

Subject-Stratified Meta-Learning for Few-Shot Adaptation in EMG-Based Gesture Recognition

Abstract—Electromyogram (EMG)-based gesture recognition faces a fundamental challenge: signal characteristics vary both across individuals (inter-subject variability) and within individuals over time (intra-subject variability). Achieving robust classification typically requires extensive calibration data, increasing the burden on users. To address this hierarchical variability structure, we propose Subject-Stratified Model-Agnostic Meta-Learning (SS-MAML), a few-shot personalized adaptation method that incorporates meta-learning into EMG-based gesture classification. SS-MAML exposes the model to diverse within-subject learning tasks, each using single-trial data for adaptation, thereby learning initial model parameters that facilitate adaptation specifically to intra-subject variability while mitigating the influence of inter-subject variability. Experiments on three public datasets demonstrate that SS-MAML achieves superior classification accuracy under limited-data conditions, highlighting the importance of task design that accounts for the hierarchical variability inherent in EMG signals.

Index Terms—Electromyogram (EMG), Pattern recognition, Meta-learning, Model-agnostic meta-learning (MAML), Machine learning

I. INTRODUCTION

Electromyogram (EMG) signals, which represent electrical activity generated during muscle contractions, are recorded from electrodes placed on the skin surface and reflect human movement intentions. Since unique patterns emerge for each gesture, EMG signals have been utilized for gesture recognition using machine learning and hold promise for biosignal-based control interfaces such as myoelectric prostheses.

However, EMG-based gesture recognition faces a fundamental challenge: the signal characteristics vary even within the same individual due to changes in measurement conditions, including muscle fatigue, variations in contraction force, and electrode shift [1]–[4]. Conventional approaches struggle to adapt to this variability with limited training data; achieving robust classification accuracy requires extensive calibration data, which increases the burden on subjects and hinders the practical deployment of EMG-based control systems.

To address this problem, fine-tuning methods have been proposed that aim to construct models specialized for new subjects (target subjects) with minimal calibration data by leveraging pre-training models learned from existing subjects (source subjects) [5]–[7]. However, pre-trained models used in fine-tuning are optimized to maximize performance on source subject data and do not directly optimize post-adaptation performance for target subjects. As a result, fine-tuning approaches may fail to perform effectively when inter-subject variability is large. Therefore, constructing models that can flexibly adapt to arbitrary target subjects requires a

pre-training framework that explicitly considers adaptation to target subjects.

In contrast, meta-learning, a paradigm for “learning how to learn,” offers a promising solution. Meta-learning acquires adaptation strategies for EMG variability from source subjects and transfers this knowledge to target subjects, thereby directly optimizing post-adaptation performance with limited calibration data. In particular, model-agnostic meta-learning (MAML) [8] can learn initial model parameters that enable rapid adaptation to new tasks by experiencing diverse learning tasks. However, its application to EMG-based gesture recognition remains limited, and there is a need to investigate meta-learning methods that explicitly account for the hierarchical variability structure inherent in EMG signals, including both inter-subject and intra-subject components.

In this paper, we propose Subject-Stratified MAML (SS-MAML), an extension of MAML tailored to the characteristics of EMG signals. SS-MAML constructs learning tasks on a per-subject basis, thereby mitigating the influence of inter-subject variability while embedding adaptation strategies for intra-subject variability (i.e., inter-trial variability) into the initial parameters. By initializing adaptation from the learned initial parameters, the proposed method enables accurate gesture classification for target subjects using only single-trial calibration data.

II. PROPOSED METHOD

A. Problem Setting and Meta-learning Framework

We consider a classification problem in which EMG signals $\mathbf{X}_t \in \mathbb{R}^{C \times L}$ at time index t , where C denotes the number of electrodes and L represents the window length, are mapped to their corresponding gesture labels $y_t \in \{1, \dots, M\}$, where M is the number of classes. In this study, we employ a meta-learning framework to achieve adaptation to target subjects under limited-data conditions.

Meta-learning is an approach that “learns how to learn”, acquiring common learning strategies from multiple tasks. Each task consists of a support set (a small amount of training data) and a query set (remaining data for evaluation), and the learning strategy is optimized so that models trained on the support set achieve high performance on the query set. Among meta-learning approaches, MAML represents the learning strategy as initial model parameters, enabling efficient adaptation to new tasks from a shared initialization.

