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RESEARCH ARTICLE

Toward Pose Invariant Bionic Limb Control: A Comparative Study of Two Unsupervised Domain Adaptation Methods

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ABSTRACT Bionic limb control through myoelectric pattern recognition, offering intuitive decoding of motor intent, can improve the quality of life for individuals with amputations. However, most work on pattern recognition only uses a small subset of the myoelectric data generated during daily life, to train an Artificial Neural Network (ANN) via Supervised Learning (SL). Scenarios substantially different from the recording session e.g. different limb positions, can lead to misclassifications by the ANN during everyday usage of the bionic limb. Recording labeled data from all scenarios encountered in daily life could alleviate the problem, but would be prohibitively time consuming. Unsupervised Domain Adaptation (UDA) offers a solution by leveraging unlabeled data from a *target domain*, not represented in the labeled dataset i.e. the *source domain*, to calibrate ANNs for improved performance. In this study we explore the potential of two UDA algorithms for domain shifts in myoelectric pattern recognition: Domain Adversarial Neural Networks (DANN) and Sliced Wasserstein Discrepancy (SWD). Offline evaluation identified SWD as the best-performing algorithm, which was subsequently validated in online experiments with 11 participants. Using UDA improved the performance on the target domain by 19% compared to an ANN trained through SL on data from the source domain only. Indeed, it nearly matched the performance of an ANN trained through SL on labeled data from both the source and target domain. Our results offer an initial validation of UDA working in an online myoelectronic control task to overcome domain shift problems caused by changes in limb position.

INDEX TERMS Myoelectric control, myoelectric pattern recognition, unsupervised domain adaptation.

I. INTRODUCTION

Bionic limb research has been making progress towards restoring lost functionality due to limb amputation. While there are several biological signals that can be used to control a bionic limb, electromyography (EMG) from residual muscles is the most prevalent measurement modality for decoding movement intentions of the user. Achieving accurate motor intent decoding from EMG signals is the central objective for myoelectric control of bionic prostheses. However, this is still an open challenge in the field, especially when the bionic limb is to be used in daily life outside of the laboratory. Indeed, many promising techniques have been validated on offline datasets [1], [2] alone. There are many factors that make reproducing offline accuracy results in online settings challenging, such as electrode shift and lift-off, or compensatory limb movements, both leading to EMG signals not accounted for during fitting of a myoelectrically controlled prosthesis.

The two main myoelectric control approaches are Direct Control (DC) and Myoelectric Pattern Recognition (MPR). In DC, individual muscle signals are mapped to specific

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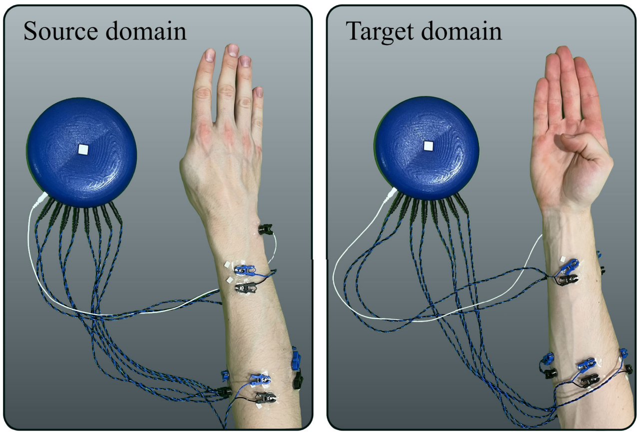


FIGURE 1. Photograph of the recording setup used for the online evaluation while performing the thumb flexion movement. The left panel illustrates the relaxed (source) domain and the right panel the supinated (target) domain.

bionic joints. DC is thus limited by the number of available independent muscles and higher-level amputations are therefore often restricted to a single degree of freedom. In contrast, MPR can handle a broader range of electrode inputs, decoding signal patterns in higher-dimensional spaces. Classical MPR methods often rely on feature extraction from EMG signals (e.g. the Hudgins set [3] and Temporal-Spatial Descriptors [4]) followed by traditional machine learning algorithms like linear discriminant analysis [5], support vector machines [6], or shallow Artificial Neural Networks (ANNs) [7]. Following recent developments in other research fields, deep learning methods, such as Convolutional Neural Networks (CNNs) [8] and Transformers [9], have largely superseded the use of traditional algorithms.

