f, (1+2)f), (2f, (2+3)f), (5f, (4+5)f), (1e, (1+2)e), (2e, (2+3)e) and (5e, (4+5)e) are clustered in the same groups. From the clustering analysis, we can observe that single and the corresponding combined finger movements are clearly clustered in the same groups. Especially, although 4f and (4+5)f movements are not clearly correlated in Fig. 2, the clustering analysis shows the clear relation.

D. Stochastic Modeling of Neural Activations—An ML-based neural decoding finger movement algorithm has been proposed in the previous work [13]. The ML method can be used to estimate an unknown parameter m , the intended movement, so that the probability function $\Pr(x_1, x_2, \dots, x_N|m)$ is maximized,

$$\hat{m} = \underset{m}{\operatorname{argmax}} \Pr(x_1, x_2, \dots, x_N|m), \quad (3)$$

where N is the total number of neurons that are used for decoding. With the assumption that the activations among the neurons are independent: $x_f(m)$ and $x_g(m)$ are independent, as in [11]. Because of the randomness of the selection of the neurons from different electrode positions and trials in this study, the probability of the observed neural activations is represented by

$$\Pr(x_1, x_2, \dots, x_N|m) = \prod_{n=1}^N p(x_n|m). \quad (4)$$

To obtain the probability of the neural activation $x_n(m)$ that is the difference between two stochastic neuronal-spike counts, the Skellam distribution [27] was used. The Skellam probability $p(x_n|m)$ of the random variable $x_n(m)$ can be obtained by

$$p(x_n|m) = \alpha_n(m) \left(\frac{\mu_n(m)}{\mu_n(0)} \right)^{\frac{x_n}{2}} I_x(2\sqrt{\mu_n(m)\mu_n(0)}) \quad (5)$$

where $\alpha_n(m) = \exp[-\mu_n(m) - \mu_n(0)]$ and $I_x(z)$ is the modified Bessel function of the first kind. $\mu_n(m)$ denotes the estimation of the expectation of $r_n(m)$ for which the independent observations were averaged, and $\mu_n(0) = E[r_n(0)]$.

Another choice for modeling the probability distribution of the neural activations is Gaussian distribution, as follows:

$$p(x_n|m) = \frac{1}{\sqrt{2\pi}\sigma_n(m)} \exp\left[-\frac{(x_n(m) - E[x_n(m)])^2}{2\pi\sigma_n^2(m)}\right] \quad (6)$$

where $E[x_n(m)] = \mu_n(m) - \mu_n(0)$ and $\sigma_n^2(m)$ is the variance of $x_n(m)$.

To complete Equations (5) and (6), $\mu_n(m)$, $\mu_n(0)$ and $\sigma_n^2(m)$ are required. Since $\mu_n(0)$ is the baseline activity that is not related to movements, $\mu_n(m)$ and $\sigma_n^2(m)$ are actually needed for multi-finger movements, which are conventionally estimated from the training datasets.

E. Neural Activity Estimation for the Proposed nBINDER—Let m_A and m_B be different single-finger movements. Then, m_{A+B} represents a combined two-finger movement. For example, if $m_A = 2e$ and $m_B = 3e$, then $m_{A+B} = (2+3)e$. In most supervised neural decoding, $\mu_n(m_{A+B})$ and $\sigma_n^2(m_{A+B})$ have been estimated using the training data of the corresponding multi-finger movements, m_{A+B} . Here, we estimate $\hat{\mu}_n(m_{A+B})$ and $\hat{\sigma}_n^2(m_{A+B})$ only from the data of single-finger movements, m_A and m_B . In other words,

$$\begin{aligned}\hat{\mu}_n(m_{A+B}) &= f_\mu(\mu_n(m_A), \mu_n(m_B)) \\ \hat{\sigma}_n(m_{A+B}) &= f_\sigma(\sigma_n(m_A), \sigma_n(m_B))\end{aligned}\quad (7)$$

