TAPAS
Training Adapted Personalised Affective Social Skills with Cultural Virtual Agents

Emotion Estimation from EEG Signals and Expected Subjective Evaluation

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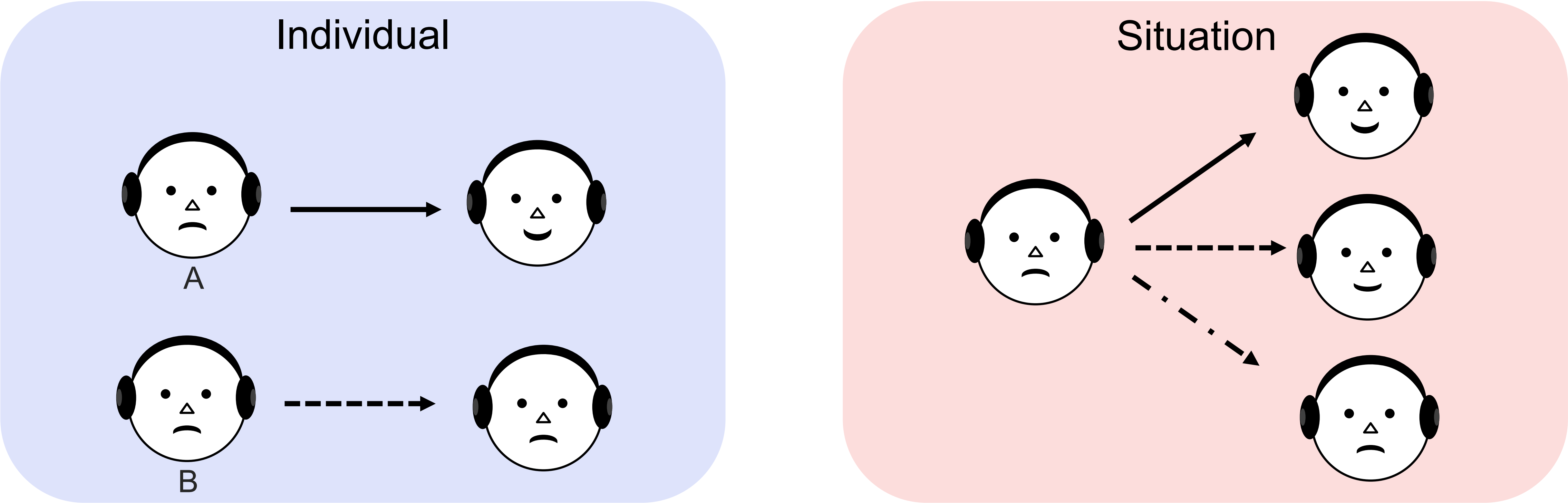
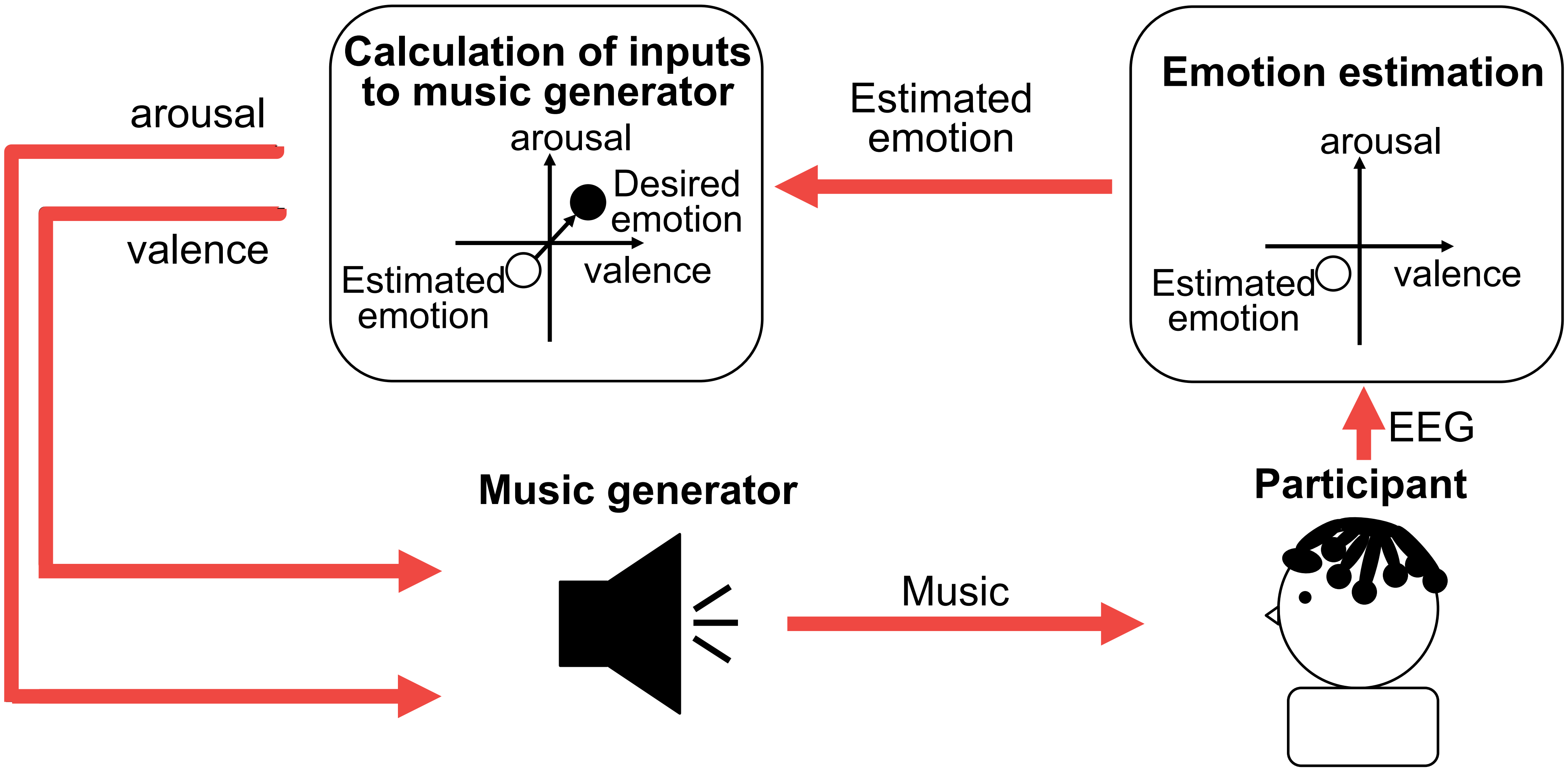
Emotion induction using music



