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Accurate neuroprosthetic control via neural manifold shaping

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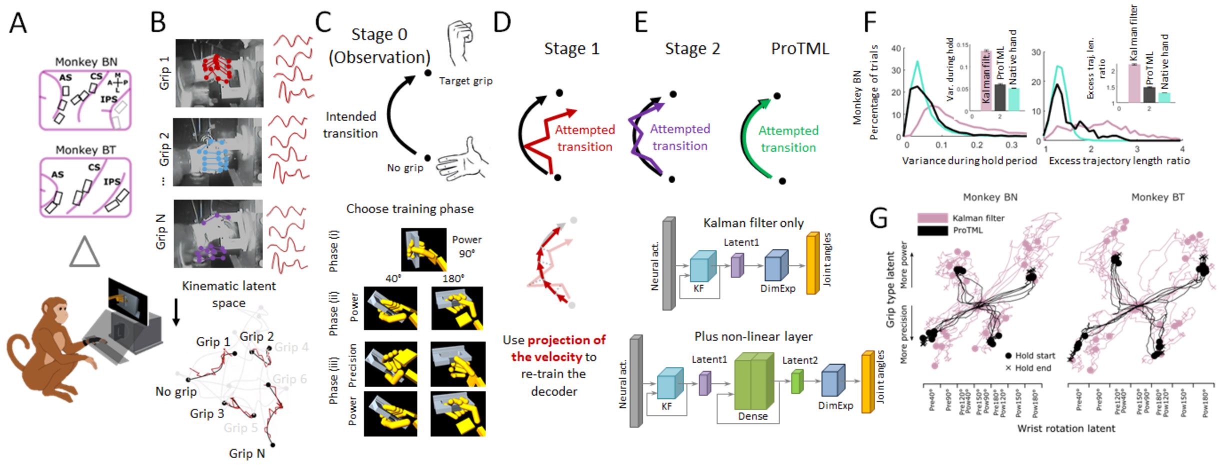
Introduction: Hand movements are an essential way primates interact with the environment and they comprise some of our most complex actions. Despite the remarkable recent progress in intracortical brain-computer interfaces, current prosthesis still lack the fine hand shape control required to interact with objects in daily living. Towards this goal, we present a training protocol to develop the neural activity patterns required for the accurate BCI control of hand shape. The method sculpts neural activity by daily training of objective patterns and enables progressively finer control of hand degrees of freedom, approaching native hand control for some metrics.

Material and Methods: We tested our approach in two rhesus monkeys implanted in key areas of the grasping circuit (Fig. A). Using a high-dimensional full hand and arm tracking system, we determined a subspace of the hand joint kinematics state space we termed the *kinematic latent space* (Fig. B). Based on knowledge of the evolution of neural manifolds [1-5], we trained the subjects to progressively control more latent variables of the hand shape subspace (Fig. C). Building upon intention-estimation training strategies [6-9], our approach takes into account trajectories in the kinematic latent space crucial to achieve final postural configurations. To preserve trajectories and in contrast to previous approaches, we replaced the executed kinematics in the decoder re-training stage with the attempted trajectories (Fig. D). Inspired by machine learning techniques, we trained the subjects with a Kalman filter (KF) but later switched to a hybrid decoder, combining the robustness of the neural patterns developed during KF control with the prediction capacity of a recurrent neural network (Fig. E). We refer to our combined approach as Progressive Training of Manifold Latents (ProTML).

Results: ProTML enables the online control of a high-dimensional hand effector that reflects the grip intention of the subject with accuracy comparable to native grasping. Performance of the BCI was superior to traditional algorithms in several metrics, including success rate and variability of the grasps (Fig. F,G). When compared to a classic intention estimation method in an environment with obstacles, our strategy achieved higher task performance.



Discussion: Our work shows that it is possible to shape neural latent variables to specific target trajectories in the context of motor control. By fitting to a set of target position and velocity targets, daily training evolves these patterns and they can be volitionally recalled by the BCI user. Recent interest on the evolution of neural manifolds in motor cortex has shown that neural patterns are constrained to a covariance space [2], training can expand this space [4], and activity prefers re-mapping to reconfiguration [3]. A protocol for manifold shaping offers an opportunity to observer the evolution and geometry of this latent structure.

Significance: Taken together, these findings propose a novel way to complement training protocols for the challenge of dexterous prosthetic manipulation and offer a training approach to shape neural activity patterns for basic research of cortical activity.

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