Feasibility Study of Dendritic Gated Networks for Upper Limb Prosthetic Control

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Abstract. This study provides insight into the synergy between neuroprosthesis control and dendritic gated networks (DGNs)—a newly introduced type of artificial neural network. These networks have demonstrated their potential in rich, dynamic environments but have yet to be deployed in the real world. We conducted an extensive offline analysis of DGNs on forearm prosthesis classification and regression tasks, and studied the influence of different hyperparameters on prediction quality. Our results suggest that DGNs are capable of learning usable predictions quickly and efficiently across different limb positions, highlighting their ability to learn in the presence of changing contexts and settings of use. Based on these findings, we recommend further investigation into dendritic gated networks for wearable robotic settings.

1 Introduction

Dendritic gated networks (DGNs) are a backpropagation-free artificial neural network architecture capable of *quickly* learning binary classification and regression tasks during use (i.e., *online*) as new data samples become available [1]. The manner in which DGNs update the network weights allows it to capture *contextual* information. Fast, contextual, online learning would be especially helpful for myoelectric prosthetic control. In this setting of upper limb prostheses and other neurorehabilitation devices, there is a continuous stream of biological signals

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from the user, and the prosthesis needs to work reliably in any situation [2–4]. For example, imagine you have a prosthetic arm and want to grab a beverage can. Despite different contexts—e.g., whether the can is on the counter, on the top shelf of the fridge, or perhaps it fell down onto the floor—the performed motor control task involves reaching for the can and then closing your prosthetic hand to grasp it. Commonly used machine learning architectures, such as multilayer perceptrons (MLPs) (Fig. 1a), are unable to recognize that different placements of the can are *different contexts of the same task*. DGNs (Fig. 1b) can quickly adapt and learn that it is, in fact, one context-dependent task. So how do they learn this contextual information so quickly?

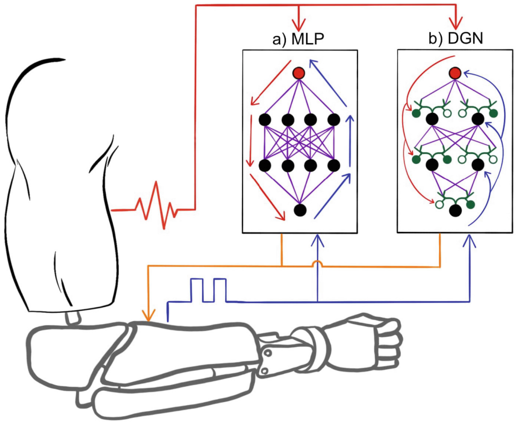

Fig. 1. Comparison of MLPs and DGNs. Biological signals (red) are used as input for each network with the intended motor control action (orange) as output. Within the networks arrows show feedforward computations (red) and feedback information (blue). DGNs (b) differ from MLPs (a) such that each inhibitory interneuron (green circles) directly receives the input signal, each neuron receives the target (blue) directly instead backpropagating error, and each dendritic branch (green) receives input from all prior-layer neurons.

Dendritic gated networks take inspiration from how the brain learns [5] by using inhibitory interneurons to gate dendritic branches on and off in an input-dependent manner. Every neuron in the network has a number of dendritic branches connecting it to the neurons in the previous layer via weights. If the inhibitory interneuron on a branch is active, then the dendritic branch is gated off and the connecting weights are not updated. If the inhibitory interneuron is not active, the branch is gated on and the weights are updated. The activity of an inhibitory interneuron is dependent on the biological signals captured from the prosthetic user. The contextual awareness of dendritic gating also makes DGNs especially resilient to (catastrophically) forgetting old tasks when learning new ones, a common problem with backpropagation-based approaches [1].

In this work we investigate the feasibility of dendritic gated networks for contextual myoelectric prosthesis control. We show that—with only two neurons—DGNs are capable of learning usable predictions for transradial classification and regression tasks across different limb positions. We conclude that DGNs are a viable option for practical myoelectric prosthesis control and are worth further exploration.

2 Methods

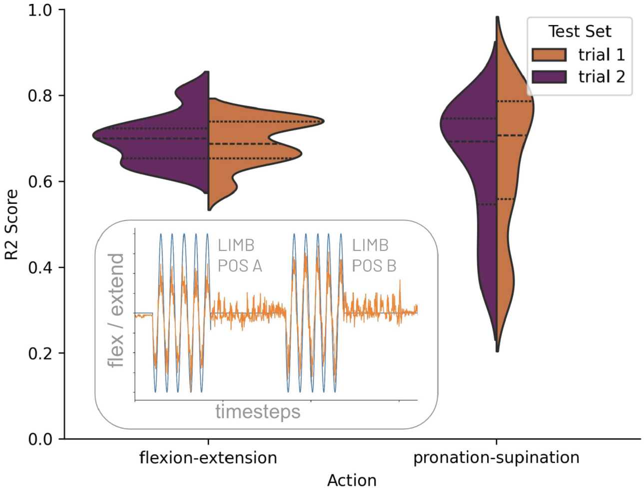

Fig. 2. Regression performance on the testing set. As prediction accuracy increases, an R^2 score increases towards one. R^2 scores shown for both movements are compatible with use for prosthesis control. *Inset:* example of learning targets (blue) v.s. learned movements (orange) over two contexts.

