Meta-Learning for Emotion Prediction from EEG while Listening to Music

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ABSTRACT

We are studying to realize an emotion induction system that generates music based on emotions predicted in real-time from electroencephalogram (EEG). Since there are individual differences in EEG while listening to music, a model trained from a single participant's data is expected to provide highly accurate emotion prediction. However, a time-consuming EEG recording is required to avoid data shortage. We need to reduce the recording time to minimize the burden on the participants. Therefore, we train a model which considers the individuality of EEG from multiple participants' data and fine-tune it from a small amount of a single target's data. In this paper, we propose a method using meta-learning for pre-training. We compared three methods: two methods using multiple participants' data (with/without meta-learning) and a method using a single participant's data. Our proposed method obtained the lowest RMSE (valence: 0.244 and arousal: 0.287). We demonstrate the effectiveness to use meta-learning to train an emotion prediction model, which is a necessary step for constructing the emotion induction system.

CCS CONCEPTS

• **Human-centered computing → Interaction design**.

KEYWORDS

Electroencephalogram; emotion induction; emotion prediction; meta-learning

ACM Reference Format:
Kana Miyamoto, Hiroki Tanaka, and Satoshi Nakamura. 2021. Meta-Learning for Emotion Prediction from EEG while Listening to Music. In *Companion Publication of the 2021 International Conference on Multimodal Interaction (ICMI '21 Companion), October 18–22, 2021, Montréal, QC, Canada.* ACM, New York, NY, USA, 5 pages. https://doi.org/10.1145/3461615.3486569

ICMI '21 Companion, October 18–22, 2021, Montréal, QC, Canada

ACM ISBN 978-1-4503-8471-1/21/10…$15.00
https://doi.org/10.1145/3461615.3486569

1 INTRODUCTION

Appropriately inducing emotions is critical in mental health problems. It has been shown that failure of emotion regulation is related to the development of depressive symptoms [6, 11]. Music is one stimulus used to induce emotions [27]. The relationship between music and emotions has been discussed [12, 13, 25]. Valence and arousal are often used to evaluate emotions based on the circumplex model [24]. Such factors as the tempo from which music is comprised affect valence and arousal [29, 30]. Emotion induction using music is attractive since music affects emotions. However, people exhibit individual differences in the emotions they feel [15]. Therefore, our previous study proposed an emotion induction system that creates personalized music with a music generator [21]. The music consists of the following parameters: tempo, rhythm, loudness, pitch, and chord. These parameters are calculated using continuous values from 0 to 1 for the valence and arousal input to the music generator. Our previous study showed that generated music induced emotions that are close to the valence and arousal that are input to the music generator [21]. However, the felt emotion does not always match the inputs of the music generator. Therefore, we proposed a feedback loop that predicts emotions and periodically updates the inputs to the music generator [21]. Since the music changes based on the participants' emotions, it is expected to provide personalized emotional induction. The emotion induction system uses EEG for emotion prediction. EEG is the electrical activity generated from the brain. Recognizing emotions from EEG is actively being studied [10, 26, 28]. Since the music is made using predicted emotions from EEG, the prediction accuracy of emotions is critical in our system.

There are individual differences in EEG [18, 20, 33]. Previous studies on emotion induction systems trained an independent model that was adapted to individuals using only a single participant's EEG to eliminate individual differences [8, 21]. The amount of EEG data obtained is small when the recording time per participant is shortened. It was time-consuming to record the EEG to prevent data shortages in training the models. If the EEG recording and the use of the system are the same days, the burden on the participants will be large because they have to put on the electroencephalograph for a long time. Therefore, the EEG was recorded for the emotion prediction model on a different day from the day on which the system will be used in our previous study [21]. Such a difference between days might slightly shift the position of the electrodes. EEG also differs from day to day [5, 19]. Therefore, we will short the EEG recording time to train the emotion prediction model and use the emotion induction system on the same day. Unfortunately, with just a small amount of EEG data, it might not be possible to train the model [31]. Transfer learning adapts a pre-trained model to another domain [23]. Highly accurate results can be obtained from a small amount of data with transfer learning. However, in some studies, the pre-training model treated the EEG of multiple participants as one piece of data [14, 21]. We believe that training cannot take into account the personal character of EEG because no individual has been recognized. In this paper, we apply model-agnostic meta-learning (MAML) [9] that makes distinctions among participants.

