Neural Subset Decoding of Finger Movements

Hyun-Chool Shin, Marc H. Schieber and Nitish V. Thakor

Abstract— **We present neural decoding results for both single and multi-finger movements depending on neural subsets. Experimentally, data were collected from 115 task-related neurons in M1 as the monkey preferred flexion and extension of each finger and the wrist (12 single and 6 multi-movements). The neural decoding is done by an optimal method which is based on the maximum likelihood (ML) inference. Each neuron's activation is quantified by the change in firing rate in before and after finger movements. The results show that with as few as 20-25 randomly selected neurons, we achieved 99% or higher decoding accuracy for single finger movements. The decoding accuracy was 5-10% lower for two-finger movements, but increased to greater than 95% with 30 or more neurons.**

I. Introduction

In the recent paper [1], we have described ML-based neural decoding results for single movements. The decoding was done by the newly introduced Skellam-based likelihood function model. As a result, we have shown that we can infer which finger intended to move based only on M1 neurons' electrical activities with high accuracy.

Here, we present supervised neural decoding results for both single and multi-finger movements. In this study we attempt to answer the following questions:
• Based only on M1 neurons's electrical activities, can we infer which multi-fingers intended to move (including the differentiation between extension or flexion)?
• Given a micro-electrode array, where should we place or implant the recording electrode within M1 area for best decoding performance?

The first and second questions are important in that for controlling a prosthetic hand, we would need to implant a multielectrode array, presumably define optimal placement, and then determine the number of neurons that would be needed to be recorded from these electrodes. Once the location and the population of neurons is obtained, we can then determine the decoding performance that could be achieved for dexterous finger movements with an implanted array.

II. Materials and Methods

We have already described data recording from M1 neurons and maximum likelihood decoding method

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[1]. Here, we briefly summarize the materials and methods. A male rhesus monkey (macaca mulatta) was trained to perform visually cued individuated finger movements. There are 12 different types of the movements: flexion and extension of the right five fingers and wrist. Sitting in a primate chair, the monkey placed the right hand in a pistol-grip manipulandum which separated each finger into a different slot. At the end of each slot, each fingertip lay between two micro-switches. By flexing or extending a digit a few millimeters, the monkey closed the ventral or dosal switches, respectively. This pistol grip manipulandum was mounted, in turn, on an 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, closing a micro-switch, the central yellow LED went out and the green LED to the left or right, respectively, came on. The yellow and green LEDs thus informed the monkey which switches were open and which were closed. Red LEDs at either end of the row were illuminated as cues instructing the monkey to close either the flexion or extension switch. A detailed description of the experimental protocol can be found in [16][17]. We abbreviate each instructed movement with the number of the instructed digit (1=thumb through 5=little finger, w=wrist), and the first letter of the instructed direction (f=flexion and e=extension). For example, '4e' indicates instructed extension of the ring finger.

The trained monkey was prepared for single-unit recording by surgically implanting both a head-holding device and a rectangular Lucite recording chamber that permitted access to an area encompassing M1 contralateral to the trained hand. A few days after this procedure, daily 2- to 3-hour recording sessions began. Data were recorded from 115 task-related neurons in the M1 neurons of the monkey. The monkey performed all 12 possible movements involving flexion and extension of a single digit or of the wrist. The neurons have been recorded for 6 trials of each type of finger movement.

III. Experimental Results

A. Dependence of Decoding Performance on Neuronal Subsets

We examined the decoding performance for different neuronal population subsets. We recorded from 115 neurons individually (i.e. one after another using single microelectrode impalement) and obtained the responses during 12 instructed finger movements. In
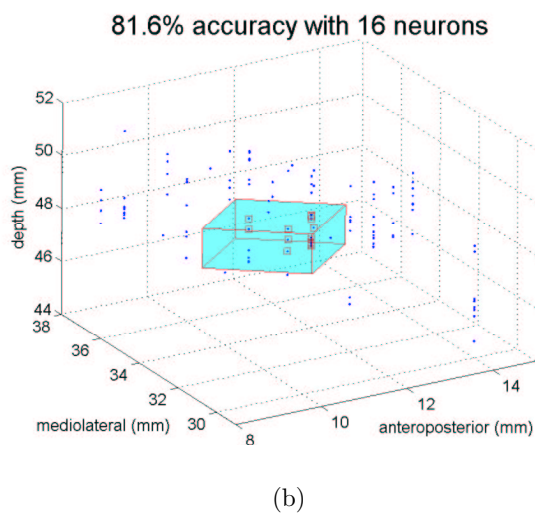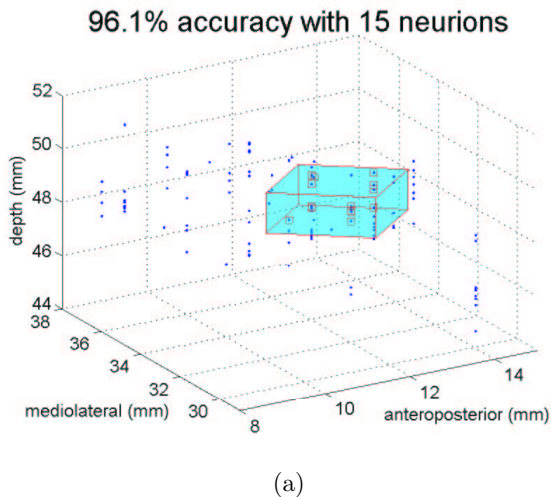
(a)