While MPR often yields superior predictive accuracy compared to DC [10], it can display a higher degree of susceptibility to environmental factors: The complex mapping of features to predict a movement class can lead to unexpected classifications when the incoming signals deviate from the ones found in the training data. This is referred to as the **domain shift problem**, which can greatly decrease the reliability of bionic prostheses. A solution to this problem would be to record training data for each movement class in every imaginable scenario one could encounter in daily life, while simultaneously obtaining labels for each class. However, this naive approach is clearly unattainable and other solutions need to be found. An alternative approach is to continuously record the myoelectric signals from people using their prosthesis in daily life. Such data is inherently representative of daily life usage but cannot directly be assigned to the correct class, therefore Supervised Learning (SL) methods cannot be applied. **Unsupervised Domain Adaptation** (UDA) is a technique that can make use of such unlabelled data, by first training a model with labeled samples from a *source* set and then adapting it with the additional unlabeled dataset to be more effective in the domain of interest i.e. *target* set [11].

In this work, we explore the use of UDA for offline and online myoelectric motor intent decoding during domain shift. Specifically, we hypothesize that UDA can significantly improve myoelectric pattern recognition performance under limb position-induced domain shift, approaching the accuracy of supervised models trained on data from both domains. In a preliminary offline experiment, we first compare different ANN architectures based on previous work by Zbinden et al. [12] and a newer architecture that shows promise for time-series data, the TSEncoder [13]. The best performing architectures are then paired with two state-of-the-art UDA algorithms, namely Domain Adversarial Neural Networks (DANN) and Sliced Wasserstein Discrepancy (SWD). Offline experiments show that the TSEncoder together with SWD achieves the highest accuracy and is consequently employed in our online experiments. To that end, 11 non-disabled participants are tasked to control a virtual limb while having their biological limb in two different poses shown in Fig. 1, thus creating a domain shift. We find that UDA achieves a significantly better online classification accuracy in a different limb pose than the SL baseline trained only on the source set.

II. RELATED WORK

Scheme and Englehart [14] describe four dynamic factors that make MPR particularly challenging: varying gesture intensity, changes in limb position, electrode shift, and the transient nature of EMG signals (i.e. signals following the onset of muscle contractions). Transient EMG signals are inherent to muscle contractions and omnipresent during real-time control, while the other three factors are a more direct source of domain shift.

Research on domain adaptation for MPR has mainly focused on domain shifts that are linked to the use of surface electromyography (sEMG), e.g. electrode shift [15]. While electrodes may shift within an EMG recording session, i.e. *intra-session*, greater differences are observed between sessions i.e. *inter-session*, as the surface electrodes are reattached. These intra- and inter-session, as well as *inter-subject* (e.g. in transfer learning research aiming to pre-train a subject-agnostic ANN) domain shift problems were explored by Ketyko et al. [16]. They employed Supervised Domain Adaptation (SDA) together with a Recurrent Neural Networks (RNN) trained on pairings of source and target datasets to compare the offline accuracy on different datasets. Domain adaptation was achieved by pre-training on samples from the source set followed by fine-tuning on samples from the target set. While they observed that fine tuning resulted in improved performance, labels from the target set must be used and the method is thus limited to cases where these are readily available.

To avoid the need for additional labels to study inter-session and inter-subject domain shifts during sEMG gesture classification, Du et al. [17] employed UDA. They combined a CNN architecture with Adaptive Batch Norm (AdaBN) [18] and found an up to 20% improvement in offline classification accuracy for both inter-session and inter-subject problems using AdaBN. Du et al. further published the CapgMyo dataset, obtained during their study. Côté-Allard et al. [19] expanded on Du et al.'s work and compared different UDA approaches, including AdaBN and DANN, combined with a CNN. They found that DANN combined with a pseudo-labelling heuristic procedure, in what they call the Self-Calibrating Asynchronous DANN (SCADANN), to provide the best performance. In our offline experiment, we expand on these findings by exploring an additional UDA approach, SWD, which has been shown to outperform other UDA approaches including DANN [20]. As an additional contribution, we also explore different ANN architectures, e.g. the TSEncoder architecture, which has been shown effective in other time-series classification problems.