MAML acquires parameters from tasks and adapts them to a target task with a small amount of data. Comparing with other existing meta-learning approaches, MAML does not expand the number of learned parameters nor place constraints on the model architecture [9]. We consider that use of MAML is expected to be useful in prediction using EEG and complex model structures. MAML has actually been used in EEG-based prediction [1, 4, 16]. In addition, MAML has been used in predicting emotions from EEG using the DEAP and SEED datasets [7]. These datasets contain not only sound but also video. The type of stimulus influences responses in biological signals [2]. In our emotion induction system, the stimulus is limited to music. Therefore, we need to investigate the effectiveness of MAML in predicting emotion using EEG while listening to music. In this paper, we compared three training methods. The first uses multiple participants' EEG with MAML. We propose to fine-tune the model trained with MAML using a single target's EEG. The second uses multiple participants' EEG without MAML. We fine-tune the model trained without MAML using a single target's EEG. This method might not be able to grasp EEG individuality. The third uses a single participant's EEG. We train the model using only a single target's EEG. This method might lack training data. We assumed that MAML trains parameters that are easily adaptable to many people from EEG while listening to music, and we hypothesized the method with MAML can reduce the error of emotion prediction compared to the other two methods.

2 EEG EMOTION PREDICTION FROM MUSIC

In this section, we describe the dataset, features and model structure.

2.1 Dataset

We used a dataset created in our previous study on emotion induction systems [21]. It contains EEG and subjective evaluations while listening to 20 sec music from 20 participants (10 males, 10 females). For this recording, completely new music that was made for the emotion induction system was used. We made a music generator based on a previous study [8]. The music generator makes music that induced emotions using valence and arousal of inputs and calculating five musical parameters. We found from crowdsourcing that the music generator is effective for making music that induces emotions that resemble the inputs [21]. The electroencephalograph was CGX Quick-30. EEG was recorded using 41 pieces of music made by the music generator. However, the data of several pieces of music from a few participants were removed due to defects in the experiment. The emotion while listening to music was evaluated using a self-assessment mannequin (SAM) [3]. Participants evaluated the valence and arousal on a 9-point scale between 0 and 1 after listening to the music.

2.2 Features

We obtained the EEG while the participants listened to 20 sec pieces of music. We cut the EEG into 1 sec slices. Then the EEG was divided into five frequency bands using bandpass filters. The logarithm of the variance of the EEG waveform that passed through the filter was calculated as features. 20 features were extracted from one piece of music. Although CGX Quick-30 can obtain 29 ch of EEG, emotion prediction using 14 ch was more accurate than using all the EEG likes in our previous study [22]. We calculated 70 dimensional features using 14 ch and made $6 \times 6 \times 5$ matrices (Figure 1), which take into account the positional relationship of the EEG and the following five frequency bands: theta (4-7 Hz), alpha (8-13 Hz), low beta (14-21 Hz), high beta (22-29 Hz), and gamma (30-45 Hz). We used zero to fill the element of the matrices where there were no EEG channels.

2.3 Model structure

We used a convolutional neural network (CNN) as an emotion prediction model. CNN is commonly used in EEG research as well as in image recognition [17, 32]. We used a CNN for training by considering the location of the electrodes. As shown in Figure 1, a CNN consists of a convolution layer (2×2 size, 1 stride), a batch normalization layer, a ReLU layer, a convolution layer (2×2 size, 1 stride), a batch normalization layer, a ReLU layer, a convolution layer (2×2 size, 1 stride), a batch normalization layer, a ReLU layer, a fully connected layer (output dimensionality of 2), and a regression output layer. We used the SGD optimizer. The number of filters in all the convolution layers was eight.

3 TRAINING METHODS

In this section, we present the three types of training methods: the proposed method and two baseline methods. The EEG can be used are for 20 participants. We trained 20 models with different data of the target participant in each method. We used a fewer hyperparameter search to reduce time required to train models.