In this study, we design gesture classification tasks by sampling support and query sets from source subject data, acquiring initial parameters that efficiently adapt to unseen EMG

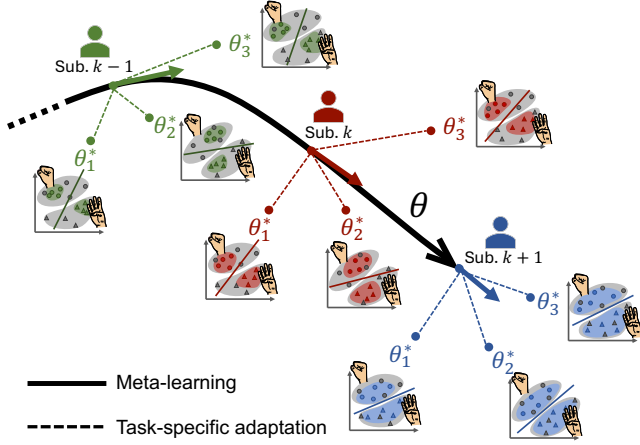


Fig. 1. Overview of the proposed SS-MAML framework. Black arrows represent meta-learning updates of the initial parameters θ , while dashed lines indicate task-specific adaptations. Learning tasks are constructed on a per-subject basis, enabling subject-invariant adaptation strategies to be progressively learned through meta-learning.

signals through MAML. The proposed SS-MAML introduces a subject-stratified task design to explicitly account for inter-subject individual variability, as detailed in Section II-B.

B. Subject-Stratified MAML (SS-MAML)

Fig. 1 illustrates the overview of SS-MAML. In the figure, black arrows indicate the meta-learning process for updating initial parameters, while dashed lines represent task-specific adaptations.

In SS-MAML, tasks are independently constructed for each source subject, and each task evaluates the model's adaptation performance to intra-subject variability. The adaptation strategy is optimized by updating the initial parameters θ of the classification model based on the adaptation performance across tasks. Through iterative updates across source subjects, subject-invariant adaptation strategies are encoded into θ . During adaptation to a target subject, high-accuracy gesture classification is achieved with limited calibration data by fine-tuning from these learned initial parameters.

1) *Task design*: SS-MAML learns initial parameters that enable efficient adaptation to intra-subject variability observed across trials. Unlike conventional meta-learning scenarios where tasks differ in their label spaces or domains, SS-MAML defines each task as a within-subject adaptation episode: one trial serves as the support set and the remaining trials form the query set. This trial-as-task formulation enables the model to learn adaptation strategies specifically tailored to intra-subject variability.

Specifically, from R trials recorded from subject k , the r -th trial is designated as the support set $\mathcal{D}_{\text{sup}}^{(k,r)}$, while the

remaining trials form the query set $\mathcal{D}_{\text{qry}}^{(k,r)}$,

$$\mathcal{D}_{\text{sup}}^{(k,r)} = \{(\mathbf{X}_t^{(k,r)}, y_t^{(k,r)})\}_{t=1}^N, \quad (1)$$

$$\mathcal{D}_{\text{qry}}^{(k,r)} = \bigcup_{\substack{r'=1 \\ r' \neq r}}^R \{(\mathbf{X}_t^{(k,r')}, y_t^{(k,r')})\}_{t=1}^N, \quad (2)$$

where $\mathbf{X}_t^{(k,r)}$ and $y_t^{(k,r)}$ denote the EMG signal and corresponding gesture label at time index t in the r -th trial of subject k , respectively, and N denotes the number of data samples per trial.

For each source subject k , SS-MAML constructs R distinct tasks by sequentially assigning each trial as the support set. By evaluating these tasks collectively, the method captures diverse patterns of inter-trial variability without dependence on any specific trial:

$$\mathcal{T}_k = \{T_{k,r}\}_{r=1}^R = \{(\mathcal{D}_{\text{sup}}^{(k,r)}, \mathcal{D}_{\text{qry}}^{(k,r)})\}_{r=1}^R, \quad (3)$$

where $T_{k,r}$ denotes the task in which the r -th trial of subject k serves as the support set.

