Electroencephalograph Based Emotion Estimation Using Multidimensional Directed Coherence and Neural Networks Under Noise

Haruka Torii[1,2][a], Takamasa Shimada[3], Osamu Sakata[4] and Tadanori Fukami[5]

[1]*Tokyo Denki University, 5, Senjuasahi-cho, Adachi-ku, Tokyo, 120-0026 Japan*

[2]*Oki Electric Industry Co., Ltd. 1-16-8, Chuo, Warabi-shi, Saitama, 335-8510 Japan*

[3]*Tokyo Denki University, 5, Senjuasahi-cho, Adachi-ku, Tokyo, 120-0026 Japan*

[4]*Tokyo University of Science 6-3-1 Niijuku, Katsushika-ku, Tokyo 125-8585 Japan*

[5]*Yamagata University, 4-3-16 Jonan, Yonezawa-shi, Yamagata, 992-8510 Japan*

Keywords: Emotion Estimation, Electroencephalography (EEG), Multidimensional Directed Coherence, Neural Network (NN), White Noise, Pink Noise.

Abstract: In recent years, research focused on emotion based on brain activity has yielded significant insights into the mechanisms of information processing in the brain. Leveraging this knowledge, studies have increasingly examined the effects of various stimuli on human emotions, with applications progressing in fields such as neuromarketing. However, existing methods for emotion estimation from EEG—such as those using power spectra, correlations, or deep learning—face challenges in generalizability due to considerable individual differences. In this study, we applied multidimensional directed coherence analysis, which can analyze the flow of information in the brain, to the measured EEG data. Following this, we trained a neural network using data augmented with noise to simulate individual differences, proposing a method capable of generalizable emotion inference. As a result, we achieved an average accuracy rate of 99.91% on training data and 90.83% on test data.

1 INTRODUCTION

Emotion plays a crucial role in human decision-making and social behavior, drawing increasing attention to the relationship between emotion and the brain, particularly in neuroengineering. This topic is considered highly significant, as understanding the connection between emotion and brain activity is expected to yield applications in fields such as brain-computer interfaces (BCI) and neuromarketing.

The relationship between brain activity and emotion has been explored extensively through fMRI studies. For example, Papez et al. examined the link between human emotions and hippocampal activity (Papez, 1937). Irwin conducted functional magnetic resonance imaging (fMRI) studies and documented amygdala activation at both poles in response to specific stimuli (Irwin et al., 1996). George used positron emission tomography (PET) on individuals experiencing sadness and happiness (George et al., 1995). Findings indicated marked activation in the limbic system and brainstem during sadness, while no similar increase in brain activity was found during happiness. Fisher identified the activation of the amygdala and hippocampus when subjects viewed faces depicting fear. These studies highlight the association between certain brain regions and specific emotions (Fischer et al., 2003). Another study assessed brain activity across various emotional states in response to diverse facial and background images (Shimada et al., 2009). However, due to the high cost of fMRI, it is challenging to apply it extensively in emotion-related brain activity studies across various fields.

Therefore, electroencephalography (EEG) is widely used as a more economical approach for brain activity measurement, particularly in areas such as psychiatry. EEG thus offers significant advantages for studying brain activity related to a range of emotions.

[a] https://orcid.org/0009-0007-6668-6075

Torii, H., Shimada, T., Sakata, O. and Fukami, T.
Electroencephalograph Based Emotion Estimation Using Multidimensional Directed Coherence and Neural Networks Under Noise.
DOI: 10.5220/0013256000003911

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) - Volume 1*, pages 647-654
ISBN: 978-989-758-731-3; ISSN: 2184-4305

If emotions can be estimated from brain waves, this could lead to applications in neuromarketing, such as product development based on consumers' unconscious reactions, as well as in safe driving assistance systems that monitor drivers' emotional states to help prevent dangerous driving.

Although several studies have reported emotion classification using EEG, many of them focused on only 2 to 3 specific emotions (Alarcão & Fonseca, 2019). However, Plutchik previously reported that human emotions can be expressed through a combination of 8 basic emotions (Plutchik et al., 1980). Thus, existing research using brainwave-based emotion classification has not fully covered this diverse range of emotions. This study aims to classify four types of emotional states based on Plutchik's eight basic emotions.

