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Mutual information analysis on non-stationary neuron importance for Brain Machine Interfaces*

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Abstract— **Decoding with the important neuron subset has been widely used in brain machine interfaces (BMIs), as an effective strategy to reduce computational complexity. Previous works usually assume stationary of neuron importance, which may not be true according to recent research. We propose to conduct a mutual information evaluation to track the time-varying neuron importance over time. We found worth noting changes both in information amount and space distribution in our experiment. When the method is applied with a Kalman filter, the decoding performance achieve is better (with higher correlation coefficient) than when a fixed subset, which shows that time-varying neuron importance should be considered in adaptive algorithms.**

I. Introduction

Brain machine interfaces (BMIs) provide an alternative pathway between the brain and an external machine. Neural activities are collected by electrodes implanted in multiple cortical areas to decode movement position or velocity, while people or animals are performing a task like 2-D or 3-D target tracking, self-feeding [1-3].

Since well-modulated neurons can't be precisely detected during surgery, as many neurons as possible are utilized to complete the decoding procedure. Generally, 20 to 40 neurons required in the mouse, while 100 to 200 for non-human primates. The number may grow up with the complexity of movement, which imposes a heavy burden on computation and hardware resources. However, only 30%-40% of these neurons contribute significantly to the decoding [4]. The rest of neurons are weakly related to the movement or noisy. Therefore, selecting a subset of important neurons is one efficient way to solve this problem.

Several methods have been proposed to evaluate neural importance. One study performs the evaluation based on a certain decoding model [5-7]. The authors provide a direct view into the effectiveness of every neuron to decoding, but the results are limited by model generalization. Different models may lead to different ranking results. Another study attempts to assess neural importance independently from the decoding approach. The authors consider the individual correlations between a single neuron and corresponding kinematic variables, using statistical methods such as ANOVA [8] or information theoretic analysis [9].

Studies have shown that the representation of movements by neural populations keeps changing over time [10]. Several reasons may contribute to this observation, such as an unstable recoding system, neuronal plastic and motor learning [11]. As a result, decoding with a parameter-fixed model will give worse prediction as time progresses into testing [12]. Many works have addressed this topic. A widely applied approach is constructing an adaptive model and updating the parameters when new observations of the neural patterns are available [13-17]. Alternatively one can find when the tuning properties change and adjust accordingly the parameters of the tuning curve [18-19]. Obviously, these methods become more sensitive with the dimension of the input space, because the computational complexity will increase with the updating.

As mentioned above, selecting an important subset and updating it in time is a good approach to provide a more stable result with less computation. In this paper, we extend a previous work on mutual information evaluation to analysis the time-variant property of the important subset, and compare the decoding performance with fixed subset and changing one in Kalman filter. A short review of method is given in section 2. And the analysis results and comparison of decoding are presented in section 3, followed by the discussion.

II. Data Collection and Methods

A. Data Collection

The experimental paradigm was implemented in Dr. Miguel Nicolelis laboratory at Duke University. Microelectrode arrays were chronically implanted into five regions of a female Rhesus monkey: right dorsolateral premotor area (PMA), right primary motor cortex (M1), right primary somatosensory cortex (S1), right supplementary motor area (SMA) and the left primary motor cortex (M1). A multi-channel acquisition processor system (MAP, Plexon, Dallas, TX) was used to record the neural action potentials. Analog waveforms were amplified and band pass filtered from 500Hz to 5 kHz. Totally, 185 neurons' were probed and sorted using a principal component analysis algorithm. Table 1 shows the assignment of the sorted neurons for different cortical areas. An optimum time interval of 10 ms was selected to translate the spike trains into a sequence of 1 (spike) and 0 (no spike) as multi-channel point process observations. The monkey was trained to move the cursor on a computer screen with a joystick to reach the target in 2D plane. The corresponding position of the joystick was synchronously recorded at a sample rate of 50Hz. We collected both the neural activities and movement data for 1750 seconds.

