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Steps Toward Knowledgeable Neuroprostheses

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***Abstract*— Advanced neuroprosthetic devices demonstrate an impressive capacity for both actuation and sensation, providing numerous controllable degrees of freedom and reportable sensory percepts. When linked to the human body by way of invasive and non-invasive brain-body-machine interfaces, neuroprostheses promise to greatly improve life for users by extending their capacity to engage with and interpret the world around them. In this work, we demonstrate how a prosthetic device can build up diverse knowledge during its ongoing operation so as to better support its user. Specifically, we show that a device can learn and update more than 18k different temporally extended predictions per second about all aspects of a sensorimotor data stream, significantly extending past work on real-time knowledge acquisition during prosthetic control.**

Due to a significant mismatch between the actuation capacity of new devices like the Modular Prosthetic Limb (MPL, Fig. 1) and the number and types signals that can be recorded from and delivered to the user's body, there remain significant barriers to the functional control and use of neuroprosthetic devices by users with and without motor impairments [1]. Intelligent control systems are now a subject of active research so as to allow devices themselves to begin to take an active role in leveraging the dense stream of information flowing between a user and their device [1], [2].

Our present demonstration provides new insight into the potential for real-time knowledge acquisition during the control of prosthetic devices [2], [4]. As described in Fig. 2, we implemented a layered architecture with $\sim$11k general value function predictors (GVFs, [2], [3]) to forecast the stream of percepts flowing from the MPL. Internal signals corresponding to prediction error were also computed for each of these predictions and used as learning targets for an additional $\sim$7k GVFs. During a period of only 6min of learning, the system was able to build up consistent forecasts of the data stream (shown via intensity values in Fig. 2a,b), detect unexpected errors in its forecasts due to starting and stopping motions or human perturbations (bright areas in Fig. 2c), and forecast areas of the data stream where future unexpected errors in its predictions might occur (bright areas in Fig. 2d). The resulting topology of GVFs forms a diverse, multi-timescale predictive state representation that can be used for improving control. These results therefore represent an important step toward prosthetic systems of all kinds becoming more knowledgable, effective counterparts in ongoing human-machine interaction.

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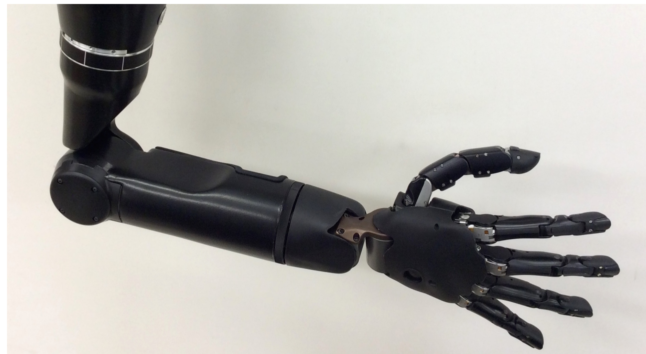

Fig. 1. The third-generation Modular Prosthetic Limb (HDT Inc.) used in these experiments, featuring independent finger and thumb control, finger abduction/adduction, three-degree-of-freedom wrist actuation, elbow flexion and extension, humeral rotation, and two axes of shoulder motion.

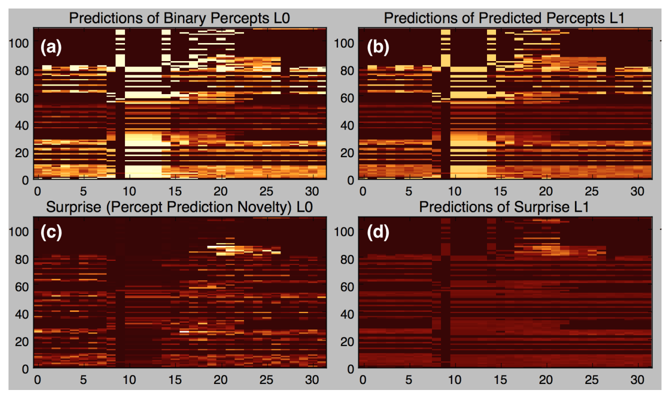

Fig. 2. A topology containing $\sim$18k GVF predictions was made to forecast $\sim$3.5k binary percepts streaming in real time from the MPL while it performed a series of cyclic actions. These binary precepts encode the position, velocity, impedance, and temperature of MPL actuators. During its motion, the arm was perturbed by human interactions, such as shaking its hand or placing heavy objects in its palm. The 3.5k short-term forecasts of these bits are shown as heat map intensity values in (a), with 3.5k longer-timescale predictions of these predictions being shown in (b). Internal signals relating to the unexpected prediction error for each of the learned predictions (computed via UDE measures [3]) are shown in (c), with 3.5k learned forecasts of these error values shown in (d).

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