TOWARD SELF-CALIBRATING PLUG-AND-PLAY MYOELECTRIC CONTROL

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ABSTRACT

Myoelectric control enables users to interact with diverse devices. However, electromyographic (EMG) signals change over time due to diverse factors, e.g., user behaviour variation, and other. These variations lead to a substantial reduction in performance of machine learning-based myoelectric control model, which in turn necessitate frequent re-calibration. In this paper, we report the results of our "self-calibrating" and "plug-and-play" random forest model. We pre-train the model and then calibrate it on new participants via one-shot calibration. The model then calibrate itself autonomously . We validated this model on 18 testing participants. Work is on-going to expand our database and study the effectiveness of the approach with people with limb difference.

INTRODUCTION

Myoelectric control systems enable users to interact with diverse devices, e.g. exoskeleton and prosthesis [1] by recognizing different patterns of the EMG signals. Diverse known or unknown factors, such as the behaviour variation of users, noises, electrode shift, muscle fatigue, limb position and other physiological factors jointly lead to the variability of EMG patterns [2], [3]. The EMG variability leads to substantially degraded performance of a model, even within a short period of time.

Training a machine learning model that can account for the variability of EMG characteristics requires a large amount of labelled data. Previous attempts to address the above issues by taking the best advantages of both labelled or unlabelled data. For instance using the notion of domain adaptation, Vidovic et al. proposed a covariate shift adaptation algorithm to adapt the basic statistical metrics of training and testing data [4]. Other studies that utilised semi-supervised learning enabled the self-training or self-calibration of a deep neural network [5], [6]. A very recent study applied a domain-adversarial neural network to generalise a model between multiple days [7].

However, these studies mostly performed one-time calibration of the model each time it was used or evaluated the model performance by pooling the testing data collected in each session together to give an overall accuracy. In practical applications, even within the same experimental session, the EMG characteristics can change [8]. This continuous change in EMG pattern causes a major challenge for myoelectric control in real-life settings. We see this challenge as an opportunity to capture intermediary data which serves our model to gradually track the change and generalise to the new EMG patterns.

We developed a self-calibrating random forest (RF) common model, which can (1) be pre-trained on data from many people and easily adapt to a new user via one-shot calibration, and (2) second, keep calibrating itself once in a while in a statistically meaningful way. The effectiveness of our method has been validated on 18 participants.

DATA COLLECTION

All participants signed an informed consent form approved by the local ethics committee at the University of Edinburgh (reference number: 2019/89177), in accordance with the Declaration of Helsinki. All settings and details of data collection are the same as our previous study [9]. Here we briefly introduce the data collection experiments.

We conducted 2 experiments. In experiment 1, we recruited 20 participants (aged 22--43 years, 12 males, 8 females). Eight electrodes were placed across the circumference of the forearm. Delsys Trigno sensors with a 2000 Hz sampling rate and 10--500 Hz passband were used for data collection. Each participant performed six hand grips ("power", "lateral", "tripod", "pointer", "open" and "rest", the same as our previous study [9]). For each hand gesture, 10 repetitions (6s each) were performed in 10 trials. Data recorded in the first 2s reaction and transition period of each trial were removed, with the last 4s retained. A 5s inter-trial resting period was provided.

In experiment 2, we recruited new participants (aged 22--28 years, 11 males, 7 females). The experiment consisted of two sessions, the calibration and the testing sessions. In the calibration session, participants performed only one repetition per gesture in a 2s trial. Only signals during the latter 1 second were retained (the same for the testing session) and used in our analyses. The testing session comprised 5 testing blocks. In each testing block, participants performed five repetitions per gesture (30 repetitions in total), with a pseudo-randomised order. Participants had 2 seconds and 5 minutes for inter-trial and inter-block rest, respectively.

METHODS

Feature Extraction

Features in each channel were extracted via a sliding window with 200 ms length and 100 ms sliding step. The following ten types of features were extracted: root mean square (RMS), mean absolute value (MAV), waveform length (WL), slope sign changes (SSC), zero crossings (ZC), skewness, mean frequency (MNF), median frequency (MDF), peak frequency (PKF), and variance of central frequency (VCF). The final length of feature vector is 80 (8 channels × 10 features).

Pre-training and Fine-tuning a RF Model

The RF model for each user was first pre-trained on data from other users. The pre-trained RF model consists of 200 decision trees. All pre-trained decision trees were then pruned using the calibration data (collected in the calibration section) from the new user. A bottom-up pruning strategy was applied. Details on decision tree pruning can be found in [9]. After pruning each pre-trained decision tree, we trained 200 new decision trees from scratch, using only the calibration data from the new user. These new decision trees were appended to the pre-trained and pruned RF model. The pre-trained and fine-tuned RF consists of 400 decision trees (200 pre-trained and pruned trees and 200 appended trees). All other details are the same as our previous work [9].

Self-calibration

When using the model, we applied a data buffer to save the latest testing samples. The size of the data buffer was set to 1500 windowed samples (about 500 KB for float32 precision). The data buffer was updated after each testing block and used to self-calibrate the model. When the data buffer reached its maximum size, the oldest sample corresponding to the gesture label (determined as pseudo-labels) with the most samples would be deleted.

