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Tracking time variant neuron tuning properties of brain machine interfaces

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Abstract. Tuning properties of neurons, which represent how information is encoded in neural firing, are well accepted as time variant. For a steady-performed brain machine interface (BMI), the decoding algorithm should be able to catch this change in time. Unfortunately, an assumption-less tuning property is too complicate to trace. Simplifying the tuning curve to linear or exponential one may lose important information. We propose to approximate the tuning curve with multiple Gaussian functions, and modeled the non-stationary tuning curves by the changes on the Gaussian parameters. Applied on in vivo neural data when the monkey is performing a 2-dimension tracking task, we found the non-stationary tuning properties can be tracked by the changes on parameters of Gaussian components, which greatly decreases the number of parameters need to be observed. Following this idea, we can design an adaptive method by updating parameters of tuning model.

Introduction

Brain machine interfaces (BMIs) constructs a substitute path for motor-impaired patients to communicate with external machines. Multiple successes have been reported from rats, non-human primates to humans. In these experiments, neuronal activities recorded by implantable microelectrodes in multi cortical areas, were used to decode control commands, such as position or velocity of arms' movement [1].

To predict kinematic variables, a decoding algorithm aims to find the functional representation of movements in neural activities. Studies have shown that this connection is time variant [2]. As a result, traditional method with static parameters will perform worse as time passed. Many works have addressed this problem [3-4]. The main idea is to update the parameters when new neural patterns observed. So it's necessary to parameterize and monitor the changing of neural firing properties. Kinds of methods have been proposed to describe the tuning curve. They usually assume a specific function, like cosine curve, linear, Gaussian and exponential [5-8], which may lose important information. Nevertheless, the assumption-less model, such as linear-nonlinear Poisson (LNP) model [9], needs too many parameters to memories it.

We plan to estimate the tuning curve using the LNP model but approximate it with multiple Gaussian functions. For a Gaussian model, it needs only three variables (weight, mean and variance) to describe. So we can track the non-stationary tuning properties with only a small number of objects need to be observed. With the rule monitored, we can predict the future tuning curve, instead of staying on the original one.

Data Collection and Methods

Data Collection. The experiment paradigm was implemented in Qiushi Academy for Advanced Studies in Zhejiang University. A monkey was trained to move a joystick to follow a moving visual target continuously using left hand. A Utah array were chronically implanted in the hand area of the right primary motor cortex (M1). Multi-channel neural activities were recorded by a 128™ cerebus data acquisition system (Blackrock Microsystems, USA) at the sample rate of 30 kHz. Analogy waveforms of the action potential were amplified and band pass filtered from 250 Hz to 7.5 kHz. About 91 neurons were detected and sorted in real time with the Cerebus™ system. 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 corresponding position of the joystick was synchronously recorded at the sample rate of 20 Hz. We collected both data for 1300 seconds

Tuning curve Estimation. We chose the cascading LNP model proposed by Simoncelli [9] to characterize the tuning curve of neurons. The diagram of the model is shown in Fig.1. Consider the kinematics variables as $x = [p_x, v_x, a_x, p_y, v_y, a_y]$, where 1 works as the bias, p is the position of the joystick, v and a are velocity and acceleration of joystick correspondingly. The model first projected the multi-dimensional x to one dimension with a linear filter k, then nonlinear function f related the projected kinematics to instantaneous firing rate λ, so we can generate the spikes using the Poisson model. Here, the nonlinear function f is the tuning curve we are most interested in. And we can observe it in 2D plane, as the linear filter has projected multi variables to one dimension.

Fig.1 Block diagram of linear-nonlinear-Poisson model

Neuron Importance Evaluation. Mutual information was exploited here to evaluate importance of neurons. We define the mutual information between a spike train spk (0 and 1 only) and corresponding delayed kinematics observations x_{lag} as Eq.1.

$$I(spk, x_{lag}) = \int_x f_x(x_{lag}) \sum_{spk=0,1} p(spk|x_{lag}) * log_2(\frac{p(spk|x_{lag})}{p(spk)}) dx_{lag} \qquad (1)$$

where $f_x(x_{lag})$ is the *pdf* of the kinematics, $p(spk)$ is the firing rate, both can be learned in train data. $p(spk|x_{lag})$ is the conditional firing rate, which can also be seen as tuning function f estimated in Fig.1. We tried different delays (from 0ms to 50ms with a step of 1ms), the one produced the maximum output is considered as best delay, and the maximum mutual information (MMI) is taken as a criteria to evaluate the importance of neurons. We refer readers to [10] for additional details.

Tuning curve approximation. We try to fit the tuning curve with multi Gaussian functions. Set the number of Gaussian as N, fitting result can expressed as Eq.2.

$$f = \sum_{i=1}^{N} a_i * exp(-(\frac{x - b_i}{c_i})^2) \qquad (2)$$

Levenberg-Marquardt algorithm (LM) [11] was taken to search for the optimal Gaussian parameters. LM method interpolates between the Gauss-Newton (GN) algorithm and the method of gradient descent. It's a popular method for curve fitting in least square family. For first segment, we started from a random point, and chose the best one among 30 trials. For the remains, we started from the result of last segment and searched in the neighborhood. The mean coefficient of determination R^2 and the square root of mean-squared error (RMSE) are selected to evaluate the fitting performance.

Results and Analysis

The data is separated into 13 segments with a length of 100 second each. In each segment, we calculate the mutual information of 91 neurons with different lags. Fig.2 gives an example of changes in neuron's tuning curve. From the light grey curve at 300s to the dark black one at 1300s, we can see the tuning curve tends to be more flat. Also, the importance is dropping as the MMI descends in fluctuation. It seems like this neuron is losing tuned, which means the correlation between movement and this neuron became weaker. It may because the monkey has done this job for a while, and the brain is tired or the movement is more like a custom.

