# Towards a real-time, interactive, incremental learning algorithm for prosthetic myocontrol

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## INTRODUCTION

**Prosthetic myocontrol** based upon **machine learning** usually requires a **large initial labeled dataset** to build its model and prescribes that said model will **never change** in the course of time. This approach has several limitations, e.g., the difficulty of building such a proper dataset and the low generalization power of the obtained model against the variety of **non-stationarities** of EMGs in daily scenarios. In Castellini 2016 [1], it is suggested the concept of **interactive learning**, in which the user can trigger an adaptation of the underlying ML model, notifying to the system the action to be mapped to the current muscular pattern. Moreover, **incremental learning** techniques [2] allow models to be updated on demand to new data distributions.

In this study we introduce an **interactive, incremental learning method for intention detection in real-time**, along with related optimization techniques. The method enables prosthetic users to quickly update the myocontrol system on demand, reducing the impact of the non-stationarity of input signals, improving the generalization power and providing an **interactive experience** to the user. Beginning with an **empty model**, we simulated the application of this approach based on **real-time labeling** to identify **best algorithm configurations**. We compared different **feature extraction** and **target remapping techniques**, assessing **sensitivity to hyperparameters tuning**. We measured performance with standard regression metrics, demonstrating the algorithm ability to **adapt model weights in real-time to new EMG data** and accurately remap predictions to previously unseen patterns, with the final goal of controlling an advanced hand [3] and wrist [4] trans-radial prostheses.

## METHODS

### Incremental Learning Algorithm

We implemented an **interactive incremental Ridge Regressor (RR)** to enable **real-time prosthetic control** (Figure 1). This algorithm updates continuously as new EMG samples and action labels are received in real-time. The **Sherman-Morrison formula** [5] allows fast matrix updates, ensuring low-latency retraining with each new sample. Each action is modeled independently, enabling **multi-action regression**.

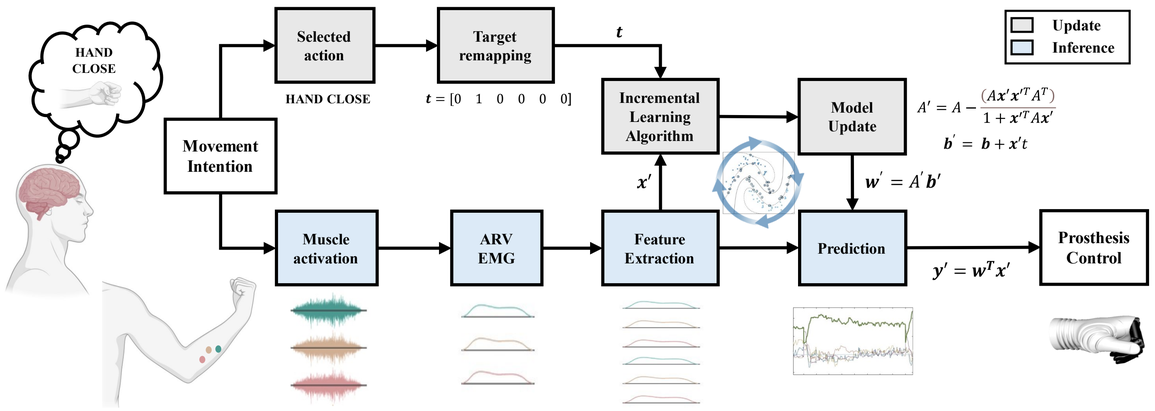



Figure 1- Interactive Incremental Learning Algorithm concept: whenever training is needed, the user, according to its movement intention, simultaneously executes the muscle activation pattern and communicates the selected action to the algorithm. After target remapping, the target vector t is sent to the incremental learning algorithm. At the same time, ARV of EMG signals are measured by the sensors. Features are extracted from signals, to obtain the input vector x'. The incremental learning algorithm updates the model weights w and updates the predictions y' accordingly. During normal operation, predictions are made using last model weights and prosthesis is controlled to execute the required action.

### Participants

We recruited **20 able-bodied participants** (ages 22–33, mean 27.1 ± 3.2) and **10 individuals with unilateral trans-radial amputation** experienced in active prosthesis use. All subjects provided written informed consent, and the study was approved by the Bologna-Imola ethics committee (CP-PPRAS1/1-01), in line with the Declaration of Helsinki.

