Learning a Novel Visuomotor Task and Performing Four-Dimensional Movements in a Closed Loop Brain-Machine Interface Using an Adaptive Dynamic Kernel Based Algorithm

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In this work we describe a visuomotor control experiment in which a monkey learned to use a Brain Machine Interface (BMI) to control the movement of an object on a screen in a 3D and 4D setting. Part of the task (consecutive target-to-target reaching in 3D) was first learned and performed using hand movements. This task was then relearned in BMI mode. At this stage, control over cursor rotation (around a single axis) was introduced and learned by the subject from scratch entirely in the BMI setting over the course of a few days. Once the monkey was able to perform cursor rotation to match given target rotations with good precision, the two tasks were combined into one 4D BMI task (reaching and rotating to match consecutive targets). This task proved substantially more difficult for the monkey than the sum of it’s parts but the subject was able to perform it with high success rates after a few more days. Hand movements (during hand control sessions) were recorded using an optical tracking device. In BMI mode the monkey had both hands restrained and appeared to keep them relaxed as gauged with high resolution video and optical sensors. The BMI was driven by single and multi-unit activity recorded from a 96 electrodes array (Cyberkinetics Inc.), implanted in primary motor cortex.

An adaptive version of a learning algorithm called KARMA (Kernel Auto-Regressive Moving Average) was used to learn and infer intended movements from the recorded neuronal patterns. This BMI algorithm is a kernel method that combines both previous predictions and current neural observations in a non-linear fashion to make new predictions. It has several attributes which were important in this work.

1. Movement prediction can be done in real-time (every 50 milliseconds). To do this with a kernel based method, the number of support points was kept small.
2. The algorithm learns extremely fast. Even though the model was learned from scratch every day, the algorithm managed to achieve the first successful trial in about 5 attempts. This means learning a usable model from 30 seconds of data.
3. The algorithm adapts continuously in the background. After movements are performed using the previously learned model, the neuronal activity from these sequences is then paired with desired movements that are based both on the cursor movements (produced by the previous model) and the target locations. As new sequences enter the algorithm’s learning process, previous examples are thrown out in a probabilistic fashion, inducing a better fit to recent observations as compared to older ones.
4. The algorithm creates an implicit model of the movement dynamics that are smooth and seem natural. This is due in part to the way in which desired trajectories are created and also to the fact that the previous predictions are provided as part of the input for the next prediction.

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