The KARMA of Hand Tracking

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The usage of machine learning algorithms to decode intended behavior from neural activity serves a dual purpose. First, these tools can be used to allow subjects to interact with their environment through a brain-computer interface. Second, analysis of the characteristics of such methods can underscore the significance of various features of neural activity, stimuli and responses to the encoding-decoding task. In this work we propose and test a machine learning method, called Kernel Auto-Regressive Moving Average, or KARMA in short, for the task of tracking hand movements, executed by a monkey in a standard motor control task, from neural spiking activity in primary motor cortex.

KARMA uses both past observations (neural activities) and past predictions (movement parameters) to make the next prediction. In the model used by KARMA one may learn to predict not only target values (hand positions) but also auxiliary features, which can be used to improve modelling of the dynamics and the prediction of the target values. For example, we predict hand velocity and acceleration and use them to better predict hand position. Other features of the task, such as distance to target, can also be estimated and incorporated into the prediction of future behavior. Unlike the standard ARMA model which is a linear model, KARMA uses non-linear similarity functions (termed kernels) to compare between tuples of (observed) neural activities and (previously predicted) motor task parameters. These kernels can be specified by the user of the algorithm to tell it how to measure the amount of similarity between pairs of tuples.

In this work we compare KARMA to several state-of-the-art methods. We used correlation coefficients (CC) between true and predicted hand positions as the measure of success. Each method was fitted with its optimal hyper-parameters by selecting the parameters that achieved best test results in 5-fold cross validation on one of 9 daily recording sessions. Results are reported on test data using 5-fold cross validation and performed on the remaining 8 sessions. We explain the differences between the methods and interpret the demonstrated superiority of KARMA (figure 1) as an indication that the algorithmic differences are important for understanding the motor control task. For example, when KARMA is implemented with an AR degree of 0 it reduces to standard support vector regression (SVR) and no longer possesses a movement model. When KARMA is used with linear kernels it reduces to ARMA and is no longer a non-linear method. We also compare KARMA with Kalman filtering (KF) which possesses both a model of state dynamics and models of system noise but lacks the kernel induced non-linearities. In figure 1, KF1 is standard KF and KF10 uses the same MA degree of 10 as KARMA. Our main conclusion is that both the nonlinear dynamics and interpretation of neural activity are key elements in the hand tracking task.

Figure 1: Win scores. Each node is an algorithm. Each directed edge tells % of time that the algorithm above achieved a better CC on test data than the algorithm below.

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