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TABLE I. ASSIGNMENT OF THE SORTED NEURONS FOR DIFFERENT CORTICAL AREAS

areas	***Right PMA***	***Right M1***	***Right S1***	***Right SMA***	***Left M1***
neurons	1-66	67-123	124-161	162-180	181-185

B. Evaluating neuron importance in time

Towards a spike train spk with 0 and 1 only, and the corresponding delayed kinematics observations y_{lag}, the mutual information is defined as

$$I(spk; y_{lag}) = \int_y f_y(y_{lag}) \sum_{spk=0,1} p(spk \mid y_{lag}) * \log_2\left(\frac{p(spk \mid y_{lag})}{p(spk)}\right) dy_{lag} \quad (1)$$

where y_{lag} is constructed as $[p_x\ v_x\ a_x\ p_y\ v_y\ a_y\ 1]$, where 1 works as the bias, p is the position of the joystick, v and a are velocity and acceleration of joystick correspondingly. $f_y(y_{lag})$ is the *pdf* of the kinematics evaluated as a function of time lag. $p(spk)$ is the firing rate, which can be calculated as the percentage of 1s in the spike trains. $p(spk|y)$ is the neuron's tuning curve. Several kinds of tuning curves have been proposed to explain how information is encoded in the spike trains. In this paper, we utilized the extended linear-nonlinear-Poisson model [19], shown in figure 1. First, the linear filter projects the kinematics vector into its preferred direction k, producing a scalar value $k \cdot y_{lag}$. Then the nonlinear f converts it to the instantaneous conditional firing probability λ_t, which applied to the Poisson model generates the spike train. We refer the reader to [9], [19] for additional details. If we replace y_{lag} in equation (1) with $k \cdot y_{lag}$, $p(spk|k \cdot y)$ it is exactly the nonlinear function f.

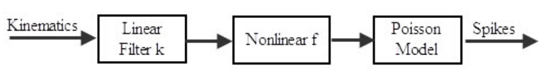

Figure 1. Block diagram of linear-nonliear-Poisson model.

C. Kalman filter

We would like to remark at this point that Kalman filter is not the sole possibility to evaluate the decoding performance. Kalman filter is a widely used decoder in BMI system. It assumes a Gaussian distribution both on system state and noise. With the state equation (2) and the observation equation (3), the Kalman filter predicts the prior distribution of the state parameters and revises the posterior distribution in a recursive manner. For more details please refer to [20].

$$y_k = Ay_{k-1} + w_{k-1} \quad (2)$$

$$spk_k = Hy_k + v_k \quad (3)$$

where y is the system state, spk is the observation of the system, w and v represent the process and measurement noise respectively.

III. RESULTS AND ANALYSIS

To avoid the effect of unstable animal behavior, we ignore the first 200 seconds data and the last 150 seconds data. The remaining data is separated into 14 segments with a length of 100 seconds each. The length of segment is open to discuss. It can't be too small, as time-variant is not obvious in short time, also it can't be too large, as computation complexity grow. In each segment, we calculate the mutual information of 185 neurons with different lags (from 0 ms to 50 ms with a step of 1 ms), and the best lag is selected as the one producing the maximum mutual information (MMI). Then, the neural importance is ranked according to MMI. Figure 2 gives the overview of the results, and shows a clearer example of MMI on the first segment.

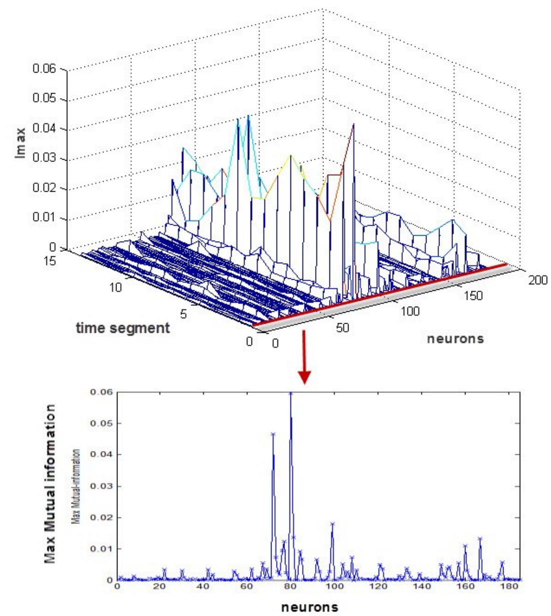

Figure 2. An overview of MMI on 14 segments (above); An enlarged example of the first segment (below).

As shown in figure 2, the neurons in PMA and left M1 give a low MMI constantly, while several neurons in right M1, S1 and SMA show a high correlation. But the number of neurons with high information is small, just around 15 to 30. And the more important thing is that the MMI of all neurons keeps changing along time. Figure 3 gives four examples of how MMI changes along 14 segments.