2) *Optimization of Initial Parameters*: Fig. 2 illustrates the procedure for updating the initial parameters in SS-MAML. The initial parameters are updated through a bi-level optimization consisting of an inner loop and an outer loop. For a classification model with parameters θ , we denote the probability that input $\mathbf{X}_t$ is classified as gesture label m by $p_{\theta}(m|\mathbf{X}_t)$, and present the update rule for subject k as follows.

Inner loop: Optimization is performed for each task $T_{k,r}$ starting from the initial parameters θ . The task-specific parameters $\theta_0^{(k,r)}$ are initialized with θ and updated for S steps using gradient descent on the support set. Here, the superscript (k,r) denotes parameters corresponding to the r -th task of subject k , and the subscript denotes the update step.

At each iteration $s = 1, \dots, S$, we minimize the cross-entropy loss on the support set $\mathcal{D}_{\text{sup}}^{(k,r)}$ using the parameters $\theta_{s-1}^{(k,r)}$, which have been updated $s-1$ times:

$$\mathcal{L}(\theta_{s-1}^{(k,r)}; \mathcal{D}_{\text{sup}}^{(k,r)}) = -\frac{1}{N} \sum_{t=1}^N \log p_{\theta_{s-1}^{(k,r)}}(y_t^{(k,r)} | \mathbf{X}_t^{(k,r)}). \quad (4)$$

Based on this loss, the parameters are updated as:

$$\theta_s^{(k,r)} \leftarrow \theta_{s-1}^{(k,r)} - \alpha \nabla_{\theta_{s-1}^{(k,r)}} \mathcal{L}(\theta_{s-1}^{(k,r)}; \mathcal{D}_{\text{sup}}^{(k,r)}), \quad (5)$$

where $\alpha > 0$ denotes the learning rate.

After S updates, the loss on the query set $\mathcal{D}_{\text{qry}}^{(k,r)}$ is computed using the adapted parameters $\theta_S^{(k,r)}$ to evaluate adaptation performance. Specifically, we evaluate how well the model, trained on only the r -th trial, generalizes to the remaining $R-1$ trials:

$$\begin{aligned} \mathcal{L}(\theta_S^{(k,r)}; \mathcal{D}_{\text{qry}}^{(k,r)}) &= -\frac{1}{N(R-1)} \\ &\times \sum_{r' \neq r} \sum_{t=1}^N \log p_{\theta_S^{(k,r)}}(y_t^{(k,r')} | \mathbf{X}_t^{(k,r')}), \end{aligned} \quad (6)$$