(b)

Fig. 1. ML decoding performance depending on selected subsets of neurons. 115 blue dots represent the single-unit neuron recording locations. The blue box represents a subset of neurons which would be simultaneously recordable using a multi-channel electrode (clearly this is a hypothetical illustration of past synthesized data that remains to be experimentally validated).

Fig. 1, each recorded neuron is shown as a single blue point where the depth, mediolateral and anteroposterior values are indicated in X, Y, and Z axes. To demonstrate that it should be possible to identify the site(s) for chronic multielectrode array implantation, and to record the signals associated with finger motion tasks in chronically instrumented primates, we chose a subset of neurons from the 115 neurons of monkey K with which to decode finger movements. The subset selection was done using a tetrahedral box approximately representing a volume covered by a microelectrode array. We call this a virtual implanted microelectrode array. For example, the blue box in Fig. 1 (a) captures only 15 neurons. Still, with only with the selected neurons we still obtained 96.10% finger decoding accuracy using the ML decoding strat-
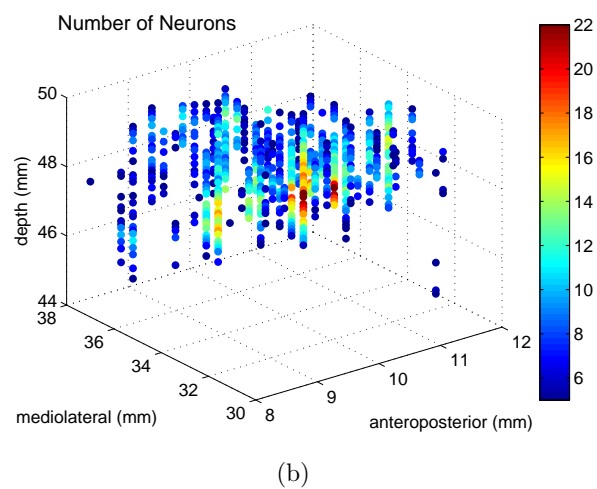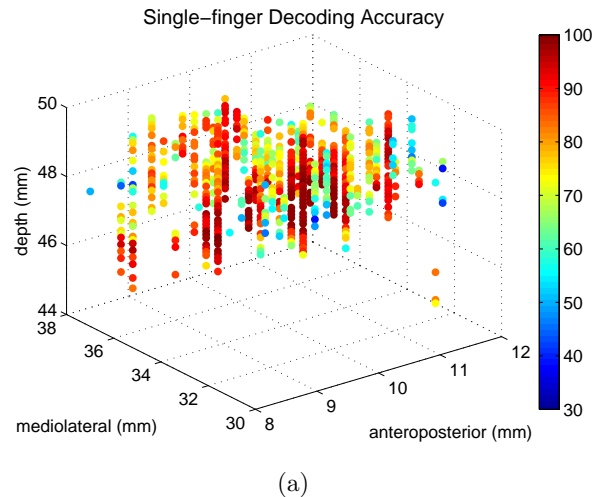

(a)

(b)

Fig. 2. Decoding performance depending on neuron subsets. Each point indicates the center of the virtual microelectrode array. (a) ML decoding accuracy in % (b) the number of neurons in selected subsets.

