Motor Cortical Adaptation Induced by Closed-Loop BCI

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Abstract— Brain-computer interface (BCI) could help disabled patients with a broken neural pathway from brain to limbs restore movements by directly exploiting brain signals. Current laboratory BCIs on nonhuman primates (NHPs) were usually started from open-loop hand control (HC) setup for calibration and training, and then progressed to closed-loop brain control (BC) setup without using natural limbs. Successful transition from HC to BC necessitated motor leaning and neural plasticity which might involve the cortical adaptation induced by learning BCI. One useful strategy is to design neural feedback procedure to assist such adaptation and learning. We present an intracortical BCI on NHP with our designed feedback training procedure. In particular, we showed the motor cortical adaptation in terms of single neuron spiking activity *in vivo* during the closed-loop motor learning induced by our designed feedback training procedure. This experimental work can complement the existing theoretical modeling works on such closed-loop learning process.

Index Terms— Brain computer interface, maximal a posterior, motor cortex, motor learning, neural decoding.

I. INTRODUCTION

Brain-computer interface (BCI) reads the neural signals from the brain and directly translates them as commands to an external device to help the disabled patients bypass the broken neural pathway from brain to limbs [1]. During the last decade, several groups have demonstrated the capability of extracting cortical neuronal activity from motor areas of brain for controlling computer cursor or robotic arm (see a recent review in [2] and more references therein), which showed great promise of BCI for such disabled patients.

Usually the BCI was started in open-loop setup through hand control (HC). It may use use some apparatus like joystick to provide calibration data for training. After training, the joystick was removed from the monkey's access for instructing the context of brain control (BC). It has been reported that the different contexts of control could introduce the change of neuronal tuning characteristics [3]–[5] and the BC immediately following HC was usually unsuccessful presumably the change of the context was too sudden [5]. Successful transition from the context of HC to BC necessitates the motor learning which may induce adaptation in the cortex [6]. There was a hypothesis [7] that the subjects may benefit from the feedback which trades feedback bias for motivation and success in the skill acquisition process, but only limited evidence was observed for it on EEG based BCI. In contrast, similar assisted feedback training principle was introduced for spiking [5], [8] and ECoG [9] based BCI,

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respectively, to help monkeys and patients successfully learn the context of BC and thus modulate their neural activity in closed-loop setup without using natural limb movement. Recently, [10] compared open-loop simulation and closed-loop experimental data, and showed the monkey could learn to compensate for certain types of bias in linear neural decoders. [11] further introduced a Bayesian framework to explicitly incorporate the assisted feedback into it and demonstrated its effectiveness through simulation. However, it is still unknown the neural basis for inducing plasticity and motor adaptation by means of BCI. We present here our intracortical BCI on NHP with this feedback training and motor learning, and in particular show the motor cortical adaptation in terms of single neuron spiking during motor learning from HC to BC in a single experimental day.

II. MATERIALS AND METHODS

All procedures and experiments described here were approved by the Singapore Health Services Institutional Animal Care and Use Committee and conform to the Guidelines for the Care and Use of Laboratory Animals.

A. Behavior Task

A male rhesus macaque was trained to perform the center-out reaches to three peripheral targets evenly spaced in the upper half-circle presented on a computer screen mounted vertically in front to it. The monkey was seated in a primate chair while his shoulder was abducted 90 degree and his elbow was supported by the primate chair, and was trained to use a joystick to control the computer cursor to reach three peripheral targets (right = 0 degree, forward = 90 degree, left = 180 degree) mainly by his wrist. Reaching to the left/right targets required wrist flexion/extension and to the forward target required ulnar deviation. The computer cursor movement speed was set constant for each target. In addition, the monkey was also trained to stop movement by holding the joystick at the neutral position. Such task design, i.e., the three directions of targets and the stop state, was mainly inspired by our further experiment on the self-driving mobile robot [12]. The feedback of joystick control was displayed as white circular cursor while the peripheral targets were displayed as a yellow square of larger size. Every trial started with acquisition of the computer cursor and waited the cue for a incoming reaching target chosen pseudo-randomly. After the target cue, the monkey has 4 sec to reach the target and hold for 0.2 sec for a successful trial to get a liquid reward.