3.1 Multiple participants' EEG with MAML

This is our proposed method using multiple participants' EEG with MAML. We used Algorithm 1 whose training procedure is shown at the top of Figure 2. We trained our models using EEG for 10 participants from the dataset with MAML. In addition, the parameters were tuned using EEG from nine participants. The obtained pre-training model was fine-tuned with the EEG of a single target participant. We explain pre-training and fine-tuning respectively.

First, we describe the pre-training. The model's parameters θ was initialized. We sampled 10 tasks and selected $\mathcal{D}_i = \{x^{(j)}, y^{(j)}\}$ which are EEG and labels for 20 pieces of music from each task. The model $\theta_i^{'}$ was trained using D_i, loss $\mathcal{L}_{\mathcal{T}_i}$ and learning rate α:

$$\theta_i^{'} = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}_i}(f_\theta).$$

The EEG and labels for the remaining 21 pieces of music of each task was set as $\mathcal{D}_i^{'} = \{x^{(j)}, y^{(j)}\}$. However, some participants' $\mathcal{D}_i^{'}$

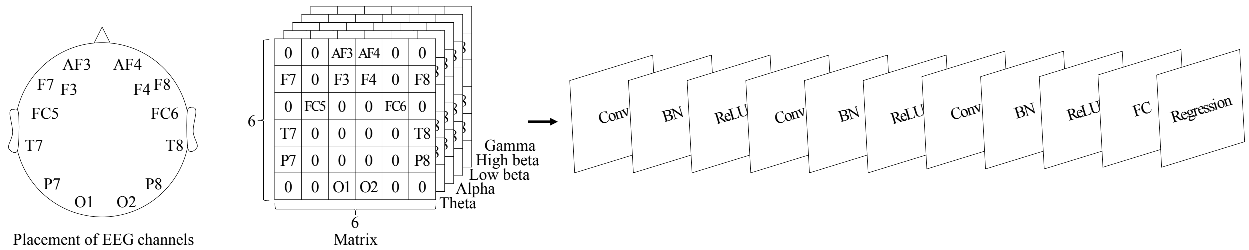

Figure 1: Structure of CNN

Algorithm 1 MAML for our emotion prediction

Require: $p(\mathcal{T})$: distribution over tasks
Require: α, β: learning rate
  randomly initialize θ
  for each *iteration* **do**
    Sample training tasks $\mathcal{T}_i \sim p(\mathcal{T})$
    for each $\mathcal{T}_i$ **do**
      Select data of 20 pieces of music $\mathcal{D}_i = \{x^{(j)}, y^{(j)}\}$ from $\mathcal{T}_i$
      Evaluate $\nabla_\theta \mathcal{L}_{\mathcal{T}i}(f_\theta)$ using $\mathcal{D}_i$ and $\mathcal{L}_{\mathcal{T}i}$
      Update parameters: $\theta_i^{'} = \theta - \alpha \nabla_\theta \mathcal{L}_{\mathcal{T}i}(f_\theta)$
      Select data of about 21 pieces of music $\mathcal{D}_i^{'} = \{x^{(j)}, y^{(j)}\}$ from $\mathcal{T}_i$
    end for
    Update $\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}i}(f_{\theta_i^{'}})$ using each $\mathcal{D}_i^{'}$ and $\mathcal{L}_{\mathcal{T}i}$
  end for

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were set to EEG and labels of 19 or 20 pieces of music due to missing data in the dataset. We evaluated updated $\theta_i^{'}$ using $\mathcal{D}_i^{'}$. After all the tasks finished these calculations, we updated θ to minimize the loss $\mathcal{L}_{\mathcal{T}i}$ of all the tasks using learning rate β:

$$\theta \leftarrow \theta - \beta \nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}i}(f_{\theta_i^{'}}).$$

The trained parameters were evaluated using the EEG of nine participants with validation data, and the parameters of the learning rate were tuned. The sets of hyperparameters were $\alpha \in \{10^{-1}, 10^{-2}\}$ and $\beta = 10^{-1}$. The model was trained until validation loss did not decrease for 5 consecutive iterations. The model trained at the best learning rate was used as the pre-trained model.