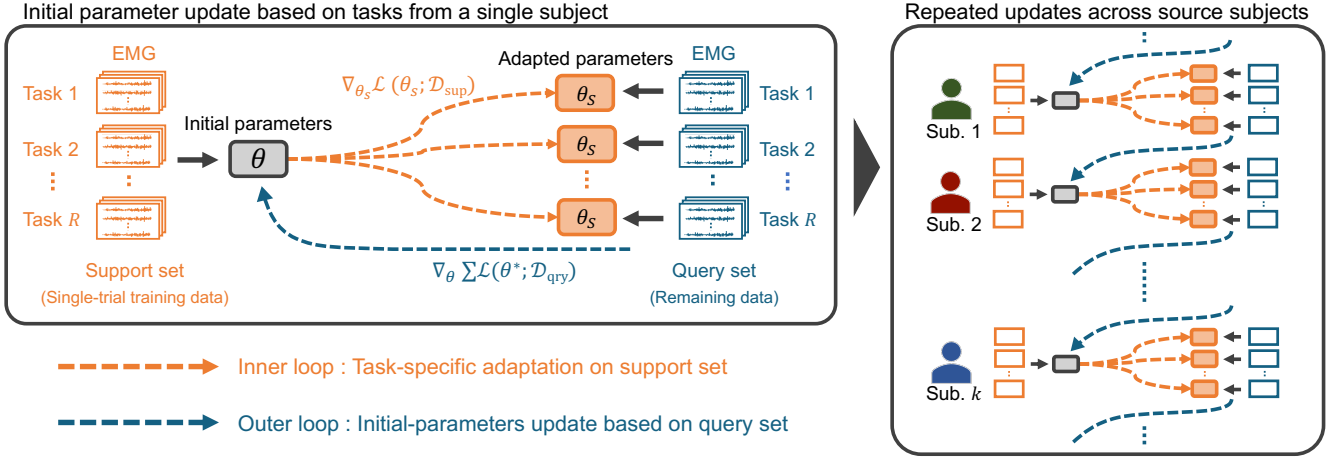


Fig. 2. Architecture of the SS-MAML update procedure. In the inner loop, task-specific adaptation is performed from the shared initial parameters θ with the support set. In the outer loop, θ is updated based on the loss evaluated on the query set. This procedure is iteratively repeated across source subjects.

where a smaller loss indicates successful adaptation from θ with high generalization performance.

Outer loop: The initial parameters are updated based on the query set loss for each task $T_{k,r}$ obtained in the inner loop:

$$\theta \leftarrow \theta - \beta \nabla_{\theta} \frac{1}{R} \sum_{r=1}^R \mathcal{L}(\theta_s^{(k,r)}; \mathcal{D}_{\text{qry}}^{(k,r)}), \quad (7)$$

where $\beta > 0$ denotes the learning rate. By performing this update sequentially for all source subjects $k = 1, \dots, K$ at each epoch, the model learns subject-invariant adaptation strategies to intra-subject variability.

C. Adaptation to target subjects

For a target subject, fine-tuning is performed using calibration data from a single trial $\mathcal{D}^{\text{trg}} = \{(\mathbf{X}_t^{\text{trg}}, y_t^{\text{trg}})\}_{t=1}^N$, starting from the initial parameters θ learned by SS-MAML. The cross-entropy function is defined as:

$$\mathcal{L} = -\frac{1}{N} \sum_{t=1}^N \log p_{\theta}(y_t^{\text{trg}} | \mathbf{X}_t^{\text{trg}}). \quad (8)$$

This loss is minimized via gradient descent to obtain model parameters adapted to the target subject.

III. EXPERIMENTS

A. Dataset and Preprocessing

To evaluate the effectiveness of the proposed SS-MAML, gesture classification experiments were conducted on three different datasets, referred to as Datasets I–III. Datasets I and II were obtained from the NinaPro DB1 [9]–[11] and DB5 [12], respectively, while Dataset III was obtained from the dataset proposed by Khushaba [13]. The characteristics of each dataset are described below.

- **Dataset I:** EMG signals were collected from 27 healthy subjects performing 52 gestures, including 12 basic finger gestures (Exercise A), 17 wrist gestures (Exercise B), and

23 grasping and functional gestures (Exercise C). In this study, to ensure a comparable number of subjects across datasets, the first 10 subjects were used. Furthermore, to evaluate the classification performance of basic gestures, Exercise A ($M = 12$) was used. Each subject performed 10 trials ($R = 10$) for each gesture. In each trial, subjects maintained gesture execution for five seconds, followed by a rest period of the same duration. EMG signals were recorded from 10 surface electrodes ($C = 10$) placed on the forearm at a sampling frequency of 100 Hz.

- **Dataset II:** EMG data were collected from 10 healthy subjects, including the same set of basic finger gestures (Exercise A) as in Dataset I. In this study, the same basic gestures ($M = 12$) as those in Dataset I were used. Each subject performed six trials ($R = 6$) for each gesture. In each trial, subjects maintained gesture execution for five seconds, followed by a rest period. EMG signals were recorded from 16 surface electrodes ($C = 16$) placed on the forearm at a sampling frequency of 200 Hz.
- **Dataset III:** EMG data were collected from eight healthy subjects, including 14 finger gestures ($M = 14$). Each subject performed four trials ($R = 4$) for each gesture, and in each trial, subjects maintained gesture execution for five seconds. EMG signals were recorded from eight surface electrodes ($C = 8$) at a sampling frequency of 4000 Hz. In this study, all signals were downsampled to 200 Hz after applying anti-aliasing filtering.