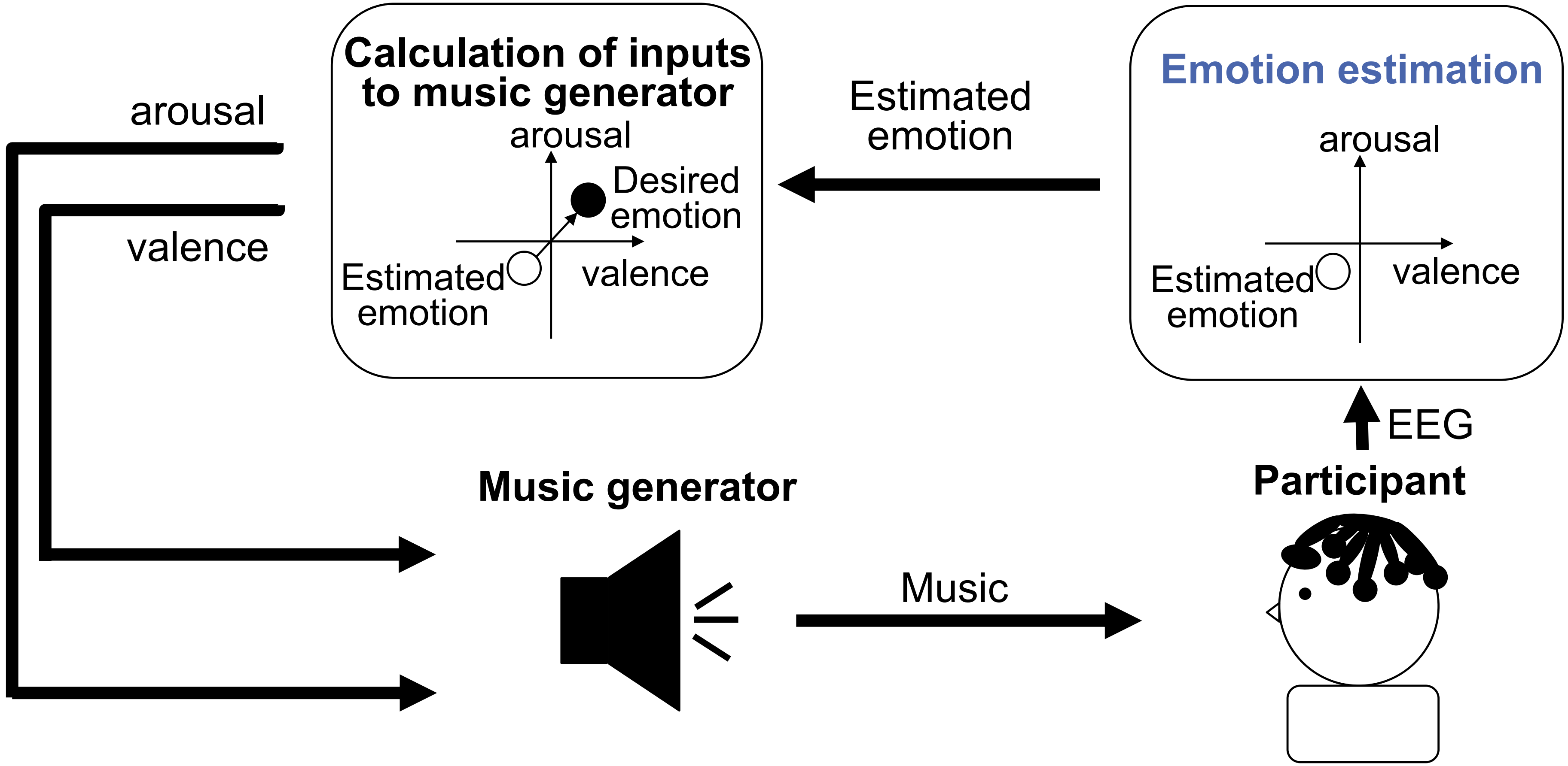
Emotions felt while listening to music vary depending on individual and situation

