ADAPTING TO INTER-SUBJECT VARIABILITY IN EEG-BASED MOTOR IMAGERY CLASSIFICATION WITH REPTILE META-LEARNING

Anonymous authors
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ABSTRACT

Motor imagery classification from EEG signals requires decoding information from EEG signals during the imagination of specific movements. However Learning representations for EEG-based motor imagery classification is a challenging task because of domain shifts caused by inter-subject variability and differences in mental imagery which result in poor generalization of deep learning models to new subjects.

Motor imagery classification from EEG signals requires decoding information from EEG signals during the imagination of specific movements. However, domain shifts caused by inter-subject variability and differences in mental imagery can impair the generalization of deep learning models to new subjects. Pre-trained deep learning models can achieve high accuracy on subjects with similar domains, but fail on subjects with dissimilar domains. Optimization-based meta-learning algorithms like Reptile can be used to learn a good initialization for the model to adapt quickly to new subjects with few fine-tuning examples. We show that our Reptile-EEGNet approach outperforms basic transfer learning on the BCI Competition IV 2a dataset. However, accuracy varies depending on domain similarity, highlighting the need for meta-learning approaches with more trainable parameters to analyze fine-tuning data and select the most relevant features or patterns for selecting an appropriate initialization of model parameters. Such approaches can help improve generalization across subjects with different domains, enabling reliable and effective communication with external devices through EEG-based motor imagery classification.

1 INTRODUCTION

Deep learning models have shown great success in many fields, including image and speech recognition. However, applying these models to new domains or tasks can be challenging, as they often require large amounts of labeled data for training. One approach to address this challenge is to use transfer learning, where a model pre-trained on a large dataset is fine-tuned on a smaller, task-specific dataset. Learning representations for EEG-based motor imagery classificationGuragai et al. (2020) is a challenging task due to the differences in mental imagery and inter-subject variabilitySub. In this paper, we investigate the effectiveness of the Reptile algorithmNichol et al. (2018) for meta-learning in the context of EEG-based motor imagery classification, with the goal of improving generalization to new subjects. We compare the performance of Reptile with basic transfer learning on the BCI Competition IV 2a dataset, and show that our Reptile-EEGNet approach outperforms the baseline on subjects with dissimilar domains.

2 RELATED WORK

Previous studies Zhang K (2020) have used transfer learning to address the problem of inter-subject variability in EEG-based motor imagery classification. However, these approaches are limited by the similarity of the domains between the training and testing subjects. Optimization-based meta-learning algorithmsHospedales et al. (2022) like ReptileNichol et al. (2018) can be used to learn a

good initialization for the model to adapt quickly to new subjects with few fine-tuning examples, which can improve the learning of representations. Recently a few people have tried to use meta-learning based approach to address a similar issue. like Li et al. (2021) showed that Meta learning outperformed however they used Model-Agnostic-Meta-Learning and they have not done data specific analysis. In Wu & Chan (2022) they used Reptile based approach however, they claimed that it doesn't work and have not analysed the reason behind that. In our work we showed that Reptile based meta-learning work for EEG signal and have analysed the results.

3 METHODOLOGY

To evaluate our approach, we focus on the ability to generalize to a single subject. We use the data from all other subjects in the dataset as our training dataset, while the data from the test subject is divided into fine-tuning and testing datasets.
Our approach involves three stages. First, we train the model on the training dataset using a learning paradigm. Then, we fine-tune the model using gradient descent on a few shots of trials from the fine-tuning dataset. Finally, we test the performance of the model on 4 shots of trials from the testing dataset.

3.1 MODEL

We utilize the EEGNet architecture as the backbone of our approach. During fine-tuning on the test subject, we freeze the feature extraction layers, and only fine-tune the classifier.

3.2 LEARNING PARADIGMS

We use the Reptile algorithm for meta-training on the 8 training subjects. In each iteration, we sample 5 mini-batches of tasks, where each mini-batch is from a different subject. By using this approach, we aim to learn a good initialization for the model, allowing it to quickly adapt to new subjects with few fine-tuning examples.

4 EXPERIMENTS

We used the BCI COMPETITION IV Dataset 2a, which consists of EEG signals recorded from 9 subjects (numbered 1 to 9). To evaluate the generalization of our approach, we performed 9 separate experiments, where we pre-trained on the EEG signals from 8 subjects and tested on the remaining subject. Specifically, for each $i = 1$ to 9, we used subject i as the test subject and pre-trained on the EEG signals from the other 8 subjects. We compared the performance of our Reptile-EEGNet approach with a simple gradient descent on EEGNet for pre-training.