2 RELATED WORK

There are several challenges in using EEG for emotion estimation. These include the fact that EEG is a time-series signal with extensive information, exhibits significant inter-individual variability, and lacks clear patterns associated with specific emotional states. Previous studies have attempted to capture and classify emotional characteristics in EEG through signal processing techniques. Common approaches have relied on power spectral analysis and electrode correlation information. More recently, machine learning-based methods have been explored to automatically extract previously unknown emotion-related features from EEG signals.

Zheng proposed a method to estimate three emotional states—positive, negative, and neutral—using the GSCCA method, which identifies correlations between electrodes and EEG frequencies (Zheng, 2017). Li et al. proposed an estimation method for quantifying happiness and sadness using CSP and LinearSVM (Li & and Lu, 2009). In their study, participants were shown facial images representing specific emotions, and their EEG was recorded. Emotion estimation with this classifier achieved an average test accuracy of 93.5%. Saha reports a method using CNN for emotion estimation (Saha et al., 2022). However, because DNN-based emotion estimation algorithms function as black boxes, they cannot reliably estimate emotion based on brain activity features identified in EEG and fMRI studies. This limitation reduces the reliability of EEG-based emotion estimation.

This study aims to analyze the relationship between emotion and brain activity using EEG by combining a signal processing method that visualizes the correlation and direction of each frequency between electrodes with a neural network (NN). In a previous study, we proposed two method using multidimensional directed coherence analysis to visualize brain activity from EEG signals (Torii et al., 2023; Torii et al., 2024). Multidimensional directed coherence analysis tracks brain activity more effectively than one-dimensional coherence and was used to estimate joy, sadness, anger, and surprise. With the exception of joy, multidimensional coherence analysis achieved significantly higher accuracy than one-dimensional coherence analysis, which does not capture the multidimensional flow of brain activity.

We extracted frequency and electrode combinations that showed statistically significant differences in the small/large relationship of multidimensional directed coherence values across emotions. These differences were used as rules for emotion estimation, termed 'relative emotion rules,' as detailed in Section 3.2. In the first method, each extracted relative emotion rule was assigned equal weight for emotion estimation. However, there are varying levels of importance among these rules in accurately estimating emotion.

We then explored a method to enhance accuracy by focusing on relative emotion rules that are highly effective for emotion estimation in the second method. NNs are widely used in various fields to provide optimal solutions by weighting data appropriately. Previous research describes a method for classifying the importance of relative emotion rules across four emotions—joy, sadness, anger, and surprise—using NNs.

This study also explored methods to classify four emotional states—joy, sadness, anger, and surprise—by combining multidimensional directed coherence analysis, noise, and NNs. By incorporating noise, we aimed to represent individual variability in EEG signals, and by utilizing all values obtained from the analysis—not just those used in the relative emotion rule—we sought to extract features that, while not statistically different, play a crucial role in accurate emotion estimation.

The contributions of this study are as follows. First, by combining multidimensional directed coherence analysis with NNs, we achieved a higher accuracy rate than previous methods in the test data. Second, by analyzing the NN weights, we demonstrated the potential to identify not only areas with significant differences between emotions but also subtle features that are important for emotion classification. This approach, which leverages cost-effective and widely accessible EEG devices to enable broader emotion classification, holds potential for applications in diverse fields such as neuromarketing, driver assistance, and robotic collaboration through emotion state inference.

3 PROPOSED METHOD

We have previously reported on methods for estimating emotion using EEG with multidimensional directed coherence. In the initial study, we applied multidimensional directed coherence analysis to EEG data representing specific emotional states, extracting statistically distinct features for each frequency and electrode combination. These features were termed 'relative emotion rules, and unknown emotional states were identified by comparing them with these rules and employing a majority voting principle.

In the subsequent research, we suggested a method for evaluating the importance of relative emotion rules by applying weighting based on a NN, rather than treating all rules as equal.