B. Neural and Kinematics Recordings

We used the same recording apparatus as described previously [12]. Briefly, four floating microelectrode arrays (Mi-

croProbes, MD, USA) were implanted anterior to the central sulcus in the proximal arm region of the contralateral primary motor cortex (MI) to the trained (right) wrist/arm. Total 96 single-electrode were available with tip impedance of ~ 0.5 MΩ. Neuronal extracellular activities were simultaneously recorded with a Plexon data acquisition system (Plexon, TX, USA) with 40kHz sampling of extracellular voltage waveforms. Spike sorting was performed manually at the beginning of neural recording to build the templates and later was automatically done by Plexon online sorter and fixed thereafter in all sessions.

Analog joystick signals accompanying the overt wrist movement made by the monkey were also recorded from Plexon system and synchronized with neural recordings. Four different classes of movement were identified by the joystick signals, which represent right/left/forward movement and stop. During offline processing and building neural decoder, the segments of sorted neuronal spiking activity given these four different classes were extracted as inputs for the decoder with the corresponding class labels. During closed-loop brain control sessions, the class labels were defined as the three reaching targets of different directions.

C. Neural Decoder

Probabilistic inference based methods have been widely used in machine learning and emerged in neuroscience for neural decoding. We employed the maximal a posterior (MAP) method with a parametric modeling for the probability distribution of spiking activity as in [13]–[15]. In the framework of rate coding, it usually assumes that the conditional probability distribution of binned spike counts follows Poisson distribution [14], [15] given the target direction θ,

$$P(r|\theta) = [f(\theta)]^r \exp[-f(\theta)]/r! \tag{1}$$

where r is the spike count of a sorted single neuron within a single bin. $f(\theta)$ is the empirical tuning curve of the sorted single neuron. By further assuming conditional independence of spike count r_n of the n-th neuron, a joint conditional distribution for the recorded population $\{r_n\}$ can be obtained.

$$P(\{r_n\}|\theta) = \prod_{n=1}^{N} \frac{[f_n(\theta)]^{r_n}}{r_n!} \exp[-f_n(\theta)] \tag{2}$$

In fact, the spike count correlation coefficients are generally very small among cortical neurons within time interval of a few hundred milliseconds [14]–[16] and thus such conditional independence is a reasonable approximation. Moreover, we define a log likelihood (LLH) function $L(\theta)$ for the population as taking log of $P(\{r_n\}|\theta)$ and further removing the terms of independent on θ as follows.

$$L(\theta) = \sum_{n=1}^{N} L_n(\theta) = \sum_{n=1}^{N} r_n \log[f_n(\theta)] - \sum_{n=1}^{N} f_n(\theta) \tag{3}$$

Given recorded population of neuronal spike counts $\{r_n\}$, the movement direction can be inferred through MAP.

$$\hat{\theta} = \arg\max_{\theta} P(\theta|\{r_n\}) = \arg\max_{\theta} P(\{r_n\}|\theta)P(\theta) \tag{4}$$

Assuming a uniform prior $P(\theta)$ over the targets, the decision rule of (4) is equivalent to the maximal likelihood estimate

$\hat{\theta}$ which can be equivalently and more efficiently computed by using the LLH function $L(\theta)$.

$$\hat{\theta} = \arg\max_{\theta} P(\{r_n\}|\theta) = \arg\max_{\theta} L(\theta) \tag{5}$$

Notice that the LLH function of (3) is *linear* on the spike counts r_n given the neuronal tuning curve, i.e., a weighted average over spike counts. In this essence, it is similar to other linear classifiers such as Fisher linear discriminant and support vector machine. However, different from other linear classifiers, the weight for each sorted neuron in the Poisson decoder is fully determined by the tuning curve of itself. In addition, a neural network model has been described in [17] to perform the probabilistic computation implicitly by spiking neurons. Here, we are particularly interested in the motor cortical adaptation and learning with respect to such decoder in the closed-loop BCI.