Music selection based on participants' current emotion is required

Proposed overall system [Miyamoto et al., 2020]



Proposed overall system [Miyamoto et al., 2020]

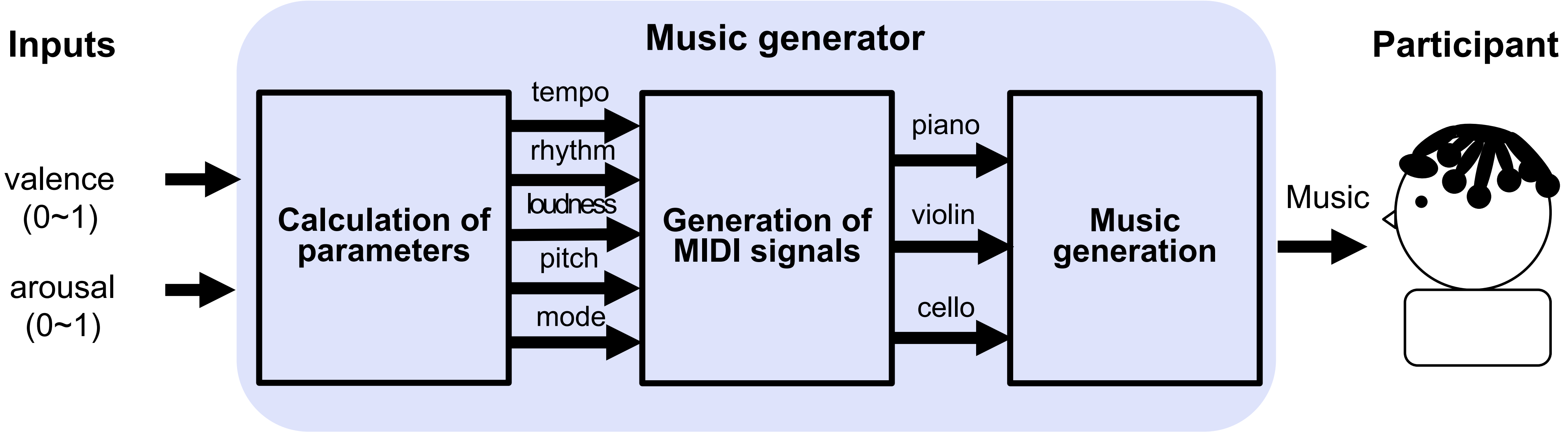