In this paper proposes an inference method that directly applies a NN to the values obtained from multidimensional directed coherence analysis without using relative emotion rules. By incorporating noise to represent individual variability, we achieved high accuracy.

3.1 Multidimensional Directed Coherence

First, multidimensional directed coherence analysis is described (Sakata et al., 1998). Studies using fMRI on emotion have reported that activity in specific regions of the brain is associated with specific emotions (Fischer et al., 2003). Therefore, in this study, a multidimensional directed coherence analysis was conducted to visualize information flow, as considering the source of EEG signals is essential for accurate emotion estimation. Other analytical methods do not consider for information flow.

The coherence analysis method in signal processing explains the level of coherence between two time-series signals x(t) and y(t) (whether they are in phase or correlated). Furthermore, the directed coherence analysis method can be used to determine the direction of coherence.

Multidimensional directed coherence analysis is an extension of directed coherence analysis.

Multidimensional directed coherence analysis estimates the direction of signal propagation at a specific frequency between electrodes, assuming both immediate, delay-free signals from sources near the electrode where the EEG is measured and delayed, attenuated signals from sources near other electrodes. Directed coherence analysis, which takes into account only signal propagation between two electrodes, can incorrectly indicate apparent signal flow, such as a 10 Hz flow between electrodes x_1 and x_3, as illustrated in Figure 1 (Kamitake et al., 1982). In contrast, multidimensional directed coherence analysis can eliminate this apparent signal flow by using phase information across all electrodes and accounting for the temporal relationship between them.

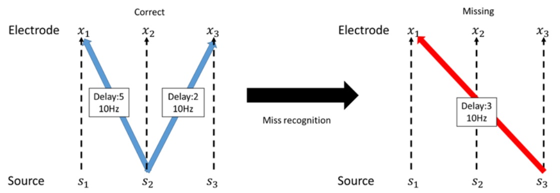

Figure 1: Instances of misinterpretation that may arise when employing directed coherence analysis.

The formula for multidimensional directed coherence analysis was derived in a previous study (Sakata et al., 1998). Multidimensional directed coherence analysis can not only detect the coherency components that conventional coherence analysis could detect, but also the temporal backward/forward relationship among them. This relationship is interpreted as information flow. Multidimensional directed coherence is calculated with multidimensional autoregressive (AR) model estimation. An AR model regresses the current values using historical data. Assume that the EEG time series $x_i(n)$ is represented by an AR model in Equation (1). Here, α is the AR coefficient, β is the disturbance, and M is the AR order.

$$x_n = \sum_{m=1}^{M} \alpha_n x_{n-m} + \beta \omega_n \quad (1)$$

Let A_{ij} and b_{ij} be the AR coefficients for the signal between electrodes i and j obtained by Fourier transforming both sides of equation (1) and predictive residual, respectively. Let the number of electrodes for measuring EEG be k, frequency be f, white noise with zero means and one variance be ω_n, power spectrum at electrode i be $P_{x_i}(f)$, and cross-spectrum between signals obtained from electrodes i and j be $P_{x_i x_j}(f)$. In this study, $\gamma_{ij}(f)$ is the multidimensional directed cross-spectrum and is defined in equation (2). Furthermore, the multidimensional directed coherence between measurement electrodes i and j can be expressed as $\left|\gamma_{ij}(f)\right|^2$, where the direction of information flow indicated by the multidimensional directed coherence is $x_j \rightarrow x_i$.

$$\gamma_{ij}(f) = \frac{P_{x_i \omega_j}(f)}{\sqrt{P_{x_i}(f) \cdot P_{\omega_j(f)}}} = \frac{A_{ij}(f) \cdot b_{jj}}{\sqrt{P_{x_i}(f)}} (i, j = 1,2,\cdots,k) \tag{2}$$

3.2 Relative Emotion Rules

For the selected EEG, the multidimensional directed coherence analysis described in 3.1 was applied to obtain the correlation and direction of information flow (information flow in the brain) for each combination of electrodes and each frequency. Figure 2 displays the shape of analyzed data. The vertical axis represents a combination of electrodes, and the horizontal axis represents frequencies from 0 to 40.48 Hz. The number of subjects is represented in the depth direction. Analysis data is obtained for all subjects and each emotion. These data were divided into training data to create an emotion estimation algorithm and test data to verify the accuracy of emotion estimation.