To evaluate the accuracy achieved by our approach on subject i, we compared the performance of our approach on a few shots of fine-tuning examples with that achieved by training on more fine-tuning examples. To do this, we divided all the trials of subject i into two sets: a fine-tuning set and a testing set. We then fine-tuned our pre-trained model on the few shots of examples from the fine-tuning set and evaluated the accuracy on the testing set.

5 RESULTS

Reptile outperforms transfer learning on EEGNet for few-shot classification accuracy. This shows that meta-learning can achieve a better accuracy with only a few fine-tuning examples. However, the accuracy of Reptile on many-shot classification still varies depending on domain similarity to the train subjcts. Our Reptile-EEGNet approach outperforms basic transfer learning on the BCI Competition IV 2a dataset, with a focus on learning representations. Our approach highlights the importance of meta-learning approaches with more trainable parameters to analyze fine-tuning data and select the most relevant features or patterns for selecting an appropriate initialization of model parameters. This can enable more reliable and effective communication with external devices through EEG-based motor imagery classification.

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A APPENDIX

You may include other additional sections here. However, please be mindful that the spirit of the Tiny Papers track is for papers to be short. Avoid overly-long appendices.

Table 1: Accuracy comparison for different number of fine-tuning shots

	Fine-tuning shots											
	0	1	2	3	4	5	6	7	8	9	10	many
Test Subject 1:												
EEGNet	63.54	60.71	64.32	66.88	68.75	69.53	69.20	70.19	71.35	73.86	72.50	83.93
Reptile-EEGNet	70.83	64.96	66.15	69.06	70.49	71.09	73.21	74.52	73.96	75.00	76.25	90.18
Test Subject 2:												
EEGNet	32.81	36.16	34.11	34.06	36.46	38.28	38.84	41.83	39.58	39.77	41.88	67.86
Reptile-EEGNet	35.42	36.38	39.58	38.44	41.67	41.41	41.96	42.79	43.75	43.75	46.25	73.21
Test Subject 3:												
EEGNet	65.10	65.40	67.97	70.31	70.49	71.88	71.88	73.08	73.44	72.73	77.50	91.96
Reptile-EEGNet	71.88	70.54	72.92	73.75	76.39	79.30	79.02	80.29	81.25	78.98	81.25	97.32
Test Subject 4:												
EEGNet	41.15	43.97	46.35	47.50	49.65	48.83	53.13	52.40	51.56	52.84	59.38	82.14
Reptile-EEGNet	48.44	48.66	48.18	50.31	52.43	53.13	54.02	54.33	56.77	55.68	56.25	83.93
Test Subject 5:												
EEGNet	34.38	32.59	34.38	34.69	36.81	38.28	37.05	37.50	35.94	39.20	38.75	56.25
Reptile-EEGNet	36.63	39.06	39.58	38.44	38.54	38.28	40.63	41.83	42.19	43.75	44.38	59.82
Test Subject 6:												
EEGNet	42.71	39.51	43.49	43.44	45.83	44.92	46.88	44.71	46.88	46.59	51.88	66.96
Reptile-EEGNet	47.74	43.53	45.83	45.94	43.75	46.09	48.21	49.52	47.92	51.70	55.63	74.10
Test Subject 7:												
EEGNet	50.52	47.54	51.04	53.75	53.47	55.08	54.91	55.29	55.21	57.39	60.00	91.07
Reptile-EEGNet	59.55	53.57	55.99	56.88	58.68	62.89	61.61	65.38	60.42	61.36	61.25	90.18
Test Subject 8:												
EEGNet	57.99	58.93	61.46	62.81	63.19	64.84	65.18	65.38	67.19	69.32	66.25	89.29
Reptile-EEGNet	66.49	61.83	64.58	65.63	69.10	71.48	69.64	69.71	70.83	71.59	73.75	88.39
Test Subject 9:												
EEGNet	58.85	58.26	63.54	63.44	65.28	68.75	66.96	69.71	69.79	66.48	68.13	87.50
Reptile-EEGNet	63.02	66.07	65.63	66.88	66.67	68.36	68.75	69.71	71.35	69.88	73.13	83.04