The purpose of this paper

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



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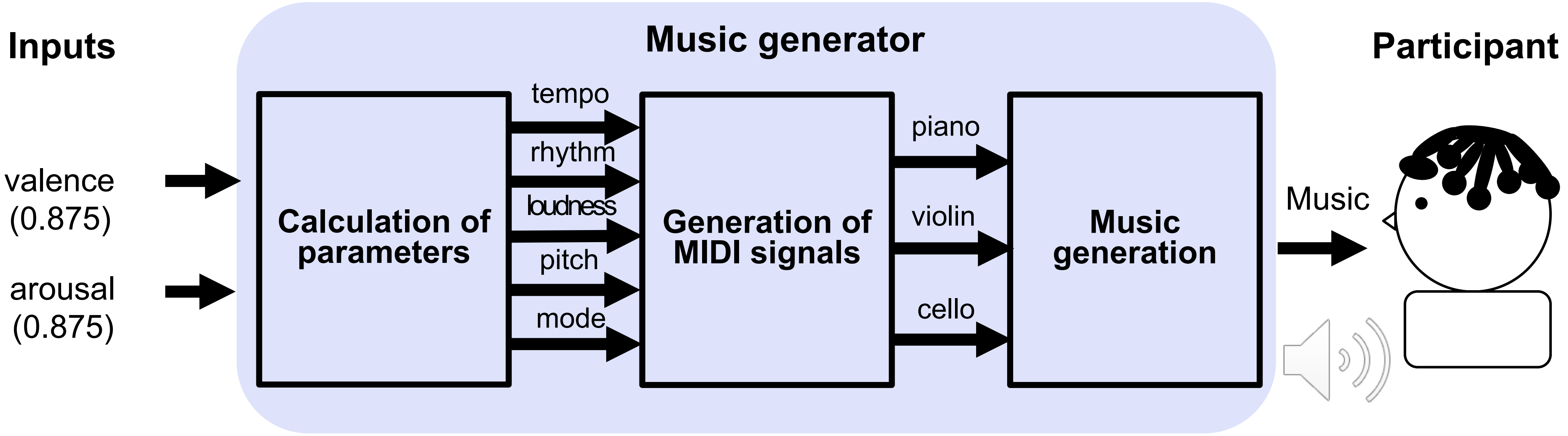
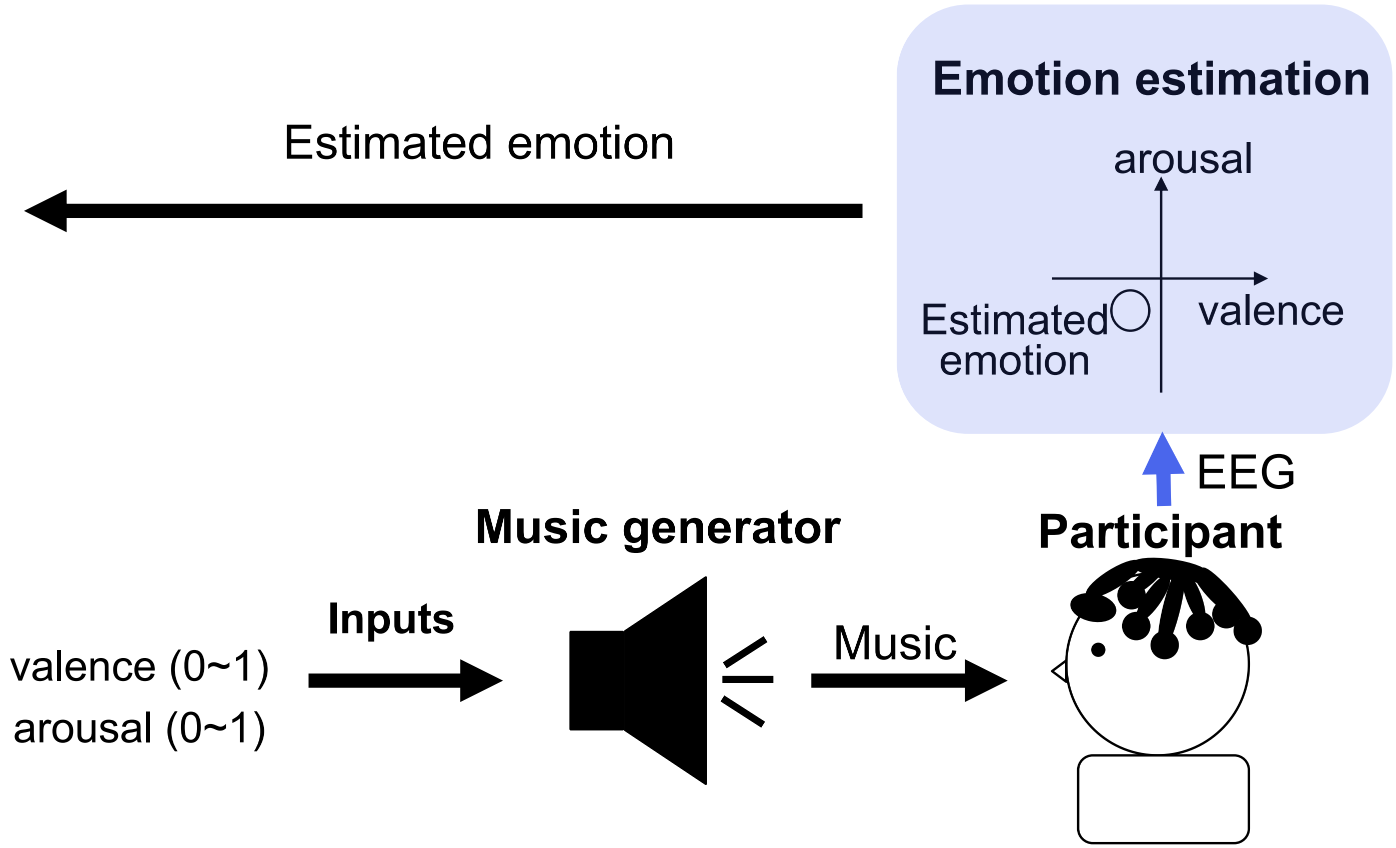