where $f_\mu(\cdot)$ and $f_\sigma(\cdot)$ are arbitrary functions. The neural relationship between single and multi-finger movements investigated in Sec II-C. shows the feasibility of Equation (7). To complete Equation (7), we assume that the energy consumed during multi-finger movement is the averaged energy of the corresponding single-finger movements. To the best of authors' knowledge, we do not have any evidence or related works supporting this assumption. Based on the assumption, we use the following estimation for Equation (7):

$$\hat{\mu}_n(m_{A+B}) = \frac{\mu_n(m_A) + \mu_n(m_B)}{\sqrt{\sum_{n=1}^N (\mu_n(m_A) + \mu_n(m_B))^2}} \sqrt{\frac{E_A + E_B}{2}} \quad (8)$$

where E_A and E_B are the energy consumption in m_A and m_B , respectively, and are calculated by

$$E_A = \sum_{n=1}^N (\mu_n(m_A))^2, E_B = \sum_{n=1}^N (\mu_n(m_B))^2. \quad (9)$$

The estimated variance is also calculated in a similar manner with that of Equation (8),

$$\hat{\sigma}_n^2(m_{A+B}) = \frac{\sigma_n^2(m_A) + \sigma_n^2(m_B)}{\sqrt{\sum_{n=1}^N (\sigma_n^2(m_A) + \sigma_n^2(m_B))^2}} \sqrt{\frac{V_A + V_B}{2}} \quad (10)$$

where V_A and V_B are calculated by

$$V_A = \sum_{n=1}^N (\sigma_n^2(m_A))^2, V_B = \sum_{n=1}^N (\sigma_n^2(m_B))^2. \quad (11)$$

III. EXPERIMENTAL RESULTS

A. Accuracy of Estimated Neural-Activation Models

The accuracy of the estimated neural activation is visually shown in Fig. 4, wherein the examples of six neurons are shown. The different between the solid and chain lines is related to the accuracy of the estimated neural-activation models. For the purpose of visualization, all of the values were normalized using the maximal value of the neural activation of the neuron. For the neurons K23800, K21301, and K13300, the estimated models are very close to the actual models, and the estimation results are not as satisfactory for neurons such as K19201, K22005 and K35301. The results in Fig. 4(c) and Fig. 5(a) are consistent. For example, for K13300 neuron, the activation model for the (4+5)f movement is highly accurate as can be seen in Fig. 4(c) while the activation one for the (2+3)e movement is relatively not so accurate.

To quantify the estimation accuracy, the Hellinger distance, a disjointness measurement regarding the difference between the two probability distributions, was used. For the probability, the two distributions P and Q , the Hellinger distance d_H between them is defined as follows:

$$d_H(P, Q) = \frac{1}{\sqrt{2}} \|\sqrt{P} - \sqrt{Q}\|_2, \quad (12)$$

d_H is bounded by $[0, 1]$, where $\sqrt{P}$ is the square root of each element of P , and $\|\cdot\|_2$ is the Euclidean norm.

Fig. 5 shows examples of the Hellinger distance between the actual model and the estimated model regarding the neural activation in three neurons. Fig. 5(a) shows the comparison between the actual and the estimated models for the two movements, (4+5)f and (2+3)e. The neuron K13300 is similar to the actual model, but a difference was observed for the neuron K14801. Fig. 5 (b) shows the Hellinger distance value for six multi-finger movements. In the case of the K13300 neuron, all six of the movements exhibited an error of less than 0.25; however, for the K14801 neuron, all of the movements are not reproducible, especially for (1+2)e, and the measured distance is as high as 0.78. Thus, the estimated procedures were not successful for all of the neurons. Fig. 6 shows the Hellinger distance for all of the neurons in each of the movements. For its presentation, it was rearranged in the increasing order of the Hellinger distance. Table I. shows the average values of the model estimation error of all of the neurons in Skellam and Gaussian.