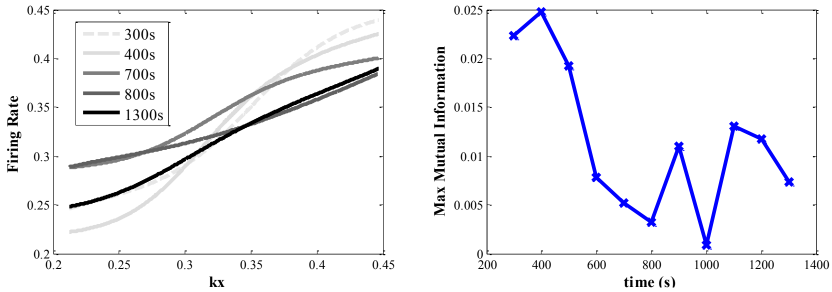

Fig.2 Example of time-varying tuning curves (left) and mutual information (right)

We tried different numbers (1 to 5) of Gaussian function to simulate the tuning curve. The test result shows that, when the number grows to two, the mean RMSE drops about 76.2% than using one Gaussian only. But when number keeps growing, the dropping speed shrinks to around 50%. In case five, the RMSE even begin to rise. Considering three more parameters need to be observed when one Gaussian function added, we decide to approximate tuning curve with two Gaussian components.

Take neuron 34 for example, we re-separate the data into 25 segments with a length of 100 second each (50% overlap), and fit the tuning curves with two Gaussian functions. The optimal parameters are presented in Fig.3. We found the mean and variance of the first Gaussian function (b1 and c1), the weight of the second one (a2) can be fitted well by a certain function (exponential, linear and power correspondingly). While the other three parameters swing in a small range (around 0.1). So when carrying out the prediction of tuning curve, we update the a2, b1 and c1 along fitting curve, and took the mean of these samples as the static value of a1, b2 and c2.

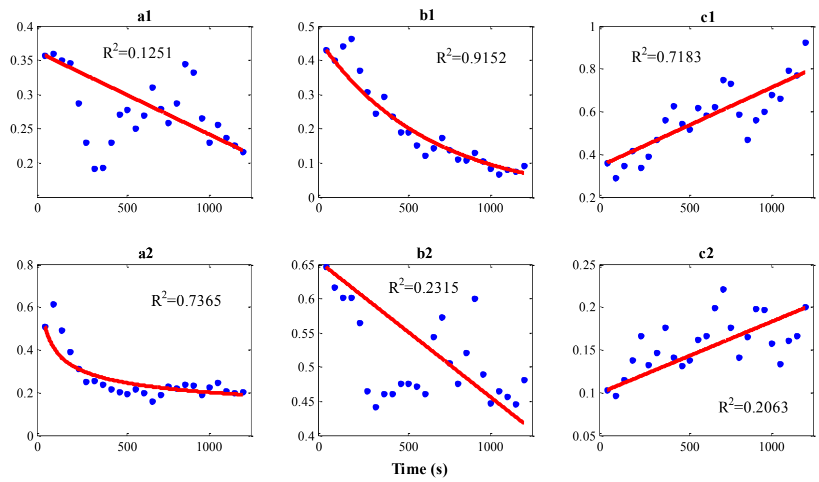

Fig.3 Fitting example of time-varying Gaussian parameters for Neuron 34

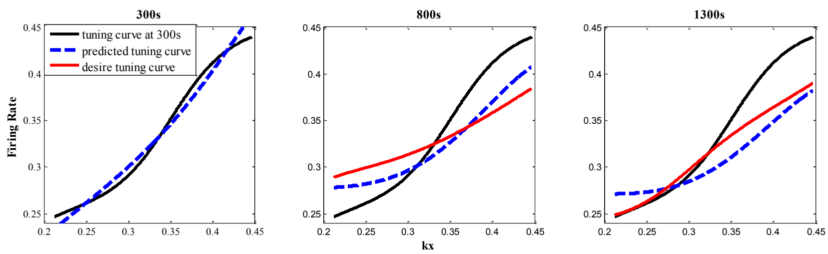

Fig.4 Tuning curve prediction example of Neuron 34

Fig.4 present the prediction result of tuning curves (neuron 34 for example) starting from 300s. Black line show the real tuning curve at 300s, red line show the desire tuning curve at different time and the blue dashed line show the prediction result with updated Gaussian parameters. We can see the blue line always gives a better estimation of red line than black reference. All the neurons show high mutual information can be analysis in this way, though not all of them present the same trend. It is hopefully to receive a more stable decoding result using the time-varying tuning curves instead of the static original one.

Summary

This passage introduces a quantized method to assess the time-varying properties of neural tuning curves. With two Gaussian functions, we can estimate the tuning curves and track for their changes by observing six variables. Then, we can summarize some rules to control parameters updating in prediction. We give an example here, but not all the neurons give the same trend. More work should be executed to discover some statistical laws.

Here, we only works on the data collected in one day. As the number of neurons collected varies along days, decoding models trained today couldn't be used directly tomorrow. The possible solution includes decoding with unsorted spike trains (indexed by electrode channels) or selecting neurons consistently existed. Both will be discussed in future work. Besides, this idea should be included in decoding model. In our analysis, parameters changes obviously as short as in 1 hour experiment. Also, these changes can be tracked and modeled by simple function like linear. In future work, we will focus on establishing a time-varying regression model with tuning curves updated in time.

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