The electrode shift problem addressed in the related work listed above occurs when sEMG is used and can be circumvented by using implanted electrodes instead. Indeed, suturing the electrodes onto the muscles prevents both electrode shift and loosening [21], [22]. An under-explored MPR problem which results in domain shift in EMG data is changes in limb position, e.g. during compensatory movements (i.e. movements that are not relating to the desired hand grasp but general limb pose changes to reposition the hand). Contrary to the electrode shift problem, limb position changes can also affect EMG data from implanted electrodes. Côté-Allard et al. [23] created a dataset containing different scenarios of domain shifts - including changes in limb position. They found clear differences in hand gesture classification accuracy depending on the elbow position, in an offline analysis. In another offline analysis, Li et al. [24] later showed that applying adversarial domain adaptation can mitigate such arm-position effects.

Relative to the work summarized in this section, the two main contributions of our paper are **i.** the offline evaluation of SWD as a more effective UDA algorithm when compared to DANN, especially when coupled with a TSEncoder network, and **ii.** the online evaluation of UDA on motor intent decoding accuracy in a domain shift problem induced by limb pose changes.

III. METHODS

The goal of this study is to further investigate how UDA methods can improve the performance of MPR when changes of limb position occur. Importantly, we aim to test the best UDA method, as determined by our offline tests, in an online experiment to validate the promising results obtained in other related works which were limited to offline tests.

While online tests are the gold standard to validate MPR policies for bionic control, such tests can be both tiresome and time consuming. Therefore, sufficient offline tests have to be carried out beforehand, to limit the number of evaluations to be done with test subjects. To that end, we first investigate the performance of different ANN architectures on inter-session data from Du et al. CapgMyo dataset [17], which specifically includes recordings containing domain shift problems. We then take the best-performing ANNs to compare two state-of-the-art UDA methods.

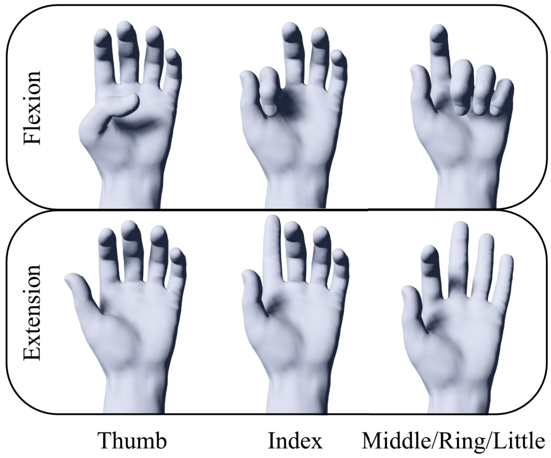


FIGURE 2. Visualization of the finger movements used during the online experiment. The movements are comprised of thumb flexion and extension, index flexion and extension, and a combined middle/ring/little finger flexion and extension. Together with a rest movement, this equates to a total of 7 different movement classes with 3 degrees of freedom.

A. ANN ARCHITECTURES

In this study, we evaluate the following network architectures: a Feed-Forward Neural Network (FFNN), a CNN with Squeeze and Excitation (CNNSE), a Temporal Convolutional Network (TCN) and a Time Series Encoder (TSEncoder).

An FFNN is a vanilla ANN, with a scalar input for each channel. The CNNSE [25] is a modified version of a regular CNN, with an additional squeeze and excitation layer which is proposed as a mechanism to help the network learn interdependencies between the channels. TCN [26] uses causal dilated convolutions, i.e. convolutions in which the output only depends on inputs that are from an earlier timestamp in some time axis. Dilation is used to keep the convolutional kernels small while retaining a large receptive field. TSEncoder is similar to TCN in the sense that it uses the same kind of convolutions. Adding a binomial timestamp masking layer to the TSEncoder architecture has been reported to result in substantial improvements to the performance in domain adaptation settings [13]. Therefore, we also evaluate the TSEncoder architecture with timestamp masking (TSEncoder-TM).