B. Proposed nBINDER Accuracy

Fig. 7(a) and Fig. 7(c) show the average decoding accuracy of the proposed nBINDER method compared to the conventional supervised decoding, which requires training data of multi-finger movements to decoding the multi-finger movements for monkey K and monkey S. Fig. 7(a) shows the accuracy for monkey K. The results for the two probability distributions, Skellam and Gaussian, are shown using an under triangle marker and a square marker, respectively. Using the Skellam distribution, the supervised neural decoding showed an average of 88.5% for 10 neurons and 99.2% for 30 neurons. The proposed nBINDER method showed a decoding accuracy of 64.3% for 10 neurons and 87.2% for 30 neurons. Also using the Gaussian distribution, supervised decoding showed an average of 84.7% with 10 neurons and 98.7% with 30 neurons. As for the nBINDER, the average decoding accuracies are 60.8% and 83.5% for 10 and 30 neurons, respectively. The results for the monkey S with the multi-finger movement datasets of (1+2)f and (1+2)e are shown in Fig. 7(c). Using the Skellam distribution, the average decoding accuracy is 99.7% for the 10 neurons using the supervised neural decoding, while the 30 neurons showed a 100.0% decoding accuracy. The proposed method, nBINDER, showed high decoding accuracy rates of 96.0% for the 10 neurons and 99.9% for the 30 neurons. Using the Gaussian distribution, supervised neural decoding showed an average of 99.4% for the 10 neurons, while 100% was shown for the 30 neurons. The nBINDER results comprise high decoding accuracy rates of 94.7% for the 10 neurons and 99.7% for the 30 neurons.

Fig. 7(b) and (d) display the decoding accuracy rates of the monkey K for six kinds of movements and those of the monkey S for two kinds of combined movements, respectively. In Fig. 7(b), it is observed that the decoding performance varies depending on the finger movements. This is because the estimated models are not accurate with small number of neurons. As the number of neurons increases, the variations reduce and the performance converges to 100% since the estimated models becomes accurate with more neurons. Table II. shows a summary of the average and standard deviation values of the decoding accuracy when using the nBINDER. Considering the feature of nBINDER, which does not require *a priori* training data for multi-finger movements, the decoding accuracy is not significantly lower compared with that of the supervised decoding.

IV. DISCUSSIONS AND CONCLUSIONS

Our important findings are: This paper presents a) a novel decoding method that can estimate the multi-finger movements without any *a priori* training information, and b) analytic results demonstrating neurological correlations between the single-finger and combined multi-finger movements.

A. Relevance of multi-finger and single-finger movement

Previous studies [14]–[16], [21], [22], [28] have shown that the M1 neurons are mostly related to the finger movements. In the past studies, however, only the relation between the neuron response and single-finger movements were considered. Although [25] confirms the relationship between the single-finger movements and multi-finger movements, it confirmed only the multi-finger movements that did not result from a simple linear combination of the

related single-finger movements, however, the relationship was not confirmed quantitatively. Related to the findings of these previous studies, the present study confirms the relationship between the multi-finger movements and the related single-finger movements using the Pearson's correlation and hierarchical clustering in Fig. 2 and Fig. 3. As a result, the correlation value of the single-finger movements that are related to multi-finger movement is as high as 0.7 when high-responding 10 neurons are used. This can be linked to [21] and [22], where one neuron is associated with more than just the single-finger movements. In addition, as confirmed by the hierarchical clustering, the related movement was merged into a higher group, which is demonstrated in by the correlation values. Also, the flexion and extension movements are connected to the last cluster, and this result is consistent with the previous research [21], which clarifies the finger movements can be divided tow types: flexion and extension. Thus, we can not only quantitatively confirm the neural relation between multi-fingers and single-finger movements, but also basically build the feasibility of the proposed nBINDER method.

B. Proposed nBINDER of multi-finger movements

There have been many previous studies decoding finger movements [13], [22], [24], [29], [30], but these studies require training data of all of finger movements for decoding. In [30], the *logistic regression* (LR) and the *softmax* (SM) estimator were used to investigate the neural decoding which does not require a training process of multi-finger movements. But the method did not produce meaningful results. The proposed nBINDER method, however, is not only a relatively simple decoding method, but also capable of achieving a high decoding accuracy without a training process of multi-finger movements. Unlikely the conventional approach focusing on developing better classifier, the proposed method tried to directly estimate the probabilistic models of neural activation for multi-finger movements based on the correlation study between single and multi-finger movements. Although here we use simple functions of (8) and (10) to complete (7) based on the assumption of the energy consumption, we expect better understanding or more analytic study on the neural mechanisms of finger movements help to find better estimation functions for (7).