Window segmentation was performed using a fixed window duration of 200 ms to ensure consistency across datasets with different sampling frequencies. For datasets sampled at 200 Hz (Datasets II and III), the window length was set to $L = 40$ samples, whereas for Dataset I, which has a sampling frequency of 100 Hz, the window length was set to $L = 20$ samples. For all datasets, the window overlap between adjacent windows was fixed at 50% (100 ms).

B. Network Architecture

A one-dimensional convolutional neural network (1D-CNN) consisting of a feature extractor and a classifier was used as the gesture classification model. The feature extractor consists of three blocks, each block comprising a one-dimensional convolutional layer (kernel size = 3, stride = 1, padding = 1), a layer normalization layer, a ReLU activation function, and a max-pooling layer (kernel size = 2, stride = 2). Dropout layers (dropout rate = 0.3) were added to the second and third blocks to prevent overfitting. The number of output channels for each block was set to 32, 64, and 128, respectively. Global average pooling was applied to the output of the final block to obtain a 128-dimensional feature vector. The classifier consists of a single fully connected layer that maps the feature vector to gesture labels.

C. Training Settings

For initial parameter learning using SS-MAML, the bi-level optimization described in II-B2 was employed. In the inner loop, stochastic gradient descent (SGD) was used with a learning rate of $\alpha = 0.05$, a batch size of 64, and 5 epochs. In the outer loop, the Adam optimizer was used with a learning rate of $\beta = 0.0005$ for 200 epochs. The outer-loop updates were performed sequentially in random order, corresponding to the number of source subjects K at each epoch.

During the adaptation phase for target subjects, fine-tuning was performed using data from a single trial, starting from the learned initial parameters. The Adam optimizer was used with a learning rate of 0.001, a batch size of 64, and 40 training epochs.

D. Evaluation Methods

To evaluate the generalization performance of the proposed method, leave-one-subject-out cross-validation was employed. Specifically, among the $K + 1$ subjects in each dataset, K subjects were used as source subjects and one subject was used as a target subject; this procedure was repeated for all subjects. To evaluate the personalized adaptation performance for each target subject, leave-one-trial-out cross-validation was used. Among the R trials, one trial was used as adaptation data and the remaining $R - 1$ trials were used as test data to calculate classification accuracy. This was repeated for all possible trial combinations, and the average classification accuracy was computed. To ensure reproducibility, each experiment was conducted with five different random seeds, and the mean and standard deviation of the classification accuracy were calculated.

E. Comparison Methods

To evaluate the effectiveness of the proposed SS-MAML, comparisons were made with the following methods:

- **No-pretrain:** A method that trains a model from scratch using only a single trial data from the target subject. The number of epochs was set to 100, and other settings were identical to those used during personalized adaptation in the proposed method.

- **Fine-tuning:** A method that fine-tunes a model pre-trained on all data from K source subjects, using single-trial data from the target subject. For pre-training, the Adam optimizer was used with a learning rate of 0.001, a batch size of 64, and 100 epochs. For fine-tuning, the number of epochs was set to 50, and other settings were identical to those used during personalized adaptation in the proposed method.
- **MAML:** A meta-learning method that constructs tasks without distinguishing between subjects. In each task, the support and query sets are randomly sampled from the pooled data of all K source subjects, without preserving subject boundaries. All other training conditions were kept identical to SS-MAML to isolate the effect of the subject-stratified task design.

IV. RESULTS

Fig. 3 shows the PCA visualization of intermediate feature representations extracted from models with initial parameters learned by MAML and SS-MAML. Here, the target subject is set to Subject 1, and for clarity of visualization, results for a single gesture class (Class 1) are shown. Similar patterns were observed for the other gesture classes. As shown in Fig. 3(a), in the case of MAML, data points from different subjects are widely scattered in the feature space, resulting in unclear inter-subject boundaries. In contrast, Fig. 3(b) shows that SS-MAML produces subject-wise clusters, indicating a clearer separation between subjects in the feature space.

Fig. 4 shows the evolution of the test loss during personalized adaptation to a target subject. Although all methods show similar loss values in the early stage of adaptation, the meta-learning approaches achieve a rapid reduction in loss within five epochs, whereas Fine-tuning exhibits slower convergence. In particular, SS-MAML shows the most pronounced loss reduction and ultimately converges to the lowest test loss among all methods.