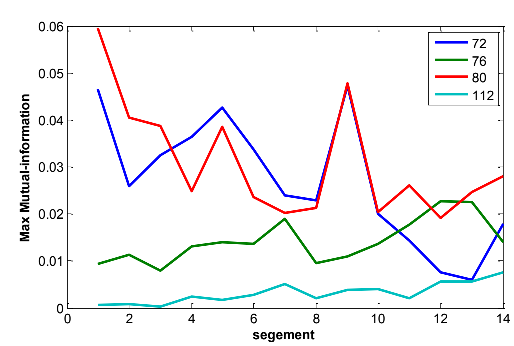

Figure 3. The variation of four typical neurons along the time.

In Figure 3, the MMI of the 72th (blue line) and 80th (red line) neuron in right M1 drops down, while the MMI of the 76th (green line) and 112th (cyan line) neuron in right M1 climb up slowly. Taking the 80th neuron as example, the MMI of the second segment drop 33% from the first segment. It means in as short as 100 seconds, an obvious change on MMI can be observered. Among the 185 neurons, about 5% show a dropping trend, while 3% neurons show climbing trend. Although 90% of the neurons seem steady along time, most of them are weakly correlated with the movement, and their MMI is always smaller than 0.005, which contribute less to decoding.

To select the important neuron subset, we sorted the importance of neurons by its MMI in descending order for each segment. Figure 4 clearly shows an inflection point around the 30th neuron on most of these 14 segments. The information contained in neurons after rank 30 is weak and can be neglected. So we choose the first 30 neurons to construct an important subset, marked as N_i, where i is the index of data segments, from 1 to 14.

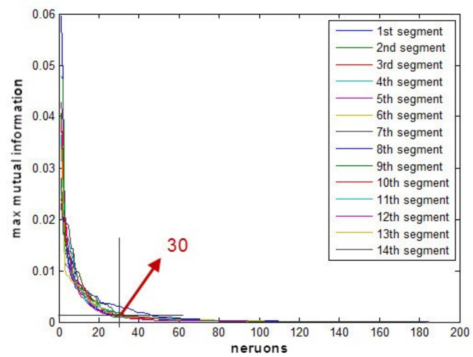

Figure 4. MMI of 185 neurons in descending order of 14 segments

Figure 5 lists the selected subsets. Every point is a selected important neuron. Each row is an important subset when the ordinate presents the index of data segments. The important neurons seem to assemble in the right M1 and SMA. About 50% of neurons remain in the important subset, while others jump outside or vice versa.

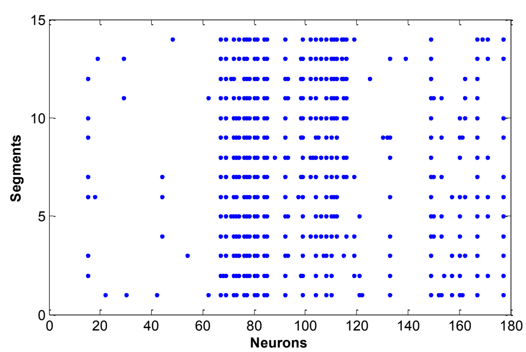

Figure 5. The distribution of important neural subset in 14 segments

As shown in figure 5, the important neural subset changes its spatial distribution. Also, we know the information amount contained in a certain neuron is changing over time. To figure out how much they changed, we further compare the total information amount contained in the first subset and in the current subset. In figure 6, the blue solid line shows the information contained in the neurons of the first important subset N_1 and the red solid line shows the information contained in the current subset N_i. The difference is obvious and grows along time. The subset N_2 contained 5.5% higher information than N_1 at the second segment, and at the last segment, the subset N_{14} gives a 24.7% higher information amount than N_1. So with the same initial value, decoding with a time-varying important subset can be expected to produce a more stable and accurate result.