The decoding accuracies of the proposed nBINDER method are compared with the previous study [13], which used the supervised neural decoding method. Unlike this previous study that focused on defining a probability model that considers the neural activity both before and after the finger movements, the focus of this paper is in defining a probability model when there is no training process for the multi-finger movements.

The results of this study on finger decoding can be used for the control prosthetic hands. The development of prosthetic hands capable of dexterous finger movements requires neural decoding of a massive number of finger movements. The proposed nBINDER technique can discriminate multi-finger movements based on independent and elementary finger movements. As such, the nBINDER helps the prosthetic hand users to skip the tedious multi-finger movement training process, which has been one of the common drawbacks of the existing methods.

C. Study Limitations and Future Extensions

In the estimation of the our probability model, it was assumed that a constant energy is consumed by the neurons. The high decoding accuracy may imply the possibility of this assumption, but the evidence of this assumption has not yet been produced. Afterwards, if a clear relationship to the energy consumption of the neurons is found, a more effective decoding strategy might be obtained with fewer neurons.

In the case of the monkey K, six types of multi-finger movements were performed, and in the case of the monkey S, only two types of multi-finger movements were performed. Therefore, only up to six results of the multi-finger movements could be confirmed in the decoding. The result of the proposed decoding method suggests that it is possible to control six multi-finger movements using the neural activities for 10 single-finger movements, but the decoding result for more variety of multi-finger movements may not be confirmed. Therefore, a further verification of the proposed decoding is needed via experiment involving a greater number of single-finger movements. As can be seen in Table II, nBINDER has lower accuracy than the conventional supervised decoding method that requires the training data although the decoding accuracy is the almost same as that of than the conventional one with more than 80 neurons. This is related with the accuracy of the estimated probabilistic models of multi-finger movements. To build the satisfactory estimated model, enough number of neurons need to be recorded.

Acknowledgments

This work was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science and ICT (No. 2017046246).

REFERENCES

- [1]. A. P. Georgopoulos, A. B. Schwartz, R. E. Kettner et al., "Neuronal population coding of movement direction," *Science*, vol. 233, no. 4771, pp. 1416–1419, 1986. [PubMed: 3749885]
- [2]. Kakei S, Hoffman DS, and Strick PL, "Muscle and movement representations in the primary motor cortex," *Science*, vol. 285, no. 5436, pp. 2136–2139, 1999. [PubMed: 10497133]
- [3]. Mason C, Gomez J, and Ebner T, "Primary motor cortex neuronal discharge during reach-to-grasp: controlling the hand as a unit." *Archives italiennes de biologie*, vol. 140, no. 3, pp. 229–236, 2002. [PubMed: 12173526]
- [4]. Collinger JL, Wodlinger B, Downey JE, Wang W, Tyler-Kabara EC, Weber DJ, McMorland AJ, Velliste M, Boninger ML, and Schwartz AB, "High-performance neuroprosthetic control by an individual with tetraplegia," *The Lancet*, vol. 381, no. 9866, pp. 557–564, 2013.
- [5]. Georgopoulos AP and Carpenter AF, "Coding of movements in the motor cortex," *Current opinion in neurobiology*, vol. 33, pp. 34–39, 2015. [PubMed: 25646932]
- [6]. Velliste M, Perel S, Spalding MC, Whitford AS, and Schwartz AB, "Cortical control of a prosthetic arm for self-feeding," *Nature*, vol. 453, no. 7198, pp. 1098–1101, 2008. [PubMed: 18509337]
- [7]. Wessberg J, Stambaugh CR, Kralik JD, Beck PD, Laubach M, Chapin JK, Kim J, Biggs SJ, Srinivasan MA, and Nicolelis MA, "Real-time prediction of hand trajectory by ensembles of cortical neurons in primates," *Nature*, vol. 408, no. 6810, pp. 361–365, 2000. [PubMed: 11099043]
- [8]. Mahmoudi B, Pohlmeier EA, Prins NW, Geng S, and Sanchez JC, "Towards autonomous neuroprosthetic control using hebbian reinforcement learning," *Journal of neural engineering*, vol. 10, no. 6, p. 066005, 2013. [PubMed: 24100047]