To assign reliable pseudo-labels on high-dimensional EMG features, we performed t-Distributed Stochastic Neighbor Embedding (t-SNE) [10] to map the original 80-dimensional EMG feature space into a 3-dimensional subspace, and at the same time preserve the local distribution structure in the original space. After that, K-Means clustering was performed on the 3-dimensional data. The initialised labels of all testing samples before clustering were assigned as the predictions directly given by the current model.

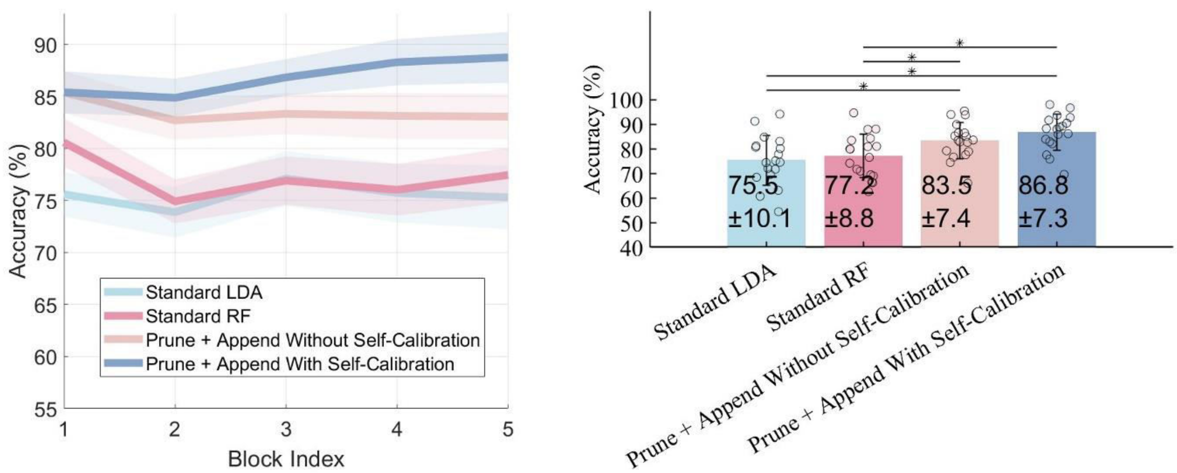
After the pseudo-label assignment, both data in the data buffer with pseudo-labels and the calibration data (used in the fine-tuning stage) with ground-truth labels were combined together to train new decision trees and replace the original ones. We kept those pruned decision trees fixed and only replaced those appended decision trees. Each time we only replaced 80 (40% of 200) randomly selected appended decision trees.

Validation

All data from the 20 participants in experiment 1 were allocated to the pre-training dataset. For data from the 18 participants in dataset 2, each participant was in turn viewed as the target testing participant, with data from the other 17 participants used as additional pre-training data. Accordingly, for each of the 18 testing participants, data from 37 participants were available for model pre-training. Given the pre-trained RF model, data collected from the testing participant in the calibration session were used to fine-tune the RF model via pruning and appending decision trees. Self-calibration was performed after each testing block. In addition to the above models, we further implemented standard user-specific linear discriminant analysis (LDA) and random forest (RF) models to provide baseline performances. The standard LDA and RF models were trained using only the data collected in the calibration session for each target testing participant.

RESULTS AND DISCUSSION

Results are presented in Figure 1. According to Figure 1 (a) and Figure 1 (b), the accuracy of pruned and appended RF model achieved a higher accuracy compared with standard RF and LDA models. With self-calibration, the accuracy of pruned and appended RF could be further improved. Specifically, as presented in Figure 1 (a), the accuracy with self-calibration showed a slowly increased trend, demonstrating that the self-calibrating model can progressively adapt to the data distribution in the testing process.



(a) Accuracy-Block Curve (b) Error Bar of Different Models

Figure 1: Results of Different Models. In (a), standard error (SE) was presented as the shaded area for the figure clarity. In (b), standard deviation (STD) was presented.

The pre-training and self-calibration steps could progressively improve the model performance compared with the standard RF model. It does so by learning more general knowledge from much more data from other participants, therefore the model generalise better with only a few calibration samples from each new participant. The self-calibration step improves the model performance by estimating a more precise data distribution using more testing data. The assigned pseudo-labels may not be 100% accurate but can still provide useful information on the overall distribution of data belonging to each class.

In our method, the pseudo-labels were assigned by integrating manifold learning via t-SNE and clustering via K-Means. EMG features are normally of high dimensions, distributed on a curved manifold in the feature space. The motivation to apply manifold learning is to simply the data distribution in the high-dimensional feature space. Through manifold learning, the curved manifold can be flattened in a low-dimensional space. The motivation for applying clustering is to jointly consider (1) the knowledge learned by the current model (for the initialisation of pseudo-labels before clustering) and (2) the statistical information and distribution structure of a batch of saved data. Without these components (i.e., directly assigning pseudo-labels using the predictions of the current model), the model would be more likely to fall into a loop to learn biased knowledge given by itself. With the joint contribution from all modules, the final self-calibrating model achieved the highest accuracy compared with all baseline methods.

CONCLUSION

We proposed a self-calibrating RF common model. The RF common model can be first pre-trained on data from many users and then fine-tuned using only one-repetition per gesture from a new target user. The RF common model would then self-calibrate itself once in a while during long-term applications. Analyses on data from 18 testing participants demonstrate the effectiveness of our model. Our work promotes the use of a plug-and-play model in real-world applications.

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