B. UDA ALGORITHMS

We explore two unsupervised domain adaptation methods: DANN and SWD. DANNs learn to produce domain-invariant representations by training two classifier heads on the output of a feature extractor i.e. an encoder [27]. The training procedure uses labeled data from a source set and unlabeled data from a target set. Each sample is assigned an additional domain label, indicating its domain of origin. The label classifier head focuses on correctly predicting the class labels of each sample, while the domain classifier head aims to identify the domain of the output representation. For samples with only domain labels, the label classifier's forward propagation is omitted. The encoder is trained to deceive the domain classifier by negating the loss derivatives using a gradient reversal layer, thereby promoting representations that obfuscate true domain origins.

SWD [20] evolved from the Maximum Classifier Discrepancy (MCD) [11] concept. Like MCD, SWD employs a distance-based loss function suitable for training with unlabeled samples. After initial encoding, two classifier branches with different random initializations are trained, yielding slightly varied decision boundaries. These classifiers, when exposed to unlabeled samples, exhibit discrepancies in classification results, leveraged as a loss function. This loss is maximized to align the classifiers with the training set's support, subsequently updating the encoder to accommodate unlabeled samples within this support. SWD differentiates itself from MCD by employing a distinct distance/discrepancy function, which has demonstrated improvements in benchmark tests [20].

While both DANN and MCD (and by extension SWD) can be considered distribution matching methods, MCD makes an attempt to align distributions while simultaneously avoiding ambiguous features near class boundaries. Both algorithm implementations used in this work were obtained from the *PyTorch Adapt* library [28].

C. OFFLINE EXPERIMENTS

Two offline experiments were conducted to select the best-performing ANN architecture and UDA algorithm. The primary goal was not to fine-tune models for our specific setup but to identify an ANN architecture that is broadly suitable for UDA within our online experiment conditions by evaluating its performance across different models in a controlled domain shift scenario.

1) DATASET AND PREPROCESSING

The CapgMyo DB-b dataset includes recordings from 10 participants, with each participant completing two sessions spaced at least one week apart. This natural inter-session domain shift makes it well-suited for testing domain adaptation techniques. However, the CapgMyo dataset was originally recorded using a 128-channel High-Density sEMG (HD-sEMG) setup, whereas our online experiment used a low-density recording setup with eight bipolar electrodes. To create a more comparable dataset, we modified the CapgMyo dataset by selecting a subset of its electrodes. Specifically, for each of the eight 16-electrode arrays, we retained signals from only a single longitudinal pair of the center-most electrodes, discarding the other 14 channels. This resulted in the Low Density CapgMyo (LD-CapgMyo) dataset, which, while not identical to our experimental setup, still captures the core challenge of bio-signal time-series classification under domain shift.

In all training procedures, the data was z-score normalized with a mean and standard deviation computed from the source data. Source and target domains correspond to the two different recording sessions from each subject in the LD-CapgMyo dataset.

Results from offline experiments are presented in terms of mean classification accuracy for all movements. Accuracy is computed by averaging 10 training runs with different pseudo-random number generation seeds per subject, resulting in a total of 100 samples.

2) SELECTION OF ANN ARCHITECTURE

Initially, all five ANN architectures described in Section III-A were trained on the LD-CapgMyo dataset in a supervised manner. Only one recording per subject was used to train the ANNs. For the FFNN, we employed the Hudgins set as input features. The network consisted of 6 hidden layers, each with 128 neurons, which is a well-established MPR setup [29]. Compared to the FFNN, the CNNSE, TCN, and TSEncoder have the inherent capability of extracting features from raw data, and therefore no feature extraction was used for the input. A more detailed description of the FFNN, as well as the CNNSE and TCN architectures and the involved pre-processing steps can be found in [12]. Training was carried out with the Adam optimizer, a constant learning rate of 0.001, a batch size of 128 and no weight decay. Models were trained for 50 epochs without early stopping, which was sufficent for convergence.

The Wilcoxon Signed rank test was used to determine statistical significance ($p < 0.05$) between the different architectures. The Bonferroni method was used to account for multiple comparisons ($m = 10$, where m is the number of comparisons).