In the context of two emotions, if Welch's t-test at a significance level of 5% reveals a significant difference in the mean values of multidimensional directed coherence for each emotion at a certain frequency for a specific combination of electrodes, then a significant difference can occur in the amount of information flow within the brain between the two emotions for that electrode combination and frequency.

We used this difference in significant information flow between emotions (relative emotion rule) for estimating emotions. All emotion combinations, electrode combinations, and frequency patterns were examined to obtain relative emotion rules.

3.3 Proposed Method

This section explains the conventional emotion estimation method based on the relative emotion rules established in Section 3.2, and compares it with the proposed method, which does not rely on relative emotion rules.

First, we describe the conventional method. Using the EEG of a specific emotion in the training data, we obtained the distribution of values of multi-

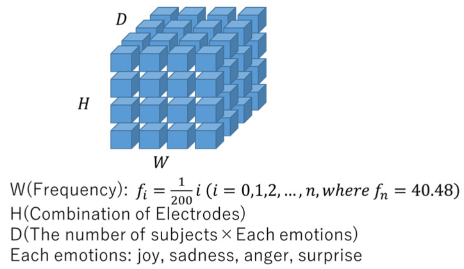

Figure 2: Shape of analyzed data using multidimensional directed coherence.

dimensional directed coherence for a specific combination of electrodes at a specific frequency, which was approximated by a normal distribution. Next, when estimating the emotion, the normal distribution was compared with the test data for which the emotion was unknown. When the value obtained by integrating the probability density function of the normal distribution from ∞ to the value of multidimensional directed coherence of the test data was larger than a predetermined smaller percentage (discrimination threshold), the value is determined to be considerably larger than the distribution of directed coherence values of the specific emotion. By, contrast, when the value obtained by integrating the probability density function of the normal distribution from -∞ to the value of multidimensional directed coherence of the test data was smaller than the discrimination threshold, the value is determined to be considerably smaller than the distribution of directed coherence values of the specific emotion.

Based on the large/small relationship with the specific emotion of the obtained training data, a relative emotion rule was extracted for which this large/small relationship was consistent. The relative emotion rule indicates the large/small relationship of values between two emotions, one of which was set to a specific emotion of the training data such that the other emotion can be inferred to be the emotion of the test data. This procedure was performed for all electrode combinations and frequencies, and the emotion of the test data inferred from all extracted relative emotion rules was used to determine the most plausible emotion based on the principle of majority rule voting, resulting in the final emotion estimation. Figure 3 displays the flow of emotion estimation as "Previous Method 1".

The second method is shown as "Previous Method 2" in Figure 3. This method based on the large/small relationship obtained by comparing testing data and discrimination threshold, 1 was set when this large/small relationship matched the relative emotion