- [9]. Aggarwal V, Mollazadeh M, Davidson AG, Schieber MH, and Thakor NV, "State-based decoding of hand and finger kinematics using neuronal ensemble and lfp activity during dexterous reach-to-grasp movements," *Journal of neurophysiology*, vol. 109, no. 12, pp. 3067–3081, 2013. [PubMed: 23536714]
- [10]. Dangi S, Orsborn AL, Moorman HG, and Carmena JM, "Design and analysis of closed-loop decoder adaptation algorithms for brainmachine interfaces," *Neural computation*, vol. 25, no. 7, pp. 1693–1731, 2013. [PubMed: 23607558]
- [11]. Serruya M, Hatsopoulos N, Fellows M, Paninski L, and Donoghue J, "Robustness of neuroprosthetic decoding algorithms," *Biological Cybernetics*, vol. 88, no. 3, pp. 219–228, 2003. [PubMed: 12647229]
- [12]. Kemere C, Shenoy KV, and Meng TH, "Model-based neural decoding of reaching movements: a maximum likelihood approach," *Biomedical Engineering, IEEE Transactions on*, vol. 51, no. 6, pp. 925–932, 2004.
- [13]. Shin H-C, Aggarwal V, Acharya S, Schieber MH, and Thakor NV, "Neural decoding of finger movements using skellam-based maximum-likelihood decoding," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 3, pp. 754–760, 2010. [PubMed: 19403361]
- [14]. Wang W, Chan SS, Heldman DA, and Moran DW, "Motor cortical representation of hand translation and rotation during reaching," *The Journal of Neuroscience*, vol. 30, no. 3, pp. 958–962, 2010. [PubMed: 20089904]
- [15]. Häger-Ross C and Schieber MH, "Quantifying the independence of human finger movements: comparisons of digits, hands, and movement frequencies," *Journal of Neuroscience*, vol. 20, no. 22, pp. 8542–8550, 2000. [PubMed: 11069962]
- [16]. Menz VK, Schaffelhofer S, and Scherberger H, "Representation of continuous hand and arm movements in macaque areas m1, f5, and aip: a comparative decoding study," *Journal of neural engineering*, vol. 12, no. 5, p. 056016, 2015. [PubMed: 26355718]
- [17]. Hochberg LR, Bacher D, Jarosiewicz B, Masse NY, Simeral JD, Vogel J, Haddadin S, Liu J, Cash SS, van der Smagt P et al., "Reach and grasp by people with tetraplegia using a neurally controlled robotic arm," *Nature*, vol. 485, no. 7398, p. 372, 2012. [PubMed: 22596161]
- [18]. Homer ML, Perge JA, Black MJ, Harrison MT, Cash SS, and Hochberg LR, "Adaptive offset correction for intracortical brain– computer interfaces," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 2, pp. 239–248, 2014. [PubMed: 24196868]
- [19]. Downey JE, Weiss JM, Muelling K, Venkatraman A, Valois J-S, Hebert M, Bagnell JA, Schwartz AB, and Collinger JL, "Blending of brain-machine interface and vision-guided autonomous robotics improves neuroprosthetic arm performance during grasping," *Journal of neuroengineering and rehabilitation*, vol. 13, no. 1, p. 28, 2016. [PubMed: 26987662]
- [20]. Wodlinger B, Downey J, Tyler-Kabara E, Schwartz A, Boninger M, and Collinger J, "Ten-dimensional anthropomorphic arm control in a human brain- machine interface: difficulties, solutions, and limitations," *Journal of neural engineering*, vol. 12, no. 1, p. 016011, 2014. [PubMed: 25514320]
- [21]. Poliakov AV and Schieber MH, "Limited functional grouping of neurons in the motor cortex hand area during individuated finger movements: A cluster analysis," *Journal of neurophysiology*, vol. 82, no. 6, pp. 3488–3505, 1999. [PubMed: 10601477]
- [22]. Georgopoulos AP, Pellizzer G, Poliakov AV, and Schieber MH, "Neural coding of finger and wrist movements," *Journal of Computational Neuroscience*, vol. 6, no. 3, pp. 279–288, 1999. [PubMed: 10406138]
- [23]. Kirsch E, Rivlis G, and Schieber MH, "Primary motor cortex neurons during individuated finger and wrist movements: correlation of spike firing rates with the motion of individual digits versus their principal components," *Arm and Hand Movement: Current Knowledge and Future Perspective*, vol. 5, no. 70, p. 20, 2015.
- [24]. Aggarwal V, Acharya S, Tenore F, Shin H-C, Etienne-Cummings R, Schieber MH, and Thakor NV, "Asynchronous decoding of dexterous finger movements using M1 neurons." *IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society*, vol. 16, no. 1, pp. 3–14, 2 2008.