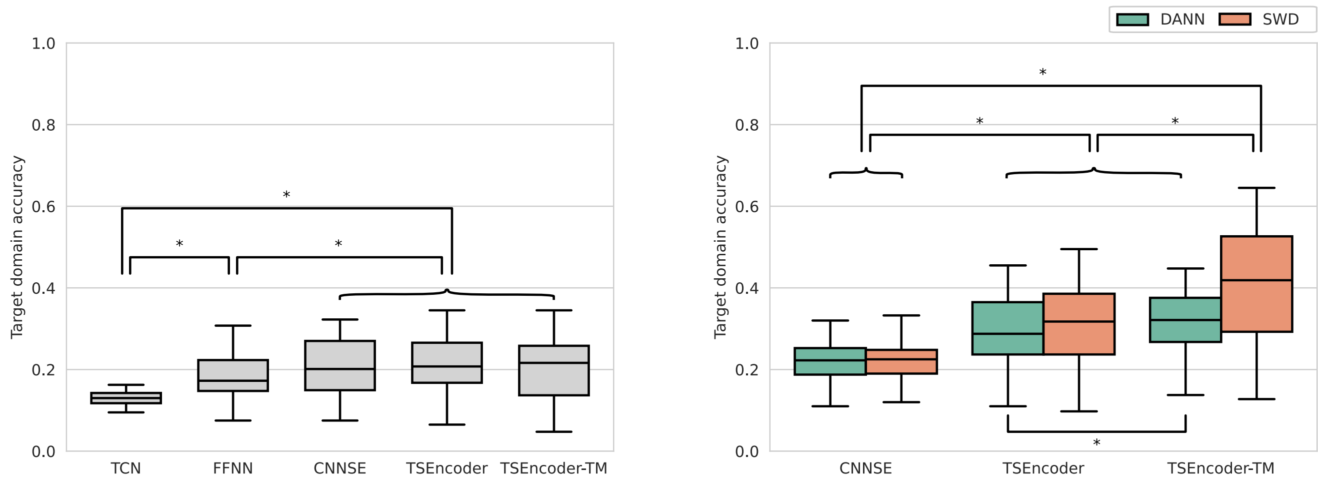
3) SELECTION OF UDA ALGORITHM

Three ANN architectures, namely CNNSE, TSEncoder and TSEncoder-TM, showed similar performance in the previous experiment, with no statistical difference between them. Therefore they were all selected to be evaluated with UDA algorithms. To determine the best performing UDA algorithm, each ANN was paired with DANN and SWD, and trained using unlabelled target domain data. The optimization algorithm and hyperparameters were identical to the training as described above, apart from the number of epochs which were increased to 5000 in order to compensate for the slower convergence of UDA methods.

The Wilcoxon Signed rank test together with Bonferroni ($m = 15$) was used to determine statistical significance ($p < 0.05$) between the different architecture and UDA combinations.

D. ONLINE EXPERIMENT

For the online experiment, we explore a limb position domain shift problem. Specifically, we introduce a domain shift by instructing the participants to either relax or supinate their forearm, as illustrated in Fig. 1. Similar to Côté-Allard et al.'s setup where elbow movements were used to create a domain shift [23], supination also leads to a change in muscle activations in the forearm.



(a) (b)

FIGURE 3. For both offline experiments, results were computed over $n = 100$ samples; 10 different inter-session source/target pairs averaged across 10 random seeds. (a) Offline prediction performance on the LD-CapgMyo dataset using SL without domain adaptation. Shown are the target domain accuracies when training all the considered ANN architectures on source domain samples only. (b) Offline prediction performance on the LD-CapgMyo dataset with domain adaptation of best performing ANN architectures. Shown are the target domain accuracies of the CNNSE, TSEncoder and TSEncoder-TM, with the two evaluated domain adaptation methods, DANN and SWD.

Eleven participants were recruited (7 male, 4 female, with an average age of 30 ± 11) for the online experiments. The number of participants was chosen based on a power analysis assuming a 10% accuracy increase at 0.1 standard deviation. The study protocol was carried out in accordance with the declaration of Helsinki. Signed informed consent was obtained before conducting the experiments. The study was approved by the Regional Ethical Review Board in Gothenburg (Dnr. 2022-06513-01).