Emotion estimation of related studies

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

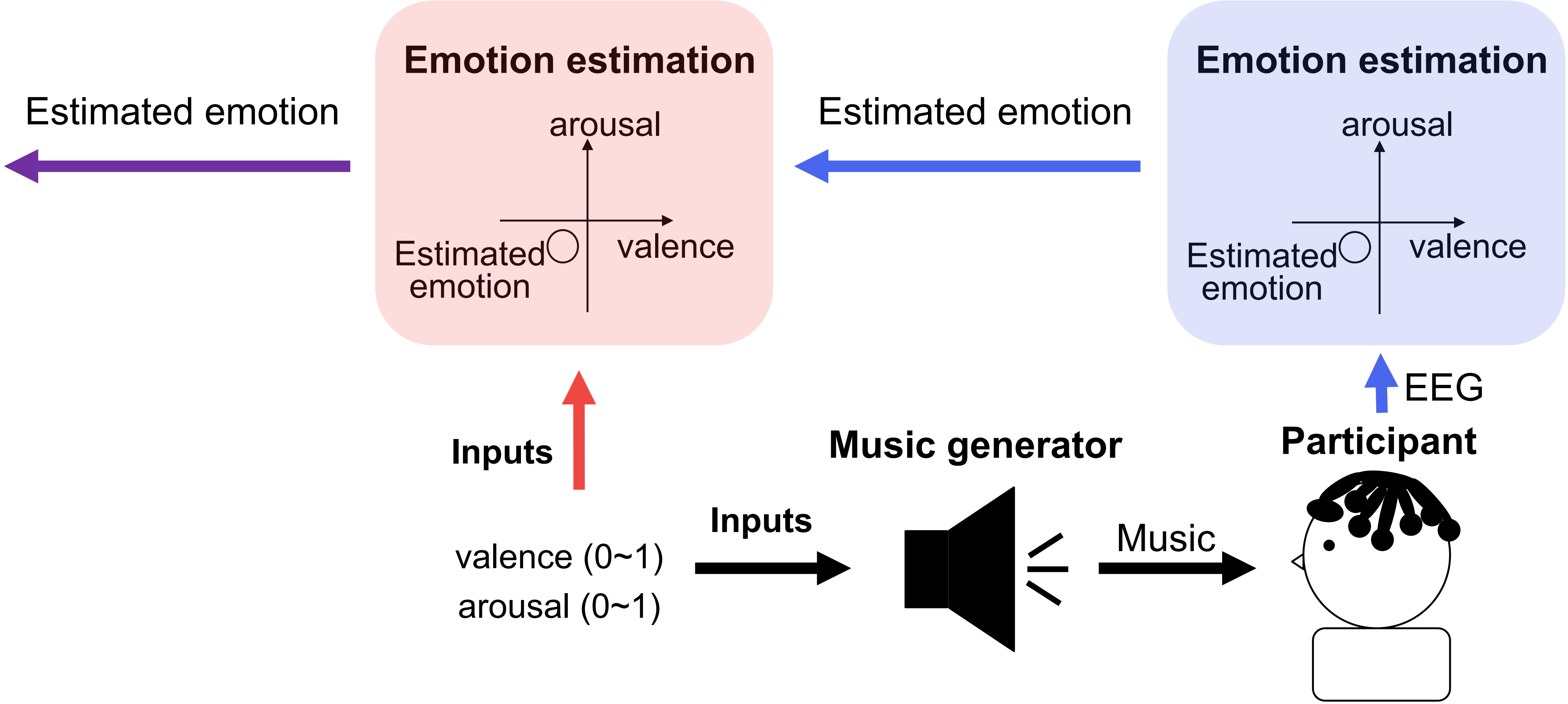
- Related studies used linear regression and convolutional neural network (CNN)



Proposed emotion estimation

Emotion estimation using EEG and expected subjective evaluations

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



EEG recording

Participants

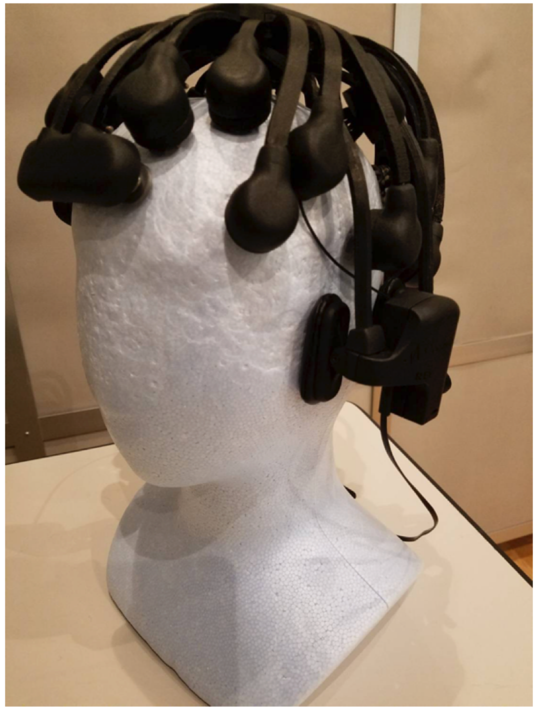
20 healthy undergraduate and graduate students

