Demonstration of Cross-Subject Hand Gesture Recognition from EMG

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By combining modern machine learning techniques with advances in neurophysiology, human-computer interfaces (HCI) are increasingly able to interpret physiological signals with sufficient accuracy to support natural and intuitive interaction with digital devices. In particular, surface EMG signals collected on the forearm are strongly correlated with the user's hand gestures. Applications of EMG-based HCIs include sign language recognition [8] and hands-free controllers, which are particularly useful in virtual reality. Also, the ability to record EMG from residual muscles near amputated limbs enables the development of robotic prostheses that are controlled *by thought* [1].

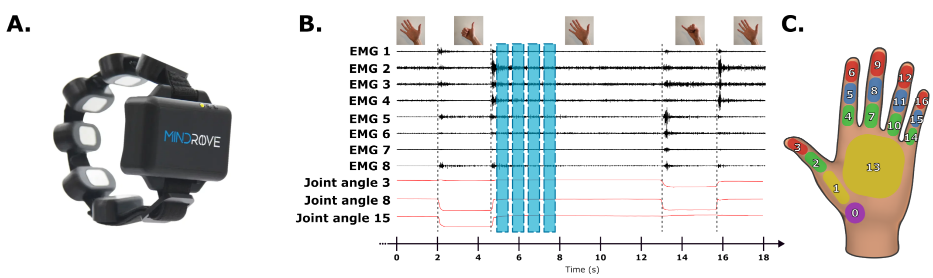

Fig. 1. A. The MindRove 8-channel EMG armband system (`https://mindrove.com/product/emg-armband`) **B.** Example of EMG signals and finger joint angles recorded during guided hand gestures. **C.** Corresponding hand model representation.

The general machine learning approach involves training a model on epochs of EMG data paired with corresponding hand shape labels (as illustrated in Figure 1.B), and subsequently using the model to continuously recognize gestures based on the most recent epoch. Current applications achieve high accuracy in intra-subject configurations, i.e., when the model is trained and used exclusively on labeled data collected from the same individual user [10]. However, their accuracy typically drops in cross-subject configurations due to variability between subjects and sessions, such as muscle size, exact sensor placement, or user fatigue [7] [5]. This reveals a significant practical limitation. For natural and widespread use, EMG-based HCIs should aim for cross-subject gesture recognition, allowing new users to operate the system immediately without requiring unnatural calibration phases.

Proposed solutions to the cross-subject problem include normalization techniques and a range of transfer learning strategies. Commercial devices most commonly adopt supervised calibration[1]. However, because factors such as fatigue and motor redundancy can alter the signal over time [6], supervised adaptation typically maintains high accuracy only for a limited duration.

Unsupervised domain adaptation (UDA), in contrast, adapts a recognition model to a new domain using only unlabeled samples from the target subject. UDA strategies are particularly relevant for HCIs, as they enable new users to operate the device immediately, allowing the system to seamlessly and continuously adapt its parameters to maintain high accuracy even against factors such as fatigue during extended sessions. We recently proposed **LDA-KM-DA** [2] (illustrated in Figure 2.A), a new approach to UDA for hand gesture recognition from EMG, building upon our previous results to characterize the domain shifts that occur in EMG across subjects during hand gestures [10].

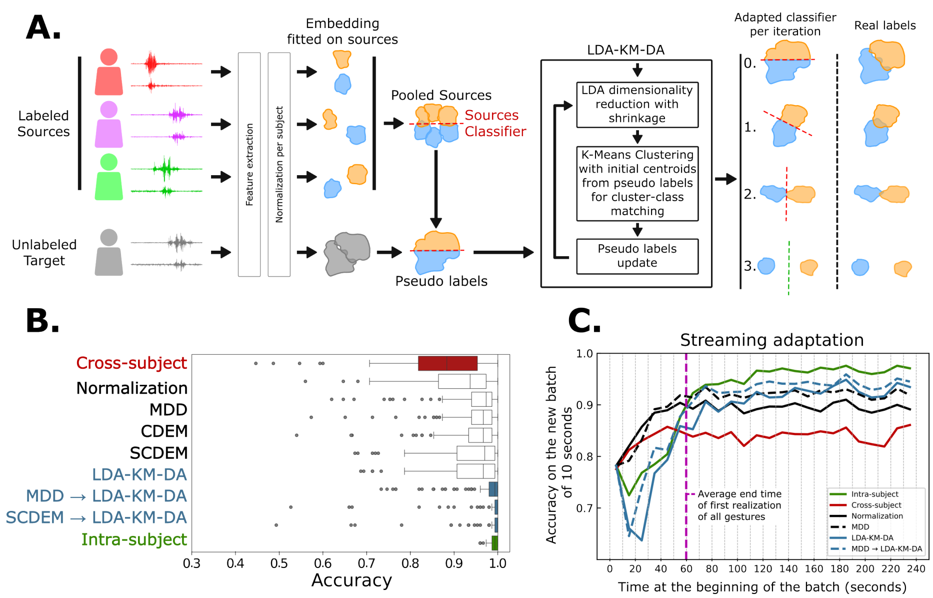

Fig. 2. A. Graphical representation of LDA-KM-DA **B.** Result of LDA-KM-DA against state-of-the-art UDA methods on the EMG-EPN-612 dataset [4] **C.** Result of LDA-KM-DA during continuous adaptation

[1] COAPT uses two minutes of guided calibration (`https://coaptengineering.com/user-manual/calibration`)

The rationale behind the proposed method is that existing approaches are constrained by domain alignment limitations, particularly in contexts where subject-specific classifiers can differ substantially. To address this issue, we explore non-conservative UDA [2] by leveraging the cluster assumption (i.e., that classifier decision boundaries should not cross high-density regions) to overcome domain alignment limitations and identify a classifier that is fully adapted to the target subject. Our solution combines the methods DIRT-T [9], for deep non-conservative UDA, and LDA-KM [3], for efficient clustering of high-dimensional data. Our results [2] from leave-one-subject-out cross-validation (illustrated in Figures 2.B and 2.C) demonstrate that LDA-KM-DA outperforms existing UDA methods across multiple datasets and during continuous adaptation.

In our live demonstration [2], we use an 8-channel EMG armband (shown in Figure 1.A) connected via Wi-Fi to a computer, along with a user interface developed in Unity that displays the EMG signals, the recognized hand shapes among five classes, and the evolution of the feature embedding computed in real time by LDA-KM-DA. This demo highlights the intuitive use of EMG for hand gesture recognition and the smooth adaptation achieved by our method, opening new possibilities for practical applications. During the showcase, visitors will be allowed to interact with the system by wearing the EMG sensors and visualizing the recognized gestures on the computer screen.

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[2] A video of the demonstration with similar EMG sensors is also available on our web page: https://martincolot.blogspot.com

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