1) DATA COLLECTION PROCEDURE

To record sEMG data, we attached 8 pairs of Ag/AgCl surface electrode to the forearm of the dominant hand of the participants, two on the front and back of the wrist along with six equally distributed in a semi-circle around the upper forearm, as shown in Fig. 1. A single electrode was attached to the Ulnar Styloid to serve as ground reference.

Participants were asked to execute the 6 finger movements shown in Fig. 2, plus rest (i.e. no movement). In order to induce the desired domain shift, we recorded a source set of sEMG data with a relaxed pose (palm down), and a target set of sEMG data in a supinated pose (palm up), as illustrated in Fig. 1. The participants were instructed to perform each movement at 50-70% of their maximum voluntary contraction strength. Each movement was recorded 6 times, for 5s. The 5s movement prompts were each followed by a 3s pause, and a roughly 30s pause between different movements. The first and last 10% of each recording was removed to exclude the transient period of the contraction. The data was recorded at a sampling rate of 1000 Hz and then filtered (a butterworth high-pass filter with cutoff frequency of 20 Hz and a second order notch filter at 50 Hz).

2) TRAINING PROCEDURE

The recorded source and target datasets were used to train three instances of a TSEncoder-TM, as this architecture performed the best during the offline experiments. The first instance only used the labeled source dataset for SL training, akin to how a myoelectrical prosthesis is normally fitted. The second instance was trained through SL on both source and target datasets to act as a baseline for a best case scenario in which labeled data from the target domain is available. The third instance used labeled source data and unlabeled target data together with the SWD domain adaptation method.

3) EVALUATION PROCEDURE

Each participant performed a total of six *Motion Tests* [30], two for each TSEncoder-TM instance. During a Motion Test the participants received prompts on a screen to perform each finger movement shown in Fig. 2. Movements were performed either for a maximum of 10s or until 40 accurate predictions were observed (equivalent to 2s, given the 20 Hz classifier prediction frequency). Note that the adaptive stopping criterion is a trade-off intended to reduce participant fatigue, but it introduces variability in the number of recorded predictions per movement class. All models were evaluated under identical stopping conditions, ensuring that this effect did not systematically favor any approach. Each classifier was used once in the relaxed (source domain) and once in the supinated (target domain) position. The order of each instance and domains was randomized. Real-time performance of the classifiers to decode motion intent was evaluated by calculating the mean classification accuracy across all movements. A Wilcoxon Signed rank test was used to determine statistical significance ($p < 0.05$) between online accuracy results, given the different instances.

IV. RESULTS

Results from the two offline experiments are summarized in Fig. 3 and the online effect of the best UDA method on a limb pose domain shift is shown in Fig. 4. All results are presented in boxplots where the bottom and top edges indicate the 25th and 75th percentiles, respectively. Outliers are represented as diamonds (◊), and statistical significance is indicated by a star ($*$). Median values are shown as a horizontal line across each corresponding box.

A. OFFLINE ANN SELECTION

Notably, all ANN architectures performed rather poorly on the target dataset. However, the classification accuracies of the CNNSE (0.206 ± 0.072), TSEncoder (0.210 ± 0.068), and TSEncoder-TM (0.202 ± 0.075) architectures were significantly higher ($p < 0.001$ in all cases) compared to the TCN (0.130 ± 0.015) and FFNN (0.181 ± 0.053) architectures, as is clear from Fig. 3a. This allowed us to narrow the scope of the following experiment, by excluding the FFNN and TCN architectures.

B. OFFLINE UDA SELECTION

By employing UDA, all results showed an improvement over the SL baselines of the previous experiment. Furthermore SWD appears to outperform DANN across architectures. The classification accuracy of the TSEncoder (minimum 0.292 ± 0.083) was significantly higher ($p < 0.001$ in all cases) compared to the CNNSE (ranging from 0.218 ± 0.048 to 0.244 ± 0.057), regardless of domain adaptation method or timestamp masking (see Fig. 3b). Using SWD in combination with the TSEncoder architecture resulted in slightly higher accuracy (0.307 ± 0.105 and 0.292 ± 0.083 with $p = 0.13$, respectively), when compared to DANN. Furthermore, adding timestamp masking when using SWD resulted in the best performing ANN, with a significant ($p < 0.001$ in all cases) accuracy increase (0.413 ± 0.142), compared to DANN (0.326 ± 0.067) aswell as all other network and UDA algorithm combinations.