egy. Using another virtual microelectrode array, we capture a subset of 16 neurons as shown in Fig. 1 (b). In this case the decoded performance is as comparatively poor, 81.6%, even though the number of neurons is greater than Fig. 1 (a). These result indicate that the decoding performance is somewhat dependent on the placement of the virtual microelectrode array and the specific neuron population selected particularly when a small number of neurons is used for decoding. Fig. 2 (a) visualizes the decoding performance of 630 different subsets and Fig. 2 (b) illustrates how many neurons are contained in each subset. Each point indicates the center of the blue box and the color of the point represent the decoding accuracy or the number of neurons. We can clearly see the performance is very sensitive to subsets, i.e., the location of the box virtually representing virtual microelectrode array. This result gives a good indication of the role the exact microelectrode placement
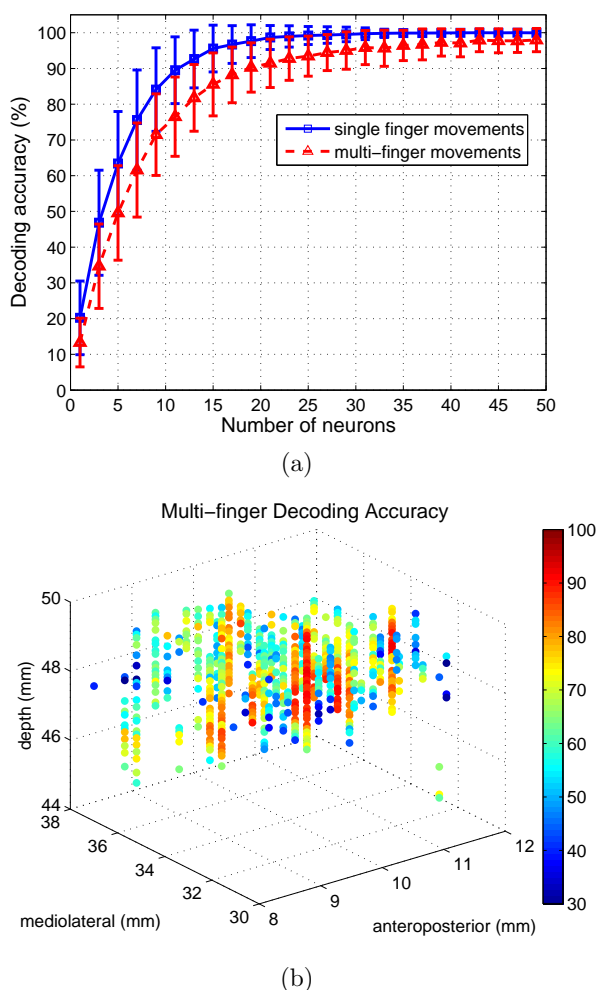
(a)

(b)

Fig. 3. Performance of the ML decoding of two-finger movements (a) ML based neural decoding results of single and multi-finger movements with training. The upper blue curve shows the accuracy of decoding 12 single fingers and the lower red curve shows the result of decoding the full 18 movements: 12 single and 6 dual-fingers. We achieved a decoding accuracy of 99% for single finger movement with fewer than 25 neurons, and 95% for multi-finger movements with 30 neurons. (b) Decoding performance of 12 single and 6 two-finger movements depending on 630 neuron subsets.

plays.

B. Neural Decoding of Two-finger Movements

In addition to single finger movements, the monkey was also instructed to perform six two-finger movements: f1+2, f2+3, f4+5, e1+2, e2+3, e4+5. Thus, there are 18 candidates of finger movements. The decoding results of single and multi-finger movements by using the trained ML decoder are shown in Fig. 3 (a). The decoding accuracy is $5 - 10\%$ lower for two-finger movements, but increases to greater than 95% with 30 or more neurons. Also in Fig. 3 (b) we plotted the multi-finger decoding performance depending for the 630 subsets. As in the single finger case, each

point indicates the center of the box virtually representing micro electrode array.

IV. DISCUSSION

We have described ML-based neural decoding results for multi-finger movements. Experimentally we achieved 99% or higher decoding accuracy for single finger movements. The decoding accuracy was 5-10% lower for two-finger movements, but increased to greater than 95% with 30 or more neurons. For six 2-finger movement sets, blind decoding accuracy was 90% with 100 neurons.

Note that Fig. 1 shows the assembled sites of all recordings made using single electrode studies (and not simultaneous recording as proposed here). The figure shows the tracks along which the recordings were made as well as the sites of recording. Therefore, the blue box identifies a "virtual electrode" region within a volume of tissue from which neurons will be captured and data recorded and analyzed. In future we will be using a 16-electrode multidrive (Thomas). Hence we will be recording from a population of neurons simultaneously (unlike individual electrode recordings reported in our preliminary studies). The multielectrode array will encompass a square region, while movable electrode traversing depths at a given site will define a volume of tissue as illustrated in Fig. 1

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