- [25]. Schieber MH, "How might the motor cortex individuate movements?" Trends in neurosciences, vol. 13, no. 11, pp. 440–445, 1990. [PubMed: 1701575]
- [26]. Szekely GJ and Rizzo ML, "Hierarchical clustering via joint between-within distances: Extending ward's minimum variance method," Journal of classification, vol. 22, no. 2, pp. 151–183, 2005.
- [27]. Skellam JG, "The frequency distribution of the difference between two Poisson variates belonging to different populations." Journal of the Royal Statistical Society. Series A (General), vol. 109, no. Pt 3, p. 296, 1946.
- [28]. Schieber MH, "Motor cortex and the distributed anatomy of finger movements," in Sensorimotor Control of Movement and Posture Springer, 2002, pp. 411–416.
- [29]. Acharya S, Tenore F, Aggarwal V, Etienne-cummings R, Schieber MH, Thakor NV, and Shin H.-c., "Decoding individuated finger movements using volume-constrained neuronal ensembles in the M1 hand area." IEEE transactions on neural systems and rehabilitation engineering : a publication of the IEEE Engineering in Medicine and Biology Society, vol. 16, no. 1, pp. 15–23, 2 2008.
- [30]. Hamed SB, Schieber MH, and Pouget A, "Decoding M1 neurons during multiple finger movements," Journal of Neurophysiology, vol. 98, no. 4 2007, pp. 327–333, 2007. [PubMed: 17428905]

Fig. 1.

Examples of perievent time histogram (PETH, top, bin size; 25 ms) and the corresponding spike-raster plots (bottom, 6 trials) of the M1 neuron (K22404 and K13409) during 16 finger movements. The data are aligned on movement timing (i.e., switch closure) at 1:0 s. The recording interval 2:0 s is divided into three non-overlapped periods; base (0:0 s to 0:7 s), onset (0:7 s to 1:4 s) and after movements (1:4 s to 2:0 s). The first and second markers indicate the time of the cue LED sign and the switch closure in each trial, respectively.

Fig. 2.

Neural correlation between single and combined finger movements during the onset period. The size and the color of the circles are proportional to the correlation coefficient between the PETHs. The number belonging to circle indicates the ranking in a row for a combined finger movement. (a) all neurons and (b) high responding neurons.

Fig. 3.
Analyses of the neural-activation data: hierarchical clustering

Fig. 4.

Comparison of the actual and the estimated activation models for six neurons (a)–(f). Solid and chain lines indicate the spike counts of the actual and the estimated data, respectively.

Fig. 5.

Examples of the actual and estimated neural-activation models, and the Hellinger distance between them in three neurons K13300 (top), K30803 (middle), and K14801 (bottom). (a) The actual model (line) and the estimated model (line with marker) where the Skellam distribution was used for the two movements (4+5)f and (2+3)e. (b) Hellinger distance in all of the movements.