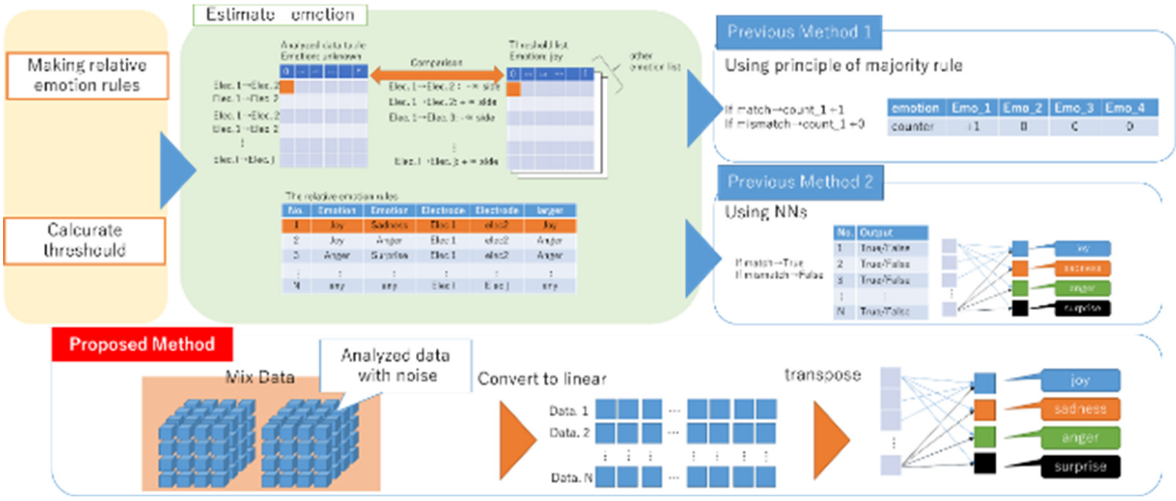

Figure 3: Estimation process of the two preceding methods and the proposed method.

rule and 0 when this condition was not satisfied.These results were used as input data to estimate the emotions using a NN. Using an NN, the rules are not treated in the same rank when estimating each emotion. However, the values are adjusted using the weight coefficients. Larger coefficients can be applied to rules that are more important for estimating emotion, and smaller coefficients can be applied to less important rules, allowing estimation to be performed with sorting of rules.

The proposed method is shown in Figure 3 as "Proposed Method". Two types of data are prepared: data obtained after multidimensional directed coherence analysis and data with added noise post-analysis. These two datasets are shuffled and divided into training and test data. Next, the two-dimensional post-analysis data are converted into one-dimensional data, and all values obtained from the analysis are used as input data for the NN.

The NNs used in both the previous method 2 and the proposed method were simple, consisting of only two layers: an input layer and an output layer. We used stochastic gradient descent (SGD) as the optimizer, Softmax as the activation function, and CrossEntropyLoss as the loss function. We stopped the training when the loss stopped decreasing to avoid overfitting.

4 EXPERIMENTS

The proposed method in this paper aims to evaluate a broader range of emotions based on Plutchik's basic emotions. Publicly available datasets did not include emotions comparable to those targeted by this method; therefore, specific emotional states were generated using images based on techniques from previous studies. (Torii, 2023).

Informed consent was obtained from the participants regarding the purpose of the experiment and the risks associated with participation in the experiment by procedures approved by the Bioethics Committee for Human Life at Tokyo Denki University. Furthermore, their written consent was obtained for participation.

EEG measurements were performed within 1 min of image presentation. The electrode arrangement was based on the international 10–20 method, and the unipolar derivation method was used with the average of the two earlobe electrodes as the reference electrode. The measured data were digitized and recorded at a sampling frequency of 200 Hz. The measured EEG data were pre-processed using a high-pass filter with a cutoff frequency of 0.5 Hz, and a low-pass filter with a cutoff frequency of 60 Hz. EEG data was measured at Fp1, Fp2, F3, F4, P3, P4, T3, T4, O1, and O2 using the average potential of earlobes A1 and A2 as a reference. During the measurements, the participants were instructed to minimize body movements and blinking. However, if a significant artifact was detected, the measurements were repeated. The subjects included 30 healthy individuals, comprising 23 males and 7 females, with an average age of 21.9 years (±1.57).

EEG data from the subsequent 20 s (from the 40th to the 60th second) of the 1 min of the measured data were used as EEG data.

In the analysis, 8096 frequencies, from 0 to 40.48 Hz at 0.005 Hz intervals were used. Two electrodes were selected from 10 electrodes. Then, a total of 90 combinations of electrodes were evaluated.

To validate the proposed method, we compared emotion estimation using relative emotion rules with a method that generates relative emotion rules through coherence analysis, which visualizes the actual correlations between electrodes, rather than using multidimensional directed coherence analysis.

The data used to create the relative emotion rules and train the NN were designated as training data, and the data that were not used were designated as test data.