C. ONLINE EVALUATION

The results of the Motion Tests confirmed that movement decoding performance substantially decreases (from 0.553 ± 0.195 to 0.486 ± 0.201, $p = 0.105$) when movements are performed in a limb position different from the original pose in which labelled data was collected (see Fig. 4). We found, as expected, that this decrease in accuracy can be mitigated through the use of labeled data originating from both domains during training (i.e. all of the data recorded from the participant before motion tests). The ANN trained using all of the available data performed similarly when tested in the relaxed (0.600 ± 0.249) and the supinated (0.615 ± 0.208, $p = 0.695$) Motion Test conditions. As expected, it also performed significantly better in the target domain compared to the ANN trained only on source data ($p = 0.019$). Curiously, having access to data from another domain marginally improved the performance

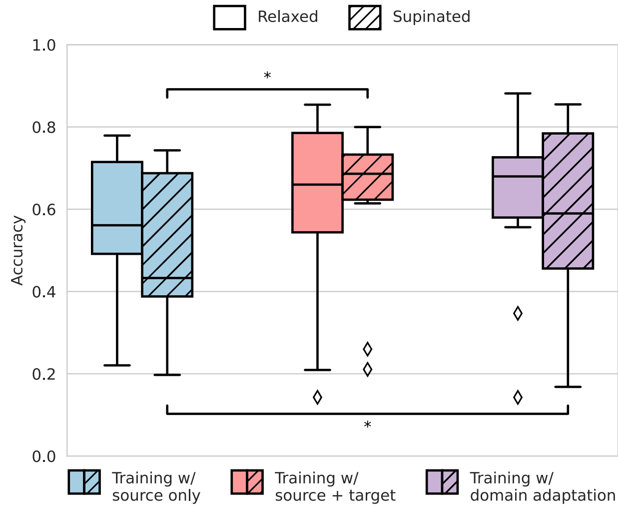


FIGURE 4. **Movement decoding accuracy during online Motion Tests, averaged over all 7 movements (for n = 10 participants, since 1 was excluded due to signal loss). Motion Tests were performed with the forearm relaxed or supinated, indicated by stripes on the boxplots. Three settings were evaluated: (left) SL training on source data; (middle) SL training on both source and labeled target data; (right) training with UDA, using unlabeled target data.**

in the source domain (from 0.553 ± 0.195 trained on the source domain to 0.600 ± 0.249 trained on both domains, $p = 0.625$).

Using UDA resulted in a decoding performance increase while performing the Motion Test in a relaxed position as well (0.553 ± 0.195 trained on the source domain to 0.619 ± 0.221 trained with domain adaptation, $p = 0.13$). Importantly, using domain adaptation resulted in a performance ($p = 0.43$) in the target domain (0.578 ± 0.234) which is comparable to the ANN trained through SL on both source and target data (0.615 ± 0.208). Finally, we observed that UDA significantly outperformed SL ($p = 0.048$) with source data, when evaluated in the target domain (0.485 ± 0.20).

Recording the source and target data set took an average of 10 minutes per set.

Note that results from one participant had to be excluded from our analysis due to loosening of a surface electrode (loss of input signal) during the Motion Test. Exclusion was based solely on signal integrity and did not affect overall outcome trends.

V. DISCUSSION

Our results showed that the reported benefits of using UDA for MPR, previously only explored through offline experiments, also carry over to online use. Indeed, using UDA resulted in a 19% increase in real-time motor intent decoding performance in the target domain, compared to a classifier that was trained via SL on source data. More importantly, the UDA approach resulted in comparable performance to an ANN trained on labelled data from both source and target domain. This is important because the latter is a much more time consuming approach, as it requires recording all desired movements for each target domain to obtain ground truth labels (recording time $\propto$ number of additional domains). While recording additional labelled datasets would be an option for a controlled research setting, dataset size for MPR is much more limited in unstructured daily life settings: patients wanting to use a MPR system with surface electrodes have to record data daily while donning the prosthesis and sometimes even multiple times a day due to electrode shift or fatigue induced signal changes. UDA offers improved performance without the need for an impractical and frustratingly long donning procedure to obtain large labelled data sets.