Electroencephalograph

Quick-30 manufactured by CGX

Stimuli

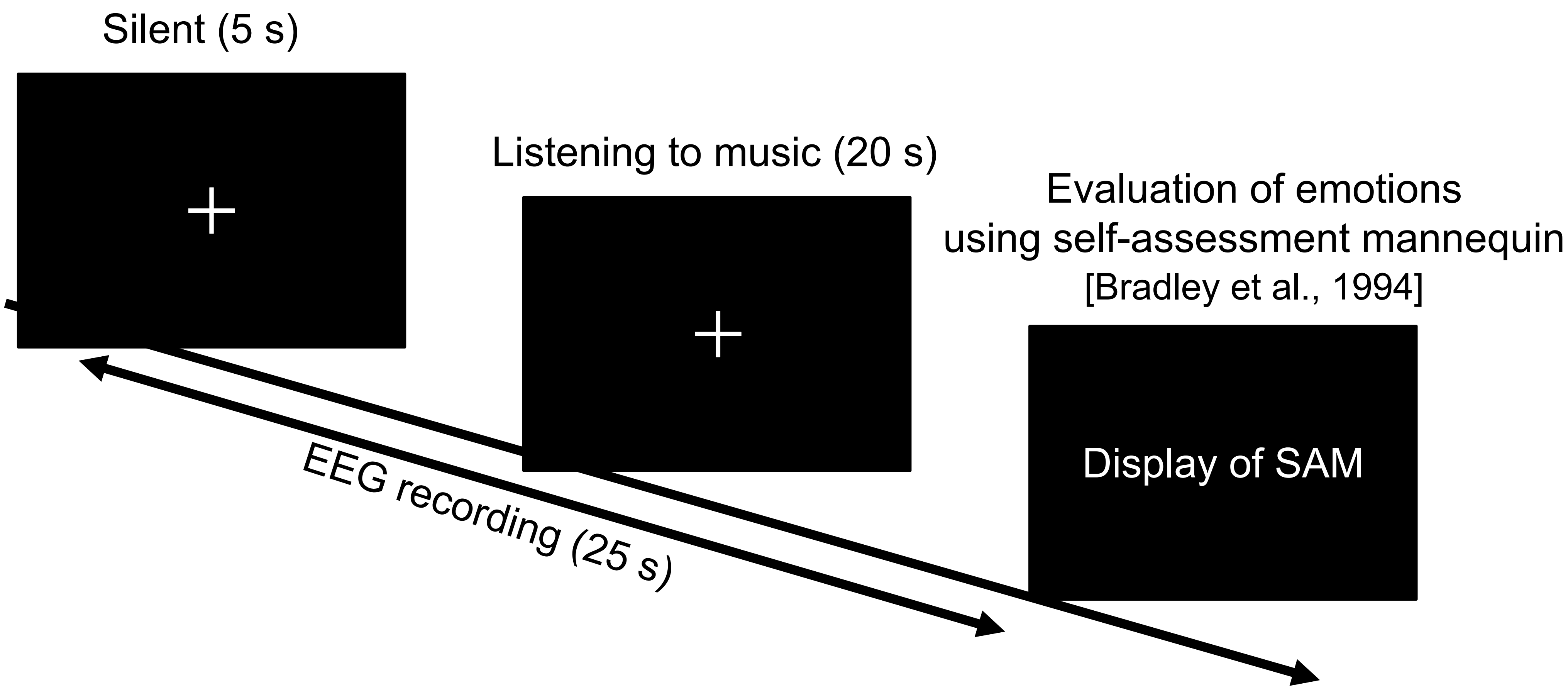
41 pieces of music created by the music generator