Table I summarizes the gesture classification results of all methods for each dataset. Performance is reported as the mean $\pm$ standard deviation across all subjects. The table also reports the number of subjects achieving the highest accuracy (#Subject(Best)) for each dataset. The best-performing method is highlighted in bold. The proposed SS-MAML achieves the highest average classification accuracy across all datasets and the largest number of best-performing subjects. For Datasets II and III, classification accuracy improves monotonically in the order of No-pretrain, Fine-tuning, MAML, and SS-MAML, confirming the effectiveness of pre-training and meta-learning. In contrast, for Dataset I, the No-pretrain approach outperformed Fine-tuning and MAML, indicating that the benefit of pre-training is limited under this condition. Nevertheless, the proposed SS-MAML consistently improves performance even in this setting.

V. DISCUSSION

Effect of subject-stratified task design: We investigated the effect of subject-stratified task design on learned feature

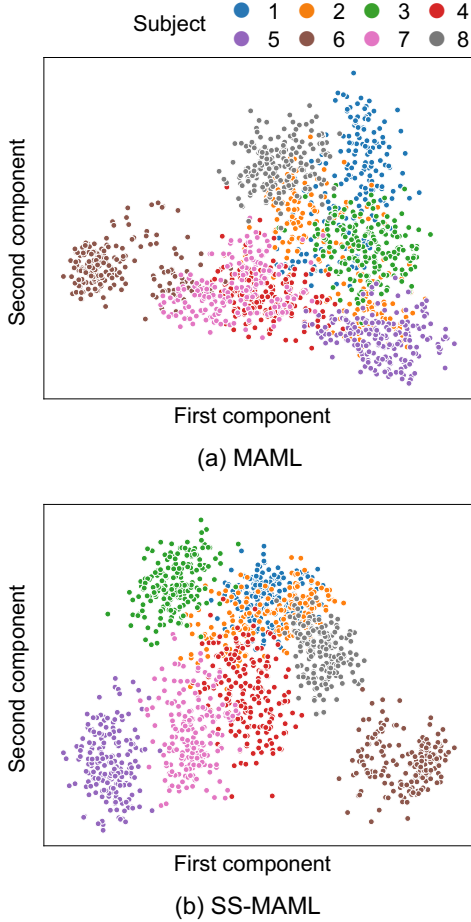


Fig. 3. PCA visualization of learned feature representations from (a) MAML and (b) SS-MAML. Features are extracted from models trained on seven subjects (excluding Subject 1) and visualized for all eight subjects. Only one representative gesture class is shown for clarity; different colors indicate different subjects.

representations through PCA visualization (Fig. 3). It is well known that EMG signals exhibit large inter-subject variability due to biomechanical and physiological factors [14], [15]. In MAML, where data from different subjects are mixed within each task, the model is encouraged to extract only subject-invariant features while discarding subject-specific information. As shown in Fig. 3(a), the boundaries between subjects become ambiguous in the feature space, suggesting that subject-specific information is lost. In contrast, SS-MAML constructs tasks on a per-subject basis, which enables the meta-learning process to preserve subject-specific characteristics while learning adaptation strategies to intra-subject variability without being affected by inter-subject variability. As shown in Fig. 3(b), subject-wise clusters are maintained in the feature space, indicating that subject-specific information can be effectively leveraged during the personalized adaptation phase.

Analysis of classification performance: Fine-tuning aims solely to maximize classification performance on source sub-

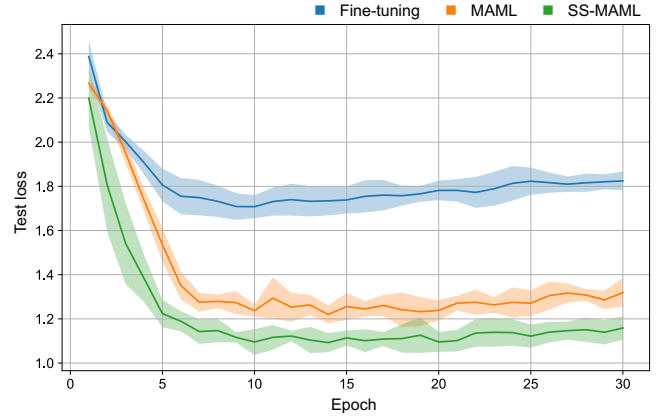


Fig. 4. Test loss curves during personalized adaptation to a target subject. Solid lines and shaded regions represent the mean and standard deviation across five random seeds, respectively.