Next, we fine-tuned the pre-trained model to adapt it to a single target participant. The EEG of 20 pieces of music was fixed as training data. We performed 5-fold cross-validation using the training data. The sets of hyperparameters were *learning rate* $\in \{10^{-1}, 10^{-2}\}$. The model was trained until validation loss did not decrease for 5 consecutive iterations. The EEG of remaining about 21 pieces of music was used as test data. Finally, the five models were evaluated using test data.

The same training data, validation data, and test data were used in the proposed method and two baseline methods.

3.2 Multiple participants' EEG without MAML

This is a baseline method using multiple participants' EEG without MAML. Its training procedure is shown in the middle of Figure 2. In the proposed method, participants were regarded as tasks, and training was performed for each task. In this method, multiple participants are regarded as one large amount of data. The parameters were calculated with a batch size of 1024 using the data. The trained model was evaluated using EEG for nine participants of validation data, and the parameters of the learning rate were tuned. The sets of hyperparameters were *learning rate* $\in \{10^{-1}, 10^{-2}\}$. The model was trained until validation loss did not decrease for 5 consecutive iterations. The model trained at the best learning rate was used as the pre-trained model, which was fine-tuned to adapt to the target task. The fine-tuning method is identical as the proposed method.

3.3 Single participant's EEG

This is a baseline method using a single target participant's EEG. Its training procedure is shown at the bottom of Figure 2. This method has no pre-training. The model was trained from initial parameters θ by the same procedure as in the fine-tuning of the proposed method. The sets of hyperparameters were *learning rate* $\in \{10^{-1}, 10^{-2}\}$.

4 RESULTS

The emotion prediction results using the proposed method and the two baseline methods are shown in Table 1, which shows the RMSE between the measured values of the dataset and the predicted values of each target participant. The model with the lowest RMSE was the one of the proposed method (valence: 0.244 and arousal: 0.287). For the Wilcoxon signed-rank test result, we found a significant difference between the multiple participants' EEG with MAML and without MAML for both valence (p<.001) and arousal (p<.001). We found a significant difference between multiple participants' EEG with MAML and a single participant's EEG for both valence (p<.001) and arousal (p<.001). We also found a significant difference between multiple participants' EEG without MAML and a single participant's EEG for both valence (p<.001) and arousal (p<.001). For emotion prediction with a small amount of a target's EEG, the prediction accuracy was higher when using the EEG of multiple participants than when using the EEG of a single participant in consideration of individuality. When the EEG of multiple participants was used, the prediction accuracy was higher when using MAML than when not using it.

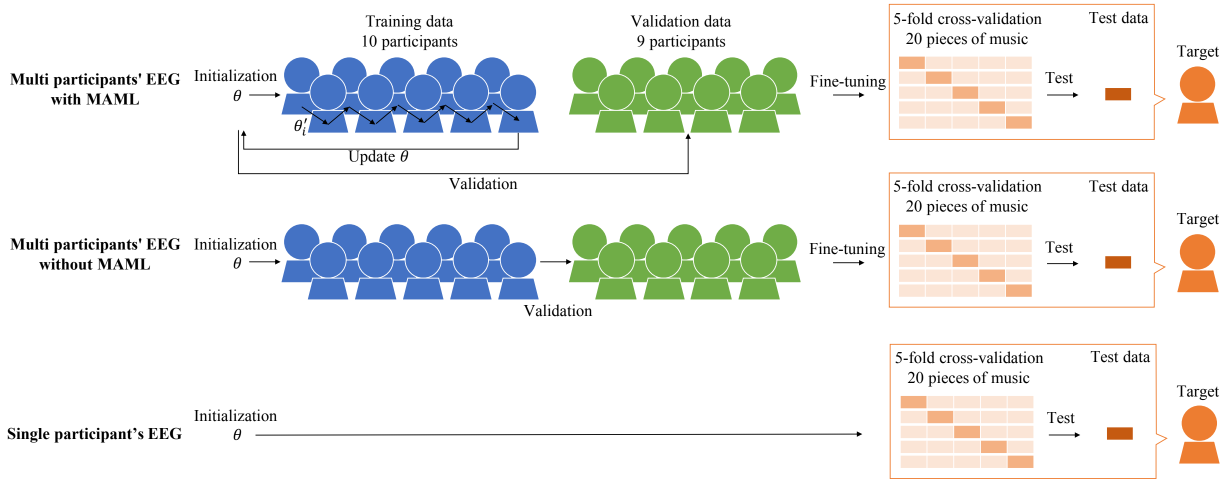

Figure 2: Three types of training methods

Table 1: RMSE of felt and predicted emotions using EEG. Bold fonts indicate the lowest RMSE.