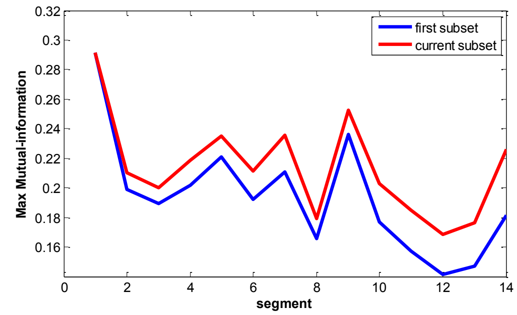

Figure 6. Comparison of total information amount contained in the first subset and in the current subset

To confirm this speculation, we carried out a decoding test using the Kalman filter. The first segment was used for training and any other segments can be used for testing. In each segment, we compare the performance by selecting the fixed neural subset and changing neural subset separately. In the fixed subset, we consistently use the neurons selected from the first segment, while in the changing neural subset, the neurons are selected from the previous segment. Figure 7 gives an example of reconstruct results comparison. The dash red line indicates the desire position in horizon (above) and vertical (below), the dash-dotted green line indicates the estimation by fixed subset and the solid blue line indicates the estimation by time-variant subset. We can see both methods could follow the desired signal, but the blue line provides a closer estimation at most peaks. The advantage may not be significant, which means there are still other time-variant properties we haven't tracked. Actually, that's what we plan to do in future work.

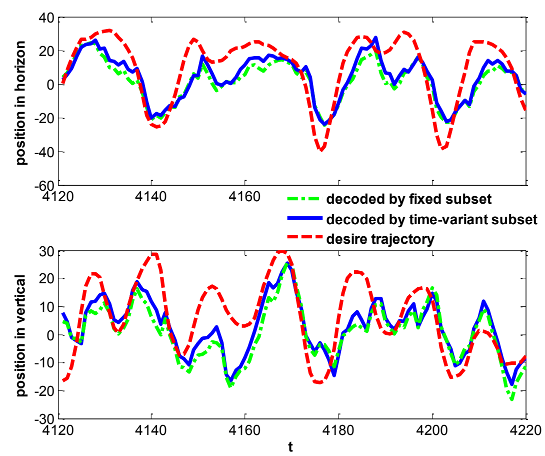

Figure 7. Kinematics reconstruction example by fixed subset and time-variant subset in horizon position (above) and vertical position (below)

To further compare the decoding performance, we examine correlation coefficient (CC) between the decoding result and the desired signal in each segment. Figure 8 gives an example. The blue line shows the results using fixed subset and the red line shows the results using time-variant subset. As time advances, the performances of these two methods all drop as a result of time-varying neural activity. In addition, the red line seemed to provide a better performance than the blue one. In the decoding result on vertical position, the CC starts 2% higher at the second segment and the advantage goes up to 36% at the last segment. However, as noticed in figure 3, some neurons jumped out of the important subset in a certain segment, and came back again later. In this situation, the important subset selected from last segment may not perform well.

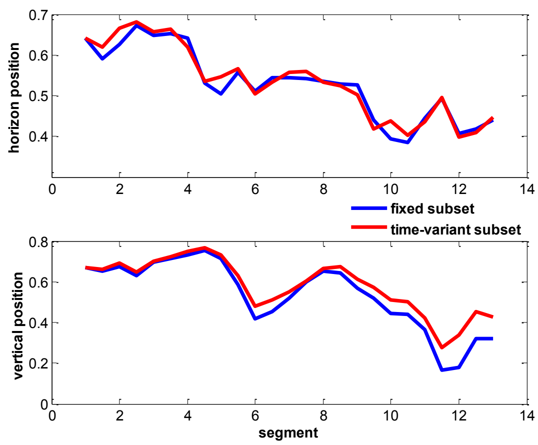

Figure 8. CC between the decoding result and desired signal on 13 segs in horizon position (above) and vertical position (below)

IV. Conclusion and Discussion

In this paper, we propose to use information analysis to select a member-changing important neural subset in movement decoding for brain machine interfaces. Mutual information shows a significant change on both the information amount and the members contained in the important subset. Then, we compare the decoding performance using Kalman filter with the fix subset and the time-variant subset. Although both performances drop along time, the time-variant important subset provides more steady result.

Besides the changing member of the important subset, the variation on tuning curve is also worth discussing. As shown in other research [10-11], neurons may respond differently as time pass. As a sequence, the tuning curve used in decoding models should be adjusted in time. In future work, we will focus on establishing a time changing tuning function regression model utilize a member-changing important subset, hoping to perform the decoding task better for the Brain-machine interfaces.

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