TABLE I
EMG CLASSIFICATION PERFORMANCE ACROSS DATASETS AND METHODS.

Dataset	Method	Accuracy (%)	#Subjects (Best) [†]
I	No-pretrain	62.26 $\pm$ 4.23	2/10
	Fine-tuning	59.36 $\pm$ 4.55	0/10
	MAML	61.56 $\pm$ 4.42	0/10
	SS-MAML (ours)	63.31 $\pm$ 4.40	8/10
II	No-pretrain	56.41 $\pm$ 5.12	0/10
	Fine-tuning	58.30 $\pm$ 6.00	0/10
	MAML	61.16 $\pm$ 5.61	2/10
	SS-MAML (ours)	61.61 $\pm$ 5.77	8/10
III	No-pretrain	85.86 $\pm$ 6.03	0/8
	Fine-tuning	89.86 $\pm$ 4.76	1/8
	MAML	91.29 $\pm$ 4.93	2/8
	SS-MAML (ours)	91.63 $\pm$ 5.32	5/8

[†]Number of subjects achieving the highest accuracy among all methods.

jects during pre-training, and post-adaptation performance is not explicitly optimized. Although Fine-tuning shows some performance improvement on Datasets II and III, it underperforms the No-pretrain baseline on Dataset I. This can be attributed to the large discrepancy in signal characteristics between source and target subjects, which may cause the knowledge acquired during pre-training to become ineffective during adaptation (negative transfer). In contrast, both MAML and SS-MAML adopt frameworks that directly optimize post-adaptation performance. While MAML achieves better performance than Fine-tuning on Datasets II and III, it similarly underperforms No-pretrain on Dataset I. This suggests that MAML is sensitive to large inter-subject variability, as its task design does not explicitly distinguish between inter-subject and intra-subject variability. SS-MAML explicitly targets adaptation to intra-subject variability by constructing tasks on a per-subject basis. As shown in Fig. 4, although SS-MAML exhibits a similar initial loss to MAML, it achieves a larger loss reduction per epoch, indicating a stronger capability to rapidly capture target-subject characteristics during adapta-

tion. As a result, SS-MAML effectively mitigates the effect of inter-subject variability while enabling efficient adaptation to intra-subject variability, leading to superior classification performance across all datasets. This improvement in classification accuracy is consistent with the preservation of subject-specific feature representations observed in Fig. 3.

Limitations: Due to its task design, SS-MAML is limited to constructing tasks proportional to the number of subjects and trials ($K \times R$), which restricts the diversity of available tasks. As shown in Table I, SS-MAML underperforms MAML for some subjects, which may be attributed to insufficient diversity in adaptation patterns learned from source subjects that are suitable for the target subject's intra-subject variability. To address this limitation, future work should investigate approaches to increase task diversity, such as data augmentation-based task generation and hybrid task designs that jointly consider both inter-subject and intra-subject variability.

VI. CONCLUSION

This paper proposed SS-MAML, a few-shot personalized adaptation method for EMG-based gesture classification. Based on MAML, the proposed SS-MAML constructs tasks on a per-subject basis, enabling the learning of initial model parameters that efficiently adapt to intra-subject variability. By initializing from these learned parameters, the method achieves high-accuracy gesture classification for new subjects with minimal calibration data.

Experimental evaluations on three benchmark datasets demonstrate that SS-MAML achieves the highest classification accuracy across all datasets. Furthermore, visualization of learned feature representations suggests that SS-MAML effectively adapts to intra-subject variability while mitigating the effects of inter-subject variability. Future work will focus on a more detailed analysis of the insights obtained from the proposed method, as well as further exploration of the applicability of MAML-based approaches to EMG-based gesture classification.

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