Emotion Estimation from EEG Signals and Expected Subjective Evaluation

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Emotion induction using music

Emotions felt while listening to music vary depending on individual and situation.

Music selection based on participants’ current emotion is required.
Proposed overall system [Miyamoto et al., 2020]

- Participant
- EEG

Calculation of inputs to music generator:
- arousal
- valence
- Estimated emotion
- Estimated emotion valence

Music generator:
- Music
- Music generator

Emotion estimation:
- arousal
- valence
- Estimated emotion

Estimated emotion:
- Desired emotion
- Estimated emotion

Music generator inputs:
- valence
- arousal

Participant:
- EEG
Proposed overall system [Miyamoto et al., 2020]

The purpose of this paper
Improving the performance of emotion estimation used for emotion induction
Music generator for inducing emotions [Miyamoto et al., 2020]

• The music generator made music that induces emotions similar to the inputs

• From the evaluation of the music generator, we concluded that it effectively induced emotions
Music generator for inducing emotions [Miyamoto et al., 2020]

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- From the evaluation of the music generator, we concluded that it effectively induced emotions.
Emotion estimation of related studies

Emotion estimation using EEG only  [Ehrlich et al., 2019] [Miyamoto et al., 2020]

- Related studies used linear regression and convolutional neural network (CNN)
Emotion estimation using EEG and expected subjective evaluations

- We regarded the inputs of the music generator as expected subjective evaluations.
EEG recording

Participants
20 healthy undergraduate and graduate students

Electroencephalograph
Quick-30 manufactured by CGX

Stimuli
41 pieces of music created by the music generator

Quick-30
EEG recording

Procedure

Silent (5 s)

Listening to music (20 s)

Evaluation of emotions using self-assessment mannequin [Bradley et al., 1994]

Display of SAM

EEG recording (25 s)
Preprocessing of EEG

1. The EEG in silence and listening to music was divided into 1 s
2. We designed second-order IIR bandpass filters
3. The features for each of the five frequency bands $f = \log(\text{var (EEGdata)})$
4. We mapped the matrix reflecting the position of the EEG channels
Comparison of two methods

1. CNN using EEG only [Miyamoto et al., 2020]
   - Training that takes into account the positional relationship of EEG channels
Comparison of two methods

2. Neural network using EEG and inputs of the music generator
   • Emotion estimation using emotions estimated from EEG and the inputs to the music generator

Inputs of the music generator

EEG ← CNN

Method 1

Fully connected layer → ReLU layer → Dropout layer → Fully connected layer → Regression output layer
RMSE of felt and estimated emotions

Range of felt emotions
valence: 0~1, arousal: 0~1

For the Wilcoxon signed-rank test result, we found a significant difference between neural network and CNN (p<0.05)

The means of RMSE for 20 participants

<table>
<thead>
<tr>
<th></th>
<th>1. CNN using EEG</th>
<th>2. Neural network using EEG and inputs of the music generator</th>
</tr>
</thead>
<tbody>
<tr>
<td>valence</td>
<td>0.214</td>
<td>0.151</td>
</tr>
<tr>
<td>arousal</td>
<td>0.239</td>
<td>0.164</td>
</tr>
</tbody>
</table>

RMSE of felt emotions and inputs of the music generator valence: 0.232 arousal: 0.213
Conclusion

Our purpose

Improving the performance of emotion estimation used for emotion induction

Proposed model

Neural network using EEG and inputs of the music generator

Result

There was a significant difference between the proposed neural network and CNN using EEG

Future work

Construction and evaluation of the proposed emotion induction system