5 RESULTS

The dataset for training the neural networks (NNs) was split into training (90%) and test (10%) sets, using 10-fold cross-validation. Emotion estimation was performed on both sets in each fold, and the average accuracy was computed over 10 folds. Figure 4 shows results of NN training and inference using noiseless data from multidimensional directed coherence analysis of EEG signals, as well as results when combining this data with noise-augmented data. White noise (mean: 0, variance: 1) was used as the noise source. Training with only noiseless data achieved average accuracies of 75.68% (±10.16) for training and 28.33% (±10.67) for test sets. When noiseless data was combined with noise-augmented data, accuracies improved to 99.82% (±0.41) for training and 71.67% (±5.20) for test sets, showing noise addition enhances test accuracy.

Subsequently, different types of noise were introduced to examine their effects on training and inference performance. Unlike white noise, which has a uniform power spectrum across all frequencies, pink noise has higher power in low-frequency components, with power spectral density decreasing as frequency increases. The noise types used are as follows:

- White Noise (mean: 0, variance: 0.1)
- White Noise (mean: 0, variance: 0.01)
- Pink Noise

Figure 5 shows the results of adding these noise types to the training data. With white noise (variance 0.1), the average accuracy was 99.49% (±0.73) for training and 75.42% (±5.09) for test data. For white noise (variance 0.01), training accuracy increased to 99.73% (±0.46), while test accuracy dropped to 68.33% (±6.77). Pink noise achieved the highest accuracy rates, with 99.91% (±0.18) for training data and 90.83% (±4.86) for test data. Among the tested noise types, pink noise provided the best overall performance.

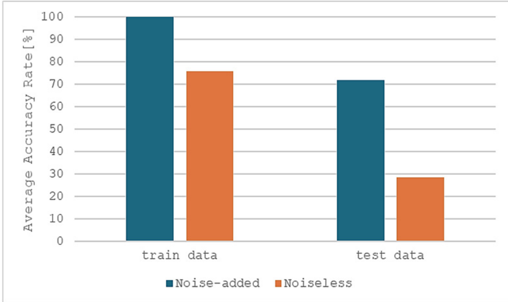

Figure 4: Average accuracy rate of the proposed method with noise and noiseless conditions.

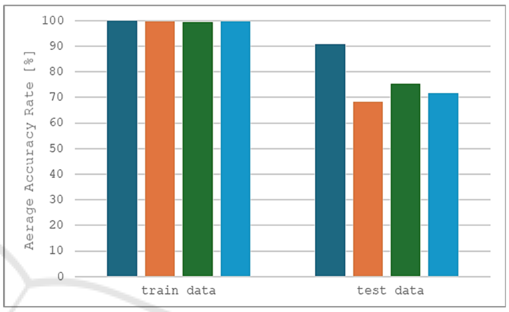

Figure 5: Comparison using pink noise and white noise with varying levels of variance is presented as follows: Blue: pink noise, Orange: white noise with a variance of 0.01, Green: white noise with a variance of 0.1, Cyan: white noise with a variance of 1.

To confirm whether the proposed method captures essential features for emotion representation better than statistically significant relative emotion rules, we compared several approaches: using only the relative emotion rule (previous method 1), combining the rule with NNs (previous method 2), and coherence-based methods without considering multidimensional flow. Figure 6 shows the estimation results. For the proposed method, we used pink noise, as it demonstrated the highest accuracy rate.

The average accuracy rates for the previous method 2 were 95.06% (±2.77) for training and 41.44% (±3.98) for test data, while for previous method 1, they were 58.51% (±4.86) and 31.07% (±3.42), respectively. The conventional coherence analysis method with relative emotion rules yielded accuracies of 45.95% (±2.81) for training and 37.98% (±3.42) for test data.

Previous method 2 uses binary values (1 or 0) for inference, whereas the proposed method incorporates correlation values from multidimensional directed coherence analysis. To examine the impact of input data flexibility, we compared results using only relative emotion rules with those using correlation values post-analysis. For matches with the rules, the correlation values were retained; for mismatches, the values were set to 0.

Figure 7 shows the results. Using correlation values for unknown emotions from all electrode combinations and frequencies in the relative emotion rules, the average accuracy was 71.31% (±19.13) for training and 40.12% (±2.25) for test data. When retaining correlation values for matches with the rules and setting mismatches to 0, the training accuracy was 83.57% (±7.78), and the test accuracy was 41.79% (±2.58).