Par.	Single par.		Without MAML		With MAML	
	val	aro	val	aro	val	aro
1	0.371	0.378	0.310	0.374	0.300	0.348
2	0.427	0.408	0.407	0.334	0.281	0.283
3	0.357	0.456	0.307	0.361	0.274	0.329
4	0.306	0.326	0.153	0.169	0.141	0.167
5	0.374	0.373	0.379	0.314	0.332	0.271
6	0.387	0.456	0.364	0.394	0.276	0.350
7	0.478	0.470	0.449	0.454	0.361	0.387
8	0.380	0.380	0.331	0.328	0.283	0.292
9	0.378	0.356	0.301	0.380	0.235	0.360
10	0.377	0.264	0.116	0.205	0.103	0.197
11	0.289	0.328	0.249	0.314	0.193	0.276
12	0.346	0.323	0.260	0.276	0.204	0.252
13	0.314	0.374	0.266	0.360	0.220	0.321
14	0.380	0.377	0.285	0.290	0.213	0.264
15	0.360	0.362	0.289	0.297	0.253	0.297
16	0.258	0.318	0.231	0.251	0.120	0.196
17	0.511	0.468	0.452	0.406	0.424	0.392
18	0.382	0.383	0.240	0.238	0.191	0.189
19	0.233	0.323	0.202	0.292	0.106	0.246
20	0.424	0.405	0.415	0.385	0.375	0.317
Mean	0.367	0.377	0.300	0.321	**0.244**	**0.287**
Std	0.066	0.056	0.092	0.071	0.090	0.066

In addition, we investigated the performance of the pre-training models and the effectiveness of fine-tuning. We evaluated the pre-training models for multiple participants' EEG with MAML and multiple participants' EEG without MAML. The RMSE was calculated from the measured values of the dataset and the values predicted by the pre-trained models. As a result, we obtained mean of RMSE for 20 participants (valence: 0.248 and arousal: 0.299) for the method with MAML and (valence: 0.310 and arousal: 0.337) for the method without MAML. We confirmed that the RMSE tended to be lowered by fine-tuning between with and without fine-tuning in the method using MAML, there were significant differences only valence (valece: p=.0228 and arousal: p=.911). We also confirmed that the RMSE tended to be lowered by fine-tuning between with and without fine-tuning in the method not using MAML, there were no significant differences (valece: p=.100 and arousal: p=.654). A previous study showed that the accuracy improves as the amount of data used for fine-tuning increases [7]. We will investigate the relationship between the amount of data used for fine-tuning and the RMSE in our future work.

5 CONCLUSIONS

In this paper, we compared three methods for emotion prediction using EEG while listening to music: two methods using multiple participants' data (with/without meta-learning) and a method using a single participant's data. The prediction accuracy was higher when using the EEG of multiple participants than when using the EEG of a single target considering individuality. This suggests that the amount of data was insufficient only with the target's EEG. In addition, perhaps the pre-training data contained EEG that resembled those of the target. When predicting emotions using EEG of multiple participants, the method with MAML was effective. This suggests that by treating each participant as a single task, training addressed the individual nature of EEG. Therefore, using MAML is effective for training an emotion prediction model, which is necessary for constructing an emotion induction system using music.

Our future task is to validate the effectiveness of MAML with a larger number of participants. We will also induce emotions by applying models trained by MAML to our emotion induction system. We will investigate how recording EEG and training the model on the same day as when using the system affects the quality of emotional induction.

ACKNOWLEDGMENTS

This work was supported by JST CREST Grant Number JPMJCR19A5, Japan, and RIKEN Junior Research Associate Program.

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