Quick-30

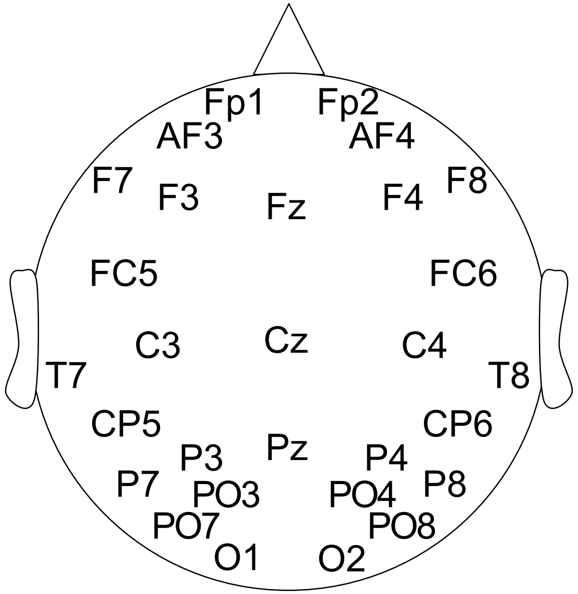
EEG recording

Procedure



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 $f = log(var\ (EEGdata))$
4. We mapped the matrix reflecting the position of the EEG channels



0	0	AF3	0	0	0	AF4	0	0
F7	0	F3	0	0	0	F4	0	F8
0	FC5	0	0	0	0	0	FC6	0
T7	0	0	0	0	0	0	0	T8
0	0	0	0	0	0	0	0	0
P7	0	0	0	0	0	0	0	P8
0	0	0	0	0	0	0	0	0
0	0	0	O1	0	O2	0	0	0

Comparison of two methods

1. CNN using EEG only [Miyamoto et al., 2020]

- Training that takes into account the positional relationship of EEG channels

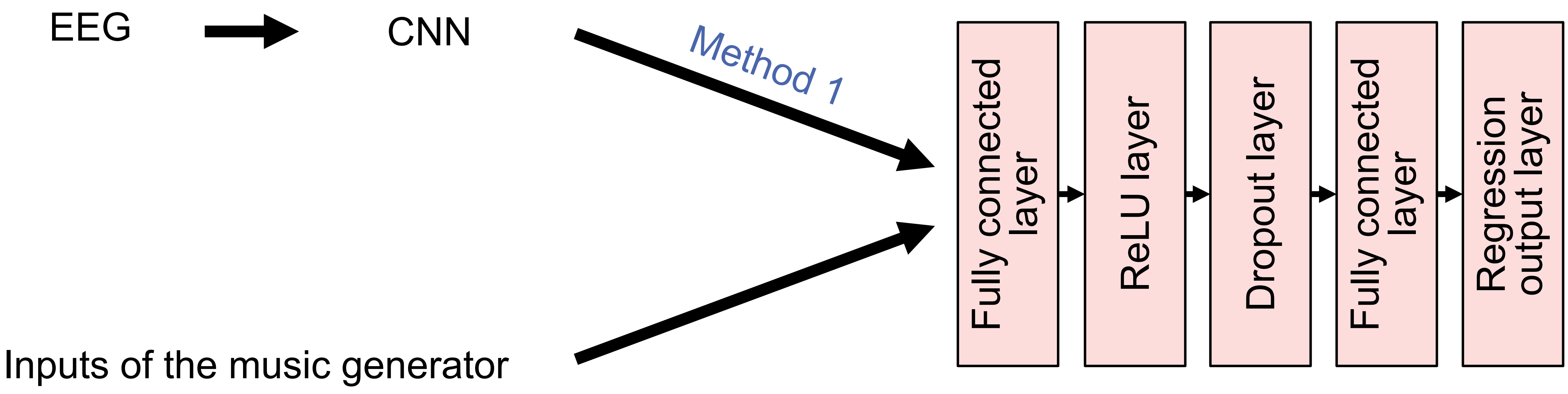
0	0	AF3	0	0	0	AF4	0	0
F7	0	F3	0	0	0	F4	0	F8
0	FC5	0	0	0	0	0	FC6	0
T7	0	0	0	0	0	0	0	T8
0	0	0	0	0	0	0	0	0
P7	0	0	0	0	0	0	0	P8
0	0	0	0	0	0	0	0	0
0	0	0	O1	0	O2	0	0	0

→ Convolution layer → Batch normalization layer → ReLU layer → Convolution layer → Batch normalization layer → ReLU layer → Dropout layer → Fully connected layer → Regression output layer

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



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

1. CNN using EEG		2. Neural network using EEG and inputs of the music generator	
valence	arousal	valence	arousal
0.214	0.239	**0.151**	**0.164**

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

Prosed 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