We performed offline analysis using the forearm prosthesis classification and regression datasets of Williams et al. [3]. Participants wore a Myo armband (Thalmic Labs) with eight surface electrodes to collect electromyography (EMG) data at a sampling rate of 200 Hz and one inertial measurement unit (IMU) sensor to collect x, y, z accelerometer data at 50 Hz (with the EMG and IMU vector used as model input). Each dataset contains data from eight different participants without amputation (note that this approach has also successfully transferred to an individual with transradial amputation [4]), for a total of 16 participants across both classification and regression datasets. Each participant carried out two full trials. For classification, machine learning targets were five discrete actions—rest, wrist flexion, wrist extension, pronation, and supination—captured in four limb positions. For regression, learning targets were two scalar values relating to dynamic actions—flexion-extension and pronation-supination movements—sampled in the same four limb positions.

We implemented DGNs for classification and regression as per Sezner et al. [1]. For each dataset we ran sweeps over the following hyperparameters: number of layers in the network $\{2, 3\}$, number of neurons in each layer $\in [5, 100]$, number of dendritic branches per neuron $\in [5, 2000]$, learning rate $\{1e^{-1}, 1e^{-2}, ..., 1e^{-8}\}$, and frame stacking history $\{1, 2, 4, 8, 16, 32\}$. Models were trained with a split-by-trial approach that alternated between using trial 1 or trial 2 for the test and training sets. Models were trained for each participant individually as well as one model with all of the participants data consolidated together; 1260 final models (180 per action/class) were trained, as compared below.

3 Results and Discussion

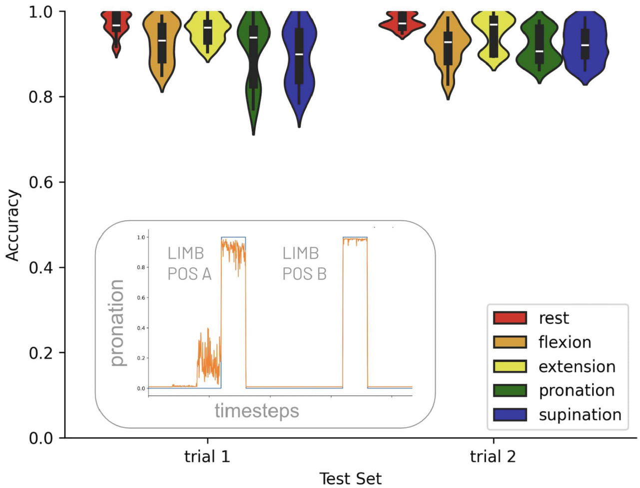

Fig. 3. Classification performance on the testing set. For all of the five tasks, the models are able to achieve high average prediction accuracy (over 90%), accuracies suitable for use in prosthesis control. *Inset:* example of pronation classification decisions (orange) v.s. true class (blue).

Both classification and regression models demonstrated performance suitable for use in myoelectric control (Fig. 2 and Fig. 3; 180 models per violin). As shown in Fig. 2 (inset), time-series evaluation of regression predictions showed meaningful alignment with learning targets across all contexts (in this case, limb positions). For regression, we observed similar performance and data distributions between the two trials and good generalization to unseen data. Tuning models on individual participants yielded more effective models. Conversely, for classification, training a generalized model on consolidated participant data appeared to result in more stable predictions. Finally, over the course of hyperparameter tuning, we found that reducing the number of layers to two and the number of neurons per layer to one resulted in the best performance for this dataset. This result was surprising and an important observation as it implies that most of the contextual learning is being done by way of the dendritic branches—in contrast to the multiple convolutional and recurrent layers of deep MLP approaches capable of similar contextualization [3]. Small two-neuron high-branching-factor DGNs are viable for embedded systems, and thus an option for practical myoelectric control.

In conclusion, this study examined the potential of dendritic gated networks for myoelectric prosthetic control, contributing insight into how hyperparameter choices influence performance, and the nuances of DGNs for classification versus regression tasks. Our findings suggest that dendritic gated networks could be a promising and practical solution for context-aware prosthetic control and that DGNs warrant continued investigation in the setting of neurorehabilitation.

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