### Experimental Setup

Six preamplified bipolar **ARV EMG sensors** (Ottobock 13E200=50) were placed ~5 cm below the olecranon, around the **forearm or residual limb**, targeting muscles commonly involved in prosthetic control. Participants performed 10 repetitions of six upper-limb movements (hand open/close, wrist pronation/supination, and flexion/extension), with **2-second** intervals, and **rest trials** included between gestures. Visual cues were provided via a **PC interface** displaying an animated **Hannes** prosthetic hand. Data were sampled at **1 kHz**, labeled in real-time, and wirelessly transferred via Bluetooth.

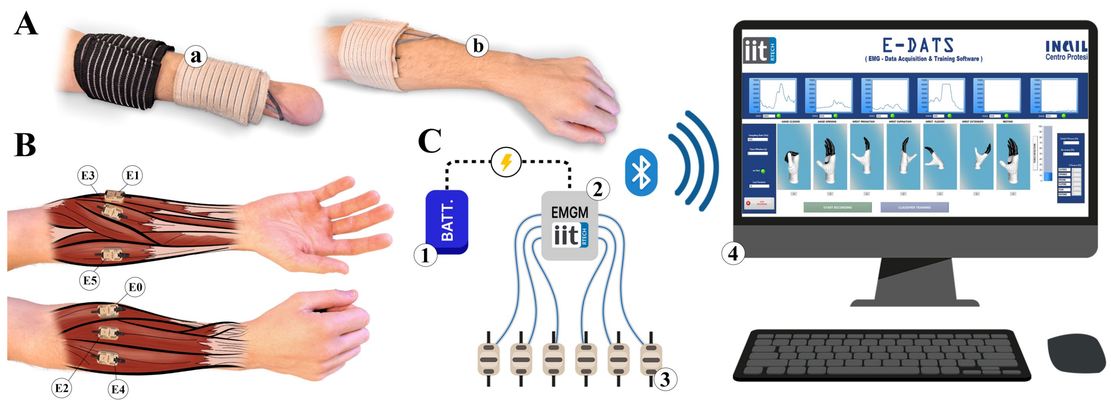



Figure 2 - Experimental Setup: (A) LD (a) and AB (b) subjects wore 6 ARV EMG sensors targeting 6 main muscles (B). (C) Signals are sampled via a custom microcontroller board (2) and streamed to the PC via Bluetooth. A custom GUI (4) was used to record signals and synchronize the 6 actions plus rest.

### Pipeline Design and Optimization

Input EMG signals were normalized and expanded using various **feature extraction** techniques: linear, quadratic, and cubic features and *Random Fourier Features (RFF)* [6] with different dimensionality. We also compared multiple **target remapping** strategies.
Moreover, we optimized key parameters of feature extraction and ridge regression, such as **γ (RFF locality), Feature dimensionality D and λ (RR regularization).**
Final **accuracy** and **model efficiency** performance was assessed using **adjusted $R^2$** and **Bayesian Information Criterion (BIC)**.

## RESULTS

### Hyperparameter Tuning and best model selection

We optimized the Random Fourier Features (RFF) hyperparameters across different dimensionalities (D) and user groups (able-bodied [AB] and limb-different [LD]). Accuracy peaked at **D over 83**, showing no significant improvement beyond this point ($p > 0.05$), indicating diminishing returns with higher complexity. Performance was generally higher and more stable in AB participants, likely due to more consistent EMG signals. We found that optimization of parameter **γ** has a great impact on performances and generalized very well among AB and LD subjects.

Comparing feature extraction methods and target remapping strategies (Figure 3), we found that **RFF outperformed polynomial methods** significantly ($p < 0.001$ in AB). The **"all-actions" remapping** strategy—assigning 1.0 to the selected action and 0.0 to others—yielded the **highest accuracy and lowest error**, while the "single-action" approach performed poorly, often worse than baseline. These findings confirm the need to train all regressors simultaneously to handle muscle co-activation and action interference. Cross-validation showed similar performance across a broad range of λ values.