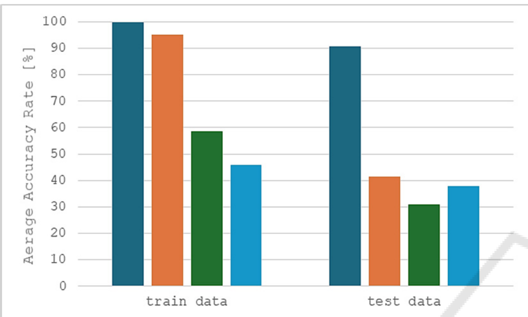

Figure 6: Average accuracy rate: Blue: Proposed method (pink noise), Orange: Previous method 2, Green: Previous method 1, Cyan: Using coherence method

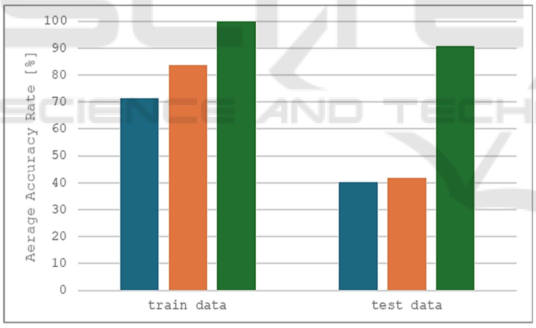

Figure 7: Comparison of the average accuracy rates: Blue: using 0 or correlation values from multidimensional directed coherence, Orange: using the correlation values specified in the relative emotion rules, Green: using all the correlation values.

6 DISCUSSIONS

Comparing the results of applying all correlation values from multidimensional directed coherence analysis to the NN showed that adding noise to the data improved accuracy for both training and test sets compared to using noiseless data. This improvement likely stems from the inclusion of noise-augmented data in the training set, which enhances learning by better reproducing regions with significant individual differences.

Among the four noise types tested, including white noise with a mean of 0 and variance of 1, no notable differences were observed in training accuracy. However, in the test data, pink noise improved accuracy by approximately 10% compared to white noise conditions. This suggests that individual differences are more concentrated in low-frequency components than distributed across the frequency spectrum.

In addition to pink and white noise, other colored noises such as brown, blue, and violet noise were also evaluated. Their definitions are based on Beran et al. (2013) and Kasdin and N.J. (1995). When applied, these noises resulted in lower test accuracies than white noise.

Blue and violet noise increase power in high-frequency components, which do not effectively represent individual differences occurring in lower frequencies. Brown noise, while similar to pink noise in emphasizing low-frequency components, exhibits a steep power decline at higher frequencies, limiting its ability to retain necessary high-frequency information. This limitation likely explains why brown noise did not achieve the same performance as pink noise.

These findings suggest that low-frequency noise is critical for reproducing individual differences and improving test accuracy, while specific high-frequency components are also necessary. Pink noise, which satisfies both conditions, is particularly effective in capturing individual variability.

A comparison between the proposed method and three conventional methods based on the relative emotion rule showed that the proposed method achieved the highest accuracy for both training and test data. This suggests that incorporating noise during training not only replicates individual differences but also highlights subtle, non-statistically distinct features essential for emotion differentiation.

Additionally, the proposed method was compared to two other cases: one using only values from the conditions recorded in the relative emotion rule, and another assigning a value of 0 when the rule conditions did not match the test data. The proposed method, which used all correlation values, outperformed both, achieving the highest accuracy for training and test data. This result suggest that using correlation values enhances the NN's flexibility during training and enables the extraction of features that, while not recorded in the relative emotion rule or statistically distinct, are crucial for accurate emotion estimation.

7 CONCLUSIONS

In this study, we propose an EEG-based method for emotion estimation, where EEG data with and without added noise are processed through multidimensional directed coherence analysis and then used to train a NN. Conventional methods have relied on features with statistically significant differences among emotions for estimation. In contrast, our proposed method utilizes all data from the coherence analysis, allowing the NN to identify important features for emotion estimation even if statistical differences between emotions are absent. By incorporating noise to account for individual differences, we aimed to capture more generalized features.