Fig. 6.
 d_H values for various multi-finger movements for which the neurons were rearranged in the short distance.

Fig. 7.

Performance(mean $\pm$ std) of the supervised decoder and nBINDER methods for the multi-finger movements with the randomly selected neurons in the case of the monkey K (top) and the monkey S (bottom). (a) Average decoding accuracies for the six movements of the monkey K, (b) nBINDER accuracies for the six movements using the Skellam distribution, (c) average decoding accuracies for the two movements of the monkey S, and (d) nBINDER accuracies for the two movements using the Skellam distribution.

Table IAVERAGED d_H FOR THE SKELLAM AND GAUSSIAN.

modeling	movements					
	(1+2)f	(2+3)f	(4+5)f	(1+2)e	(2+3)e	(4+5)e
Skellam	0.337	0.346	0.315	0.448	0.317	0.325
Gaussian	0.396	0.393	0.343	0.487	0.360	0.353

Table II

SUMMARY OF THE DECODING RESULTS FOR THE COMBINED TWO-FINGER MOVEMENTS(%
MEAN $\pm$ STD, NEURONS ARE RANDOMLY SELECTED.)

modeling	mov	10 neurons	30 neurons	80 neurons
Skellam	(1+2)f	60.6 $\pm$ 32.5	79.3 $\pm$ 26.6	96.7 $\pm$ 8.6
	(2+3)f	50.8 $\pm$ 32.5	80.6 $\pm$ 23.5	98.6 $\pm$ 4.9
	(4+5)f	66.2 $\pm$ 28.7	90.1 $\pm$ 16.1	99.9 $\pm$ 0.9
	(1+2)e	74.0 $\pm$ 29.4	95.5 $\pm$ 12.7	100.0 $\pm$ 0.0
	(2+3)e	63.1 $\pm$ 30.0	83.3 $\pm$ 21.0	98.8 $\pm$ 5.9
	(4+5)e	71.1 $\pm$ 26.0	94.4 $\pm$ 11.3	100.0 $\pm$ 0.0
	AVG	64.3 $\pm$ 8.3	87.2 $\pm$ 7.1	99.0 $\pm$ 1.3
K	(1+2)f	51.7 $\pm$ 32.0	64.2 $\pm$ 31.1	82.0 $\pm$ 24.2
	(2+3)f	53.4 $\pm$ 29.1	86.0 $\pm$ 18.0	99.6 $\pm$ 2.7
	(4+5)f	61.4 $\pm$ 29.8	85.9 $\pm$ 19.0	99.9 $\pm$ 1.6
	(1+2)e	64.6 $\pm$ 31.5	89.6 $\pm$ 17.8	99.6 $\pm$ 2.7
	(2+3)e	72.1 $\pm$ 27.2	93.5 $\pm$ 13.8	100.0 $\pm$ 0.7
	(4+5)e	61.5 $\pm$ 29.0	82.3 $\pm$ 20.3	98.8 $\pm$ 4.6
	AVG	60.8 $\pm$ 7.5	83.5 $\pm$ 10.2	96.6 $\pm$ 7.2
Skellam	(1+2)f	94.0 $\pm$ 15.6	99.8 $\pm$ 1.9	100.0 $\pm$ 0.0
	(1+2)e	98.0 $\pm$ 8.2	100.0 $\pm$ 0.0	100.0 $\pm$ 0.0
	AVG	96.0 $\pm$ 2.8	99.9 $\pm$ 0.1	100.0 $\pm$ 0.0
S	(1+2)f	92.2 $\pm$ 15.7	99.4 $\pm$ 3.7	100.0 $\pm$ 0.0
	(1+2)e	97.1 $\pm$ 9.9	100.0 $\pm$ 0.5	100.0 $\pm$ 0.0
	AVG	94.7 $\pm$ 3.4	99.7 $\pm$ 0.4	100.0 $\pm$ 0.0