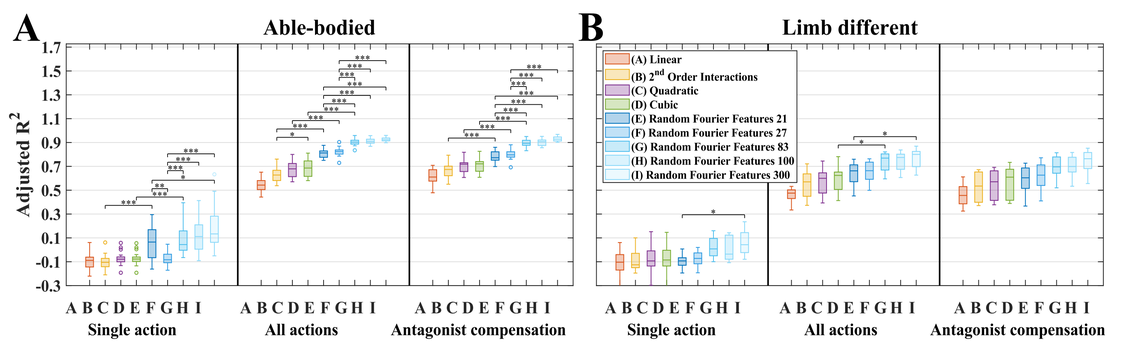



Figure 3 – Performance of different feature extraction methods and target remapping strategies, for AB (A) and LD (B).

### Real-Time Model Adaptation

Using the best configuration (RFF with D = 83, all-actions target remapping), we demonstrated real-time model updates on limb-different participants. Weights for each action adapted progressively in 10-second intervals. This led to stable predictions as each action was introduced, illustrating the model's **incremental learning capability** and **responsiveness to new EMG patterns** over time.

**Limitations:** Current results were obtained under stationary, prosthesis-free conditions. Future work will include **dynamic limb positions and prosthetic payload** to better reflect real-world use.

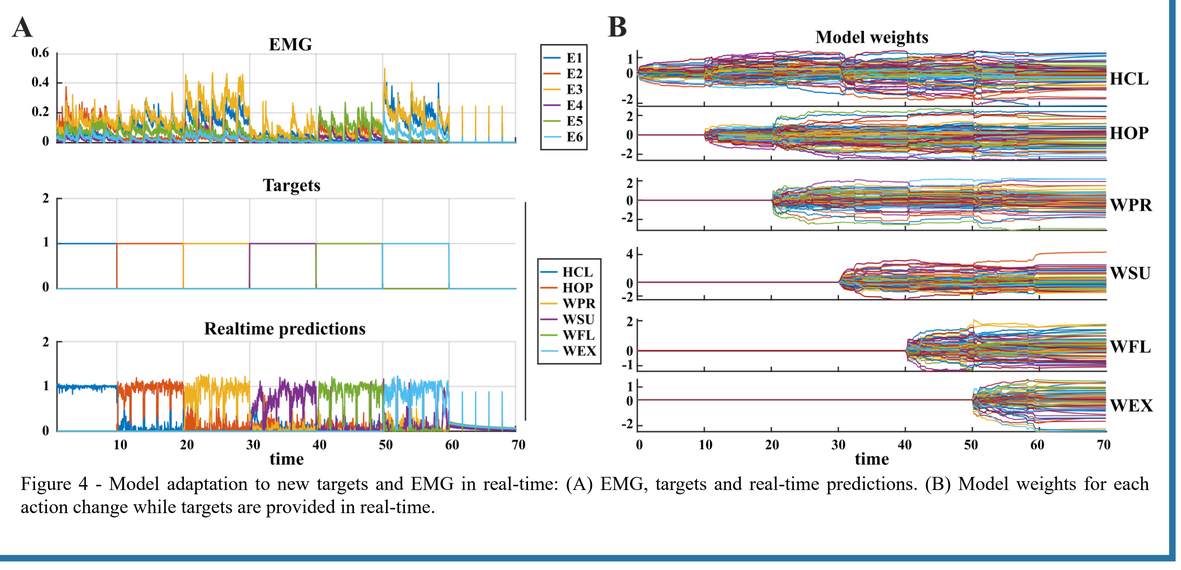



Figure 4 - Model adaptation to new targets and EMG in real-time: (A) EMG, targets and real-time predictions. (B) Model weights for each action change while targets are provided in real-time.

## CONCLUSION

This study introduces a novel **incremental learning approach** for myoelectric prosthetic control that allows users to **train and personalize** their intention-detection model in real time.

By embedding the algorithm directly into a prosthetic device and pairing it with an intuitive action selection interface, users can **independently adapt the model** to match their unique EMG patterns. Thanks to its **low computational demand**, the algorithm supports **on-the-fly retraining**, addressing a key challenge in prosthetics: coping with the **variability of EMG signals** over time.

This method enables **instantaneous model updates**, supporting dynamic use throughout the day. Future work will focus on **real-time implementation** in a complete prosthetic system, testing the ability of this adaptive method to continuously align EMG input with user intention during real-world use.

## REFERENCE

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