UDA opens up another avenue to improve prosthetic control without additional time-burden on the user: simply by storing unlabeled data from daily use (e.g., on a SD card), our UDA method can be expanded to a target domain that not only includes a single position shift, but data representative of daily use.

Regardless if UDA is used on just source training data or daily life data, this method can be seamlessly integrated into commercial prosthetic systems, as they do not require additional sensors or complex modifications to existing prostheses and they can be simply implemented in the already existing MPR training apps without any additional compute or memory burden for the target device.

The results of the offline experiments are in line with previous results, where a CNNSE architecture performs slightly better than the FFNN and TCN architectures [12]. The TSEncoder performing similarly to the CNNSE further suggests that such a architecture is a viable alternative to decode movement intent. As expected, due to the downsampling (which probably has led to a suboptimal signal representation) from 128 unipolar to 8 bipolar channels, the obtained absolute offline accuracies of all the tested architectures were lower compared to the reported values for the CapgMyo DB-b dataset.

Comparing the relative accuracy improvements, we can conclude that domain adaptation generally leads to increased motor intent decoding performance. With domain adaptation compared to SL, we observed an accuracy increase of at least 11% (CNNSE) to up to 104% (TSEncoder-TM with SWD) in our offline experiment. Using domain adaptation on the original CapgMyo DB-b dataset led to 16% improvement compared to not using domain adaptation [17], which matches the above reported 19% performance increase in our online experiment. With regards to why SWD performs better than DANN, we speculate that a combination of the SWD's alignment strategy, gradient behavior, and robustness to noise, class imbalance, and multi-modal distributions make it better suited to handling the variability and domain shifts characteristic of EMG signals.

This study was limited to an online experiment that only tests a single cause of domain shift. It remains to be shown if unsupervised domain adaptation can be equally effective when presented with other or additional causes of domain shift. An alternative to using UDA methods could be using Reinforcement Learning [31], [32], where a classifier trained on an initial dataset could be fine-tuned on data collected in a different use-case scenario. Furthermore, training stability and overfitting risks are important considerations for UDA. In our setup, adopting conservative optimizer settings aligned with SL and library defaults yielded qualitatively stable training without signs of divergence. Nevertheless, early-stopping criteria, systematic hyperparameter sweeps, and multi-seed replication in the online phase are valuable extensions for future work as long as they are balanced against participant time and calibration overhead.

Another limitation of our study was the lack of an offline dataset that perfectly matched our experimental setup while also providing a controlled domain shift scenario. Although the CapgMyo dataset differs from our setup in terms of electrode type, placement, and movement selection, the fundamental challenge (bio-signal time-series classification under domain shifts) remains the same. While our adaptation of the CapgMyo dataset introduces some discrepancies, the original structure of EMG time-series remains, and it enabled a meaningful offline comparison of different ANN architectures and UDA algorithms under domain shift, allowing us to identify a model that performed robustly within our experimental conditions.

Moreover, while our focus was on decoding motion intent, we did not evaluate key aspects such as controllability (i.e. the ease of controlling a prosthesis) and functionality (i.e. the extent to which a prosthesis enhances daily life activities). Both controllability and functionality are critical for the successful transition of prosthetic technology from the laboratory to everyday use. For future work, it would be advantageous to involve participants with amputation who are actual users of prostheses. This approach would enhance the relevance of the study to its intended clinical applications, providing more practical insights into the real-world effectiveness of the research findings.

VI. CONCLUSION

In this work, we validated through online experiments that unsupervised domain adaptation for MPR can lead to a significant increase in motor intent decoding performance compared to traditional SL training on source data, when a domain shift is caused by a limb pose change. Furthermore, we presented a comparative study which showed that Sliced Wasserstein Discrepancy can outperform Domain Adversarial Neural Networks when applied to myoelectric pattern recognition with domain shifts. These findings offer encouraging prospects for future applications of UDA, when fitting bionic limbs using MPR. Domain adaptation has the potential to effectively handle daily usage scenarios not included in a labeled EMG recording session as well as improve control performance in settings already included in the training dataset. For people using MPR-controlled prostheses, advancements in UDA could mitigate the issue of unintended prosthesis activation that currently limits prosthetic functionality.

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