D. Assisted Feedback Training in Closed-Loop

During the assisted feedback training, we modified the neural feedback computed from our neural decoder (5) to assist the cursor movement towards the correct direction. The previous works on velocity decoding [5], [8], [9] designed the assistance by blending the neural decoded velocity with an attracting velocity towards the correct target during the *entire* trial. Different from that, we designed the assistance by conditioning on the neural decoded direction in which *only* when the decoded direction $\hat{\theta}$ is different from the target direction θ^{targ}, the forthcoming neural feedback θ^{fb} would be modified in a probabilistic sense with strength s, i.e., $Pr(\theta^{\mathrm{fb}} = \theta^{\mathrm{targ}}|\hat{\theta} \neq \theta^{\mathrm{targ}}) = s$, with $s \in [0, 0.8]$. This *time multiplexed* feedback design blending brain and assistance control effectively ensured an overall success rate of $\geq 70\%$ in a session which could keep the monkey engaged and motivated. The hypothesis of this biased feedback was to shape the monkey's behavior and neural modulation by operant conditioning. As the performance improved, the bias was gradually reduced to zero in which the cursor control was solely from our neural decoder.

III. RESULTS AND DISCUSSION

We have built an intracortical BCI with the Poisson decoder for a rhesus monkey to learn the closed-loop BC on the center-out task. The input vector $\{r_n\}$ to our neural decoder was the spike counts of the online automatically sorted units with a time bin of $\Delta t = 500$ ms. For continuous control to reach targets, the decoder was operated in 20 Hz (i.e., every 50 ms) on the time bin without any time lag.

Here, we reported the results of multiple experimental sessions within a single day. We trained our decoder during HC session by estimating the tuning curves $f_n(\theta)$ of sorted neurons ($n = 43$). After that, we started closed-loop BC sessions by removing the joystick from monkey's access. The neural feedback for controlling the computer cursor movement was firstly dependent on both the assisted feedback training and our neural decoder, and was later solely determined by neural decoder when setting $s = 0$. During all the BC sessions, the spike sorter and the neural decoder were fixed to allow us studying the cortical adaptation induced by
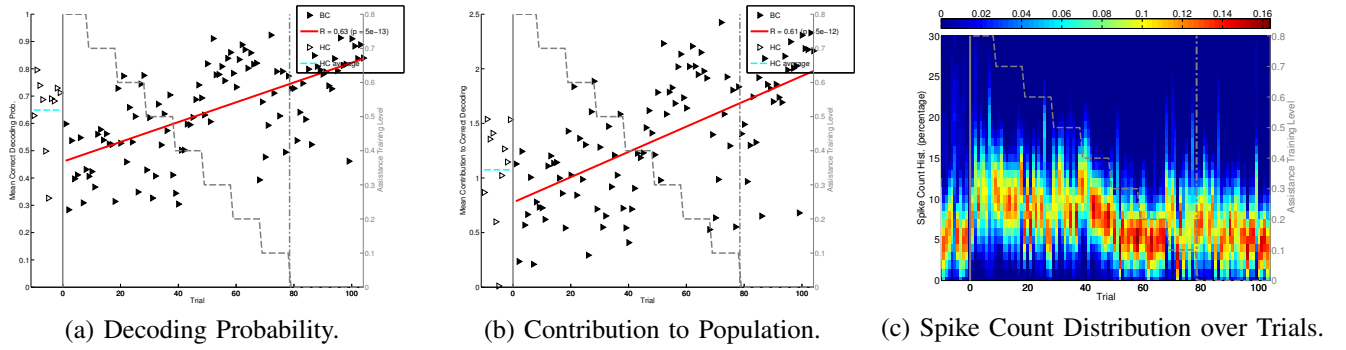
(a) Decoding Probability.   (b) Contribution to Population.   (c) Spike Count Distribution over Trials.

Fig. 1.   Single neuron (unit 28) spiking adaptation for the target direction of 0 degree (data set C20141024).

BCI[1]. The following results for these BC session data were computed offline by restricting decoder ouputs only to three targets, i.e., renormalizing the probabilities by excluding the stop state. In this dataset, we have 104, 100 and 96 successful BC trials for directions of 0, 90 and 180 degree, respectively.

A. Improvement of Brain Control by Assisted Feedback

Fig. 1 shows a typical example of single-neuron exhibiting spiking adaptation during closed-loop BC sessions. We show the correct decoding probability $P(\theta|r_{28})$ computed offline by this sorted neuron alone. Note that although the assistance feedback training was applied when $s > 0$, here we only showed the decoding probability *before* feedback assistance and thus truly reflected the ongoing neural activity and its BC performance. The decoding probability for each trial was computed as the arithmetic mean of the decoding probabilities for all the bins within a given trial. Fig. 1 shows all successful trials to the direction of 0 degree. The unfilled symbols before trial 0 (at the left gray solid vertical line) in Fig. 1(a) show the results from the HC session for comparison. All the filled symbols represent the results from BC sessions. The right gray dot-dash vertical line shows the end time of the feedback training and after that the monkey took full control of cursor by the neural decoder ($s = 0$). In between were the feedback training sessions where the gray dash line showed the assistance level s. We fitted the linear regression line shown overlaid in red. The correlation coefficient is 0.63 and it is statistically significant based on its *p*-value. Although at the beginning of BC sessions (a few tens of trials), this neuron performed worse than the HC session, it slowly improved its decoding performance along the feedback training trials. After about 50 trials, it almost reached the level of HC session and further improved which clearly showed the motor learning process.

Besides the above single neuron analysis, we also show how about this single neuron's contribution to the population decoding in Fig. 1(b), with similar format and notation as in Fig. 1(a). For each bin, we computed the *ratio* between the decoding probability by this neuron and the probability by the whole population. Then for a given trial, we computed

the *geometric mean* of all such ratios within the given trial (For averaging ratios, geometric mean is more appropriate and conservative than arithmetic mean.). As shown in Fig. 1(b), it can be seen similar trend as in Fig. 1(a). In addition, this neuron had a significant contribution on decoding since the ratio was often larger than one. By linear regression, it also showed significant positive correlation with feedback training trials on motor learning. We also show two other neurons contributing to the other two directions of targets in Fig. 2(a) and (c) and in Fig. 2(b) and (d), respectively, which showed the similar trend as in Fig. 1.

B. Induced Adaptation of Single Neuron Spiking

Since the neural decoder was fully determined by the neuronal spiking rate, we further investigated the adaptation of single neuron spiking along with the above decoding probabilistic analysis. Fig 1(c) shows the evolution of the spike count distribution of this single neuron along with all successful trials to the target of 0 degree. Each column of the image shows the spike count distribution for a trial and we also show the distribution of HC session for comparison. It can be seen that at the beginning of BC sessions, the monkey increased the spike count greatly which deviated the HC session (decoder building session) and thus affected the correct decoding performance by this neuron. After about 40 trials, the monkey gradually declined the spike count and matched that of HC session and thus improved the performance. We also show the similar figures for two other neurons for the other two targets in Fig. 2(d) and Fig. 2(f), respectively. In particular, the neuron shown in Fig. 2(f) shows a different learning pattern. It slowly increased its spike count after about 50 trials to match that of HC session. This showed both excitation and inhibition of neuronal spiking were involved in the cortical adaptation during motor learning, and their effects on neural decoding were similar.

C. Discussion

Although the principle of assisted feedback training were reported in [5], [8], [9] to help monkey's leaning, there are still some questions about the neuro-feedback procedure to affect the extent of induced cortical adaptation [7], [18] in BCI community. Especially, the relation between feedback accuracy and the induction of motor adaptation remains not well understood, and the effectiveness of the biased feedback was speculative [7] in EEG based BCI. In addition, the learning process was not well reported partly due to the long

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[1]We did not wrap the monkey's right arm during BC sessions, but the monkey had learned the context of brain control after practicing for a while and just rested his hand on the primate chair. Although we did not measure the EMG signal of the monkey's forearm muscle, we did not see any movement of its forearm from the recorded video of the monkey's behavior and thus loosely confirmed the brain control without hand usage.

(a) Decoding probability.

(b) Decoding probability.

(c) Decoding contribution.

(d) Decoding contribution.

(e) Spike count distribution.
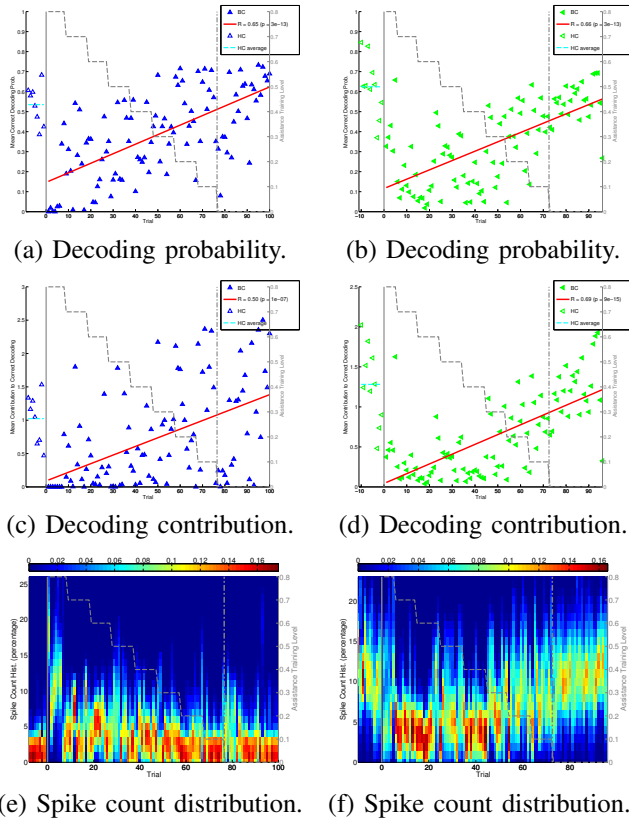

(f) Spike count distribution.

Fig. 2. Single neuron spiking adaptation for the directions of 90 degree (unit 26) and of 180 degree (unit 27), respectively (data set C20141024).

period of days or weeks [19]. In this work, we showed a relatively fast learning process for cursor control task. We modified the assisted feedback training for our decoder by controlled randomly biasing the decoding error towards to the target. Our result clearly demonstrated its effectiveness for motor learning, even just over about a few tens of trials.

Recently, the closed-loop learning also attracted attention in theoretical modeling. [20] presented a feedback error learning model to interpret the closed-loop learning process. In addition, [11] introduced a Bayesian framework to explicitly incorporated the assisted feedback training into it, which demonstrated its effectiveness by simulation. Our work complements these theoretical modeling studies by showing the cortical adaptation in the level of single neuron spiking *in vivo*. Due to the causal nature of the neural decoder, the improvement on the performance was indeed induced by the learning process during which the monkey successfully modulated the spiking rates of some neurons. Other forms of cortical adaptation were also reported in rats on the simpler 1D task of two directions [21] for the motor skill learning of real movements and in [22] for a BCI task only conditioning on one preselected single neuron.

IV. CONCLUSION

This paper presented a time multiplexed assisted feedback training for BCI and showed its effectiveness on motor learning in closed-loop BCI of cursor control. In particular, we showed the cortical adaptation in terms of single neuron spiking activity *in vivo* during the closed-loop motor learning

induced by our designed feedback training procedure. Both excitation and inhibition mechanisms were seen in single neuron spiking, and their effects on neural decoding were similar in terms of the correctly decoding probability and the relative contribution to the population. It remains to be understood the mechanism and function of cortical adaptation in the levels of single neurons, populations and networks when motor contexts change, given the same task.

REFERENCES

[1] J. P. Donoghue, "Bridging the brain to the world: a perspective on neural interface systems," *Neuron*, vol. 60, pp. 511 – 521, 2008.

[2] J. C. Kao, S. D. Stavisky, D. Sussillo, P. Nuyujukian and K. V. Shenoy, "Information systems opportunities in brain-machine interface decoders," *Proc. IEEE*, vol. 102, pp. 666 – 682, 2014.

[3] D. M. Taylor, S. I. Tillery, and A. B. Schwartz, "Direct cortical control of 3D neuroprosthetic devices," *Science*, vol. 296, pp. 1829 – 832, 2002.

[4] M. A. Lebedev and M. A. L. Nicolelis, "Cortical ensemble adaptation to represent velocity of an artificial actuator controlled by a brain-machine interfaces," *J. Neurosci.*, vol. 25, pp. 4681 – 4693, 2005.

[5] M. Velliste *et al.*, "Cortical control of a prosthetic arm for self-feeding," *Nature*, vol. 453, pp. 1098 – 1101, 2008.

[6] J. N. Sanes and J. P. Donoghue, "Plasticity and primary motor cortex," *Annu. Rev. Neurosci.*, vol. 23, pp. 393 – 415, 2000.

[7] A. Barbero and M. Grosse-Wentrup, "Biased feedback in brain-computer interfaces," *J. NeuroEng. Rehabil.*, vol. 7, pp. 1 – 4, 2010.

[8] J. L. Collinger *et al.*, "High-performance neuroprosthetic control by an individual with tetraplegia," *Lancet*, vol. 381, pp. 557 – 571, 2013.

[9] A. G. Rouse, J. J. Williams, J. J. Wheeler and D. W. Moran, "Cortical adaptation to a chronic micro-electrocorticographic brain computer interface," *J. Neurosci.*, vol. 33, pp. 1326 – 1330, 2013.

[10] S.M. Chase, A. B. Schwartz and R. E. Kass, "Bias, optimal linear estimation, and the differences between open-loop simulation and closed-loop performance of spiking-based brain-computer interface algorithms," *Neural Networks*, vol. 22, pp. 1203 – 1213, 2009.

[11] Y. Zhang, A. B. Schwartz, S. B. Chase and R. E. Kass, "Bayesian learning in assisted brain-computer interface tasks," in *Proc. Int. Conf. IEEE EMBS*, San Diego, CA, USA, Aug. 2012, pp. 2740 – 2743.

[12] Z. Xu *et al.*, "On the asynchronously continuous control of mobile robot movement by motor cortical spiking activity," in *Proc. Int. Conf. IEEE EMBS*, Chicago, IL, USA, Aug. 2014, pp. 3049 – 3052.

[13] R. S. Zemel, P. Dayan, and A. Pouget, "Probabilistic interpretation of population codes," *Neural Computation*, vol. 10, pp. 403 – 430, 1998.

[14] N. Hatsopoulos, J. Joshi, and J. G. O'Leary, "Decoding continuous and discrete motor behaviors using motor and premotor cortical ensembles," *J. Neurophysiol.*, vol. 92, pp. 1165 – 1174, 2004.

[15] G. Santhanam *et al.*, "A high-performance brain-computer interface," *Nature*, vol. 442, pp. 195 – 198, 2006.

[16] K. Padmanabhan and N. N. Urban, "Intrinsic biophysical diversity decorrelates neuronal firing while increasing information content," *Nature Neurosci.*, vol. 13, pp. 1276 – 1282, 2010.

[17] T. D. Sanger, "Neural population codes," *Curr. Opin. Neurobiol.*, vol. 13, pp. 238 – 249, 2003.

[18] M. Grosse-Wentrup, D. Mattia and K. Oweiss, "Using brain-computer interfaces to induce neural plasticity and restore function," *J. Neural Eng.*, vol. 8, pp. 1 – 5, 2011.

[19] K. Ganguly and J. M. Carmena, "Emergence of a stable cortical map for neuroprosthetic control," *PLoS Biol.*, vol. 7, pp. 1 – 13, 2009.

[20] R. Héliot, K. Ganguly, J. Jimenez and J. M. Carmena, "Learning in closed-loop brain-machine interfaces: modeling and experimental validation," *IEEE Trans. Systems, Man Cybern. - Part B*, vol. 40, pp. 1387 – 1397, 2010.

[21] D. Cohen and M. A. L. Nicolelis, "Reduction of single-neuron firing uncertainty by cortical ensembles during motor skill learning," *J. Neurosci.*, vol. 24, pp. 3574 – 3582, 2004.

[22] P.-J. Arduin *et al.*, ""Master" neurons induced by operant conditioning in rat motor cortex during a brain-machine interface task," *J. Neurosci.*, vol. 33, pp. 8308 – 8320, 2013.