The results show that training with noise-added data achieved higher accuracy than methods without noise or those based solely on the relative emotion rule. Among the four noise types tested, pink noise yielded the highest accuracy, suggesting its effectiveness in representing individual differences.

Future work will focus on understanding the relationship between brain activity and emotion by analyzing information flow and frequency between electrodes through NN weight analysis. This will help identify key features for emotion discrimination, even in the absence of statistical differences. Additionally, comparisons with other NN-based methods will be conducted to further evaluate the effectiveness of the proposed approach.

REFERENCES

J. W. Papez (1937). A proposed mechanism of emotion. *Arch. Neurol. Psychiatry.* 79. 217-224. doi:/10.1001/archneurpsyc.1937.02260220069003

W. Irwin, R. J. Davidson, M. J. Lowe, B. J. Mock, J. A. Sorenson, and P. A. Turski (1996). Human amygdala activation detected with echo-planar functional magnetic resonance imaging. *Neuroreport,* 7. 1765–1769. doi:/10.1097/00001756-199607290-00014

M. S. George, T. A. Ketter, P. I. Parekh, B. Horwitz, P. Herscovitch, and R. M. Post (1995). Brain activation during transient sadness and happiness in healthy women. *Am. J. Psychiatr,* 152*,* 341-351. doi:10.1176/ajp.152.3.341

H. Fischer, C. L. Wright, P. J. Whalen, S. C. Mclnerney, L. M. Shin, and S. L. Rauch (2003). Brain habituation during repeated exposure to fearful and neutral faces: a functional MRI study. *Brain Res. Bull.* 59*.* 387-392. doi:10.1016/s0361-9230(02)00940-1

T. Shimada, T. Fukami, and Y. Saito (2009), Brain activation in response to face images with backgrounds. *Int. J. Innov. Comput. Inf. Control.* 5(3). 589-600. doi:10.1007/978-3-540-36841-0_640

Soraia M. Alarcão and Manuel J. Fonseca (2019). Emotions Recognition Using EEG Signals: A Survey. *IEEE Transaztions on Affective Computing.* 10(3). July-September. doi:10.1109/TAFFC.2017.2714671

R. Plutchik and H. Kellerman (1980). *EMOTION Theory. Research. and Experience.* 3-33, ACADEMIC PRESS. https://www.amazon.co.jp/Emotion-Research-Experience-Robert-Plutchik/dp/0125587015

W.Zheng (2017). Multichannel EEG-Based Emotion Recognition via Group Sparse Canonical Correlation Analysis. *IEEE Transactions on Cognitive and Developmental Systems.* 9(3). 281-290. doi:10.1109/TCDS.2016.2587290

M. Li and B.-L. Lu (2009). Emotion classification based on gamma band EEG. *Proc. Annu. Int. Conf. IEEE Eng. Med. Biology Soc.*. 1223-1226, Minneapolis. doi:10.1109/IEMBS.2009.5334139

O. Saha, M.S. Mahmud, S.A. Fattah, M. Saquib (2022). Automatic Emotion Recognition from Multi-Band EEG Data Based on a Deep Learning Scheme with Effective Channel Attention. *IEEE Access.* doi:10.1109/ACCESS.2022.3224725

H. Torii, T. Shimada, O. Sakata, and T. Fukami (2023). Emotion estimation by EEG using multidimensional directed coherence analysis. *Inst. Electron. Inform. Comm. Eng.*. J-106-D(6). 401-408. https://search.ieice.org/bin/summary.php?id=j106-d_6_401&category=D&year=2023&lang=2&abst=j

H. Torii, T. Shimada, O. Sakata, and T. Fukami (2024). Emotion Estimation Using Signal Processing and Neural Network by EEG. In *The International Council on Electrical Engineering Conference 2024*. Kitakyushu. https://orbit-cs.net/icee2024/detailedprogram.pdf

O. Sakata, N. Imanishi, T. Shimada, T. Shiina, and Y. Saito (1998). Causality analysