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# Changes in Modulation Characteristics of Neurons in Different Modes of Motion Control Using Brain-Machine Interface

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*Abstract*— **In the research of motion control using brain-machine interface (BMI), analysis is usually conducted on one ensemble of neurons whose activity serves as direct input to the BMI decoder (control units). The number of control units is diverse in different control modes. That is to say, the size of dimensions of neural signals used in motion control is diverse. However, how will the behavioral performance change with this kind of diversity? What effects does this diversity have on modulation characteristics of control units? To answer these questions, we designed three modes of motion tasks using neural signals with different dimension sizes to control. Our results imply that as the dimension reduces, some deviations appear in behavioral performance. At the same time, the control units tend to have a directional division of control, then enhance their stability and increase modulations after division.**

## I. Introduction

Since the technical concept of "brain-machine interface (BMI)" was put forward, it has become promising frontier research in the field of neuroscience [1]-[5]. To date, BMI has been increasingly used as a tool to study the underlying mechanisms in the motor cortex. An ensemble of units is involved here: control units -- a group of units that are involved in the movement of external actuators, usually from the primary motor cortex (M1). Thereafter, we will refer to the dimension of signals from control units as control dimension. The more the control units are, the higher the control dimension is. However, the effects of the changes of control dimension on modulation characteristics of units are still opaque.

Studies demonstrated that these control units have different modulation characteristics in different control modes of the neural prosthesis [6]-[14]. Ganguly et al. found that the modulations of the control units switched with control mode by analyzing a small ensemble of units involved in motion [7]. Golub et al. projected neural control signals generally larger than 90D into low-dimensional subspace by dimensionality reduction and observed the characteristic changes in each dimension [10]. Xiao et al. introduced perturbed mapping on control units to study a long-term change in control units modulation after changing control modes [11]. Lansdell et al. proposed that dissociation of motor units required by a simultaneous BMI control and motion control can occur with individual unit specificity [14].

However, in previous studies, there were generally dozens of control units involved, which brings a huge computation burden to analyze each control unit from the perspective of single units. At the same time, the influence of the changes of control dimension on the modulation characteristics of control units is still unknown. Therefore, we designed an experimental paradigm of controlling 2D cursor movement by only two units, alongside traditional BMI control in all channels and manual control with a joystick. Since the control dimension sizes in the three modes are all diverse (manual control > all-channel brain control > 2-unit brain control), we can compare and analyze control units in the three control modes.

## II. Methods

### A. Experimental Subjects and Platform

The monkey implanted with one 96-channel intracortical microelectrode array (Blackrock Microsystems, US) in the primary motor cortex (M1) was raised in the Experimental Animal Center of Zhejiang University, China. All experimental procedures involving animal models described in this study were approved by the Animal Care Committee of Zhejiang University. We built an experimental platform that provided paradigm training for monkeys and recorded neural signals and kinematics information synchronously (Figure 1). After training, the monkey can complete three modes (manual control and two modes of brain control) of center-out control tasks.

### B. Training Process

During training each day, the monkey was required to complete two sessions of center-out tasks: the brain control session (BC) and the manual control (MC) session (Fig.1), respectively. In the brain control session, the neural signals from the monkey were transmitted to a Kalman filter to decode the cursor velocity and then updated the cursor position in the screen until the cursor hit the visual target within the fixed time. When each trial succeeded, the monkey can get some water as a reward. We used the methods described by Fraser & Schwartz [15] to access the stability of the units, so that the effects of the recording instability was excluded. We designed two modes of brain control: after the monkey achieved proficient cursor control with all channels, it was trained to

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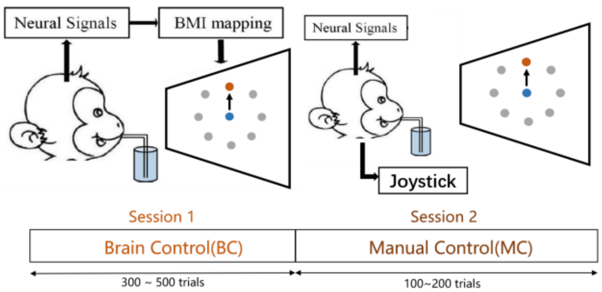


Figure 1. Schematic of the training process. The monkey controls a cursor to reach the target in different control modes.

control the cursor with only 2 units (2-unit brain control). We picked up several pairs of control units, and after training, the monkey also achieved successful control.

In the manual control session, the monkey completed the same center-out tasks with a joystick, and the neural signals were recorded synchronously.

### C. Single Unit Analysis

In this study, we performed the neural modulation analysis on every single unit. The firing rate of a unit during the total experiment time can be described by a cosine function of the movement direction according to the directional tuning model [16]. On account of this, we quantified two indicators to describe its modulation characteristics, namely, R square and modulation depth (MD) [16]. R square describes the goodness of fit, indicating how well the regression equation (i.e., the directional tuning model) fits the observed value. The modulation depth is the amplitude of the tuning model, which describes the gap between the firing rate in the preferred direction and the basal firing rate. It represents the modulation ability of the unit. Basal firing rate is the offset of the fitted cosine model relative to the origin and represents the average firing rate of the unit in all directions. The preferred direction is the direction corresponding to the maximum firing rate in the tuning model.

### D. Granger-causal Inference

Suppose we perform the *Full Regression* to predict variate $X$ based on its own past and the past of variate $Y$, and the *Reduced Regression* given by omitting the "historic" (past) $Y$ dependency [17]. To quantify the contribution that one unit has on movement, we adopted a Granger-causality type metric through the log-likelihood ratio:

$$\Gamma_{X\to Y} \equiv \ln\frac{|\Sigma'_{xx}|}{|\Sigma_{xx}|}. \quad (1)$$

where $\Sigma_{xx}$ and $\Sigma'_{xx}$ are the residuals covariance matrices of the "full regression" and "reduced regression" respectively.

Several former studies [17]-[19] have proved that Granger-causal Inference can be applied in neuroscience and $\Gamma$ has quantitative meaning. Thus $\Gamma$ can quantify how much each unit contributes to cursor movement. To make sure that all data used in Granger-causal Inference are stationary time series, we averaged neural signals and kinematic data across trials before analysis.

In this study, we quantified the contribution of the units to the horizontal and vertical motion, denoted as $\Gamma_x$ and $\Gamma_y$, by calculating the Granger-causal Inference between the firing rate and the horizontal and vertical velocity. In order to figure out whether the unit has some division in horizontal and vertical directions, we defined a directional-preference index. The directional-preference index of unit $i$ was then:

$$\mathcal{P}_i = (\Gamma_x - \Gamma_y) / (\Gamma_x + \Gamma_y). \quad (2)$$

This index ensured that an index of 0 corresponds to a unit that showed no preference to both directions; An index of 1 corresponds to a unit that only contributes to horizontal motion, and in contrast, an index of -1 corresponds to a unit that only contributes to vertical motion.

## III. Results

After training, the monkey successfully completed the 2D center-out cursor control task in three control modes: manual control, all-channel brain control and 2-unit brain control (average success rate all up to 0.9). Notably, we selected several pairs of control units and after training, the monkey can complete the task with the selected 2 units. In the Results, we selected data from three representative pairs of control units: Unit 12&32, Unit 35&51 and Unit 35&93 in 2-unit brain control, comparing with two other control modes, 10-15 sessions for each mode. The difference in data collection time used for comparison is no more than 500 trials, and there is no significant difference in neural signal stability.

Therefore, how do the behavioral performance and the modulation characteristics of the control unit change in different control modes since they have different control dimension sizes? We will use the methods mentioned above to discuss this problem.

### A. Reduction of Control Dimension Increases Motion Control Difficulty

Theoretically, if the number of control units decreases, the task may become more difficult, and there should be some decreases in performance. We analyzed two quantitative indicators of behavioral performance, success rate and reach time, after reaching proficient control in three control modes. In this paper, Fig. 2 shows the comparison results of three modes. We calculated the success rate and reach time during 10-15 experimental blocks, above 400 trials, for each control mode. In Fig. 2, bars in green, blue and red represent

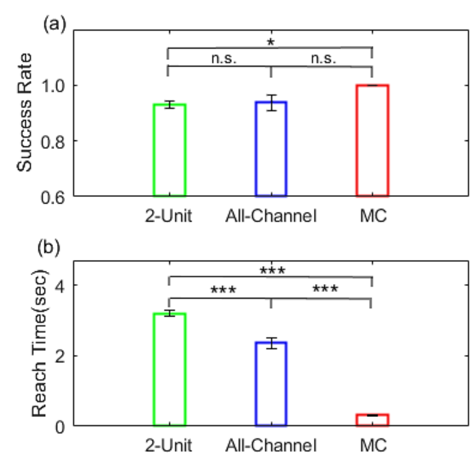


Figure 2. Behavioral performance comparison. (a) Success rate comparison of three control modes. (b) Reach time comparison of three control modes. Error bars represent the mean ± SEM. *** $p < 0.001$, * $p < 0.05$, n.s. not significant, Kruskal-Wallis test.

behavioral indicators of 2-unit brain control, all-channel brain control and manual control, respectively. Hereafter, we abbreviated three control modes as "2-unit", "all-channel" and "MC" in figures.

Fig. 2 indicates that manual control obviously performs much better than the brain-control mode in both the success rate and the time to reach the target. Moreover, the performance of all-channel brain control is also better than that of 2-unit brain control, comparing the mean and standard error of the mean (SEM): success rate: $0.93 \pm 0.01$, $0.94 \pm 0.03$ and $1.00 \pm 0.00$, respectively; reach time: $3.20 \pm 0.08$, $2.36 \pm 0.15$ and $0.31 \pm 0.02$, respectively. These results indicate that when the number of control units reduces from tens of thousands to dozens, and then reduces to only two, the behavioral performance will decrease. It corresponds with the theory that if the control dimension decreases, the control difficulty will increase.

### B. *Reduction of Control Dimension Motivates Directional Division of Units*

To investigate whether control units have a division of motion direction, we quantified the contributions of the same unit in three modes to the horizontal and vertical directions, denoted as $\Gamma_x$ and $\Gamma_y$, respectively. And then calculated the directional-preference index $\mathcal{P}$ for each control mode to compare and analyze. Neural signals and kinematic data were from 10-15 blocks, above 400 trials for each mode.

In Fig. 3, we plotted the distribution histogram of index $\mathcal{P}$ comparing three modes. In order to highlight the distribution rule of each mode, the median $\mathcal{P}_{median}$ was marked in the figure with inverted triangles. If a unit has no obvious directional preference, it will result in a $\mathcal{P}_{median}$ near 0. We can see from Fig. 3, the 2 control units always have directional division when performing the 2-unit brain control, but have less obvious division when performing two other control modes. For 2-unit brain control, there are always one unit whose index $\mathcal{P}$ has distributions peak near -1 (with $\mathcal{P}_{median}$ near -1), and the other unit whose index $\mathcal{P}$ has distributions peak near 1 (with $\mathcal{P}_{median}$ near 1). However, compared with the index distributions in the other two modes (bar in blue and bar in red), there are no such obvious distribution rules. This indicates that control units' division between directions can be very strong in the 2-unit control mode but nonexistent in all-channel brain control or manual control mode. In addition, the control units have a slight directional preference in all-channel brain control, compared to manual control. Thus, we can conclude that as the control dimension decreases, the control units have a trend to express division in motion directions, and even when the control dimension reduces to 2, the 2 control units will have a division in the horizontal and vertical motion directions respectively when controlling two-dimensional motion.

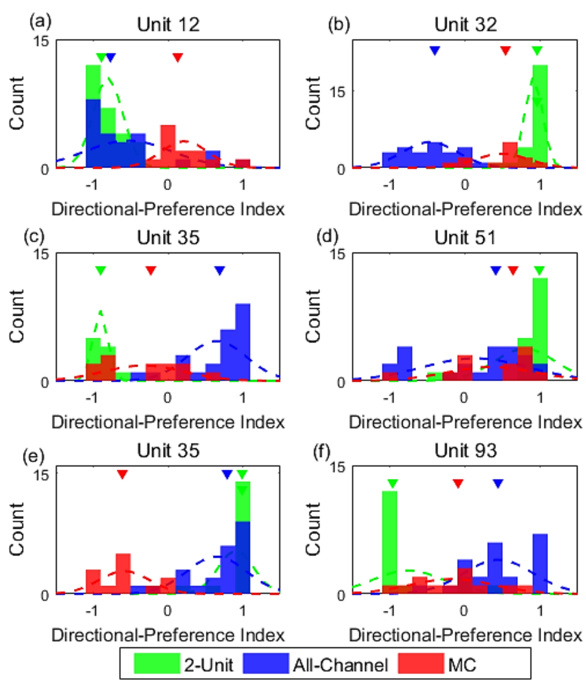


Figure 3. Directional-preference index distribution histogram in three control modes. Inverted triangles in green, blue and red represent the medians of the distributions of each mode.

### C. *Reduction of Control Dimension Enhances the Stability of Units after Division*

In this study, we calculated several modulation indicators mentioned before to investigate the stability of the control unit. One pair of units, Unit 35&93, which participated in all three control modes, was taken as an example, and the results were shown in Fig. 4. Fig. 4(a) and (b) show that the R square of unit 35&93 in brain control mode is generally larger than that in manual control mode, and the R square in 2-unit brain control mode is also significantly larger than that in all-channel brain control mode. In Table 1, two modulation indicators (mean $\pm$ std) of control units are listed, and a similar phenomenon as described above can be observed.

Therefore, we can conclude that in the 2-unit control mode, the R square is the largest among the three control modes, which indicates that the units have the highest correlation with the motion direction, thus maximizing the modulation to the task. Further analysis of Fig. 4 and Table 1 shows that the variance of R square in different control modes is significantly

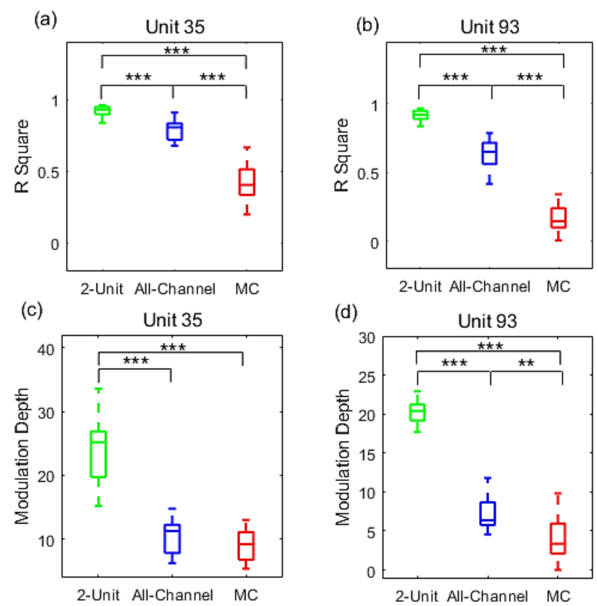


Figure 4. Modulation indicators comparison. (a)-(b) R square. (c)-(d) Modulation depth. *** $p < 0.001$, ** $p < 0.01$, Kruskal-Wallis test.

diverse: as the control dimension decreases, the variance drops, which means the stability of the units increases. The results of stability analysis show that the two units need to have greater and more stable discharge to the task during the process of decreasing the control dimension.

TABLE I. MODULATION INDICATORS FOR CONTROL UNITS

| Control Unit Group | Id | Mode | R Square | MD |
|---|---|---|---|---|
| Unit 12&32 | 12 | 2-unit | 0.89±0.06 | 10.79±3.32 |
| | | All-channel | 0.76±0.12 | 8.44±1.89 |
| | | MC | 0.37±0.16 | 6.58±2.47 |
| | 32 | 2-unit | 0.93±0.03 | 15.58±1.22 |
| | | All-channel | 0.85±0.06 | 14.39±2.16 |
| | | MC | 0.21±0.12 | 4.78±1.86 |
| Unit 35&51 | 35 | 2-unit | 0.88±0.06 | 27.91±4.22 |
| | | All-channel | 0.79±0.08 | 10.44±2.78 |
| | | MC | 0.44±0.13 | 10.12±1.48 |
| | 51 | 2-unit | 0.89±0.05 | 16.20±2.75 |
| | | All-channel | 0.82±0.14 | 14.35±6.44 |
| | | MC | 0.18±0.20 | 3.60±1.86 |
| Unit 35&93 | 35 | 2-unit | 0.92±0.03 | 23.85±4.53 |
| | | All-channel | 0.79±0.07 | 10.44±2.78 |
| | | MC | 0.41±0.13 | 9.16±2.51 |
| | 93 | 2-unit | 0.92±0.04 | 20.28±1.31 |
| | | All-channel | 0.64±0.11 | 7.31±2.23 |
| | | MC | 0.16±0.11 | 4.06±2.93 |

### *D. Units Increase Modulation Depth after Division*

After previous analysis, we discovered that in the 2-unit brain control mode, the two units have a division in motion direction and maintain stable contributions to motion control. Fig. 4(c) and (d) show that the modulation depth of Unit 35&93 is the smallest in manual control, followed by the all-channel brain control, and the largest in the 2-unit brain control mode. A similar phenomenon can also be found in Table 1, indicating that as the control dimension decreases, the modulation depth of the units increases, thus achieving a more stable and powerful control of the cursor and enabling the completion of the center-out task.

## IV. CONCLUSION

The control dimension for the three control modes is diverse. For in manual control mode, there are tens of thousands of control units involved in motion, the control dimension is very high; While in all-channel brain control, the control dimension declines to approximately 90; In the 2-unit brain control, there are only two control units, thus the control dimension declines to 2. In all three modes, since the kinematic degrees of freedom are 2, the redundancy of the control dimension to kinematic degrees of freedom gradually decreases until there is no redundancy. This kind of redundancy could be the cause of changes in modulation characteristics of control units in different control modes.

Since in naturalistic motion control, the control dimension is highly redundant to the dimension of motion, and a very simple behavior may be encoded by tens of thousands of units. As a result, a single unit may not need to have a stable firing pattern to complete the task. Such individual variability cancels out with other individual variabilities at the motion output level, so it does not have a significant impact on overall performance. When this redundancy reduces, the impact of this individual variability on overall outcomes is amplified, leading to deviations in behavior. At the same time, individual units need to stabilize their firing patterns. Until this redundancy is nonexistent, control units need to have a division in orthogonal directions of motion, enhance stability and increase discharge, trying to eliminate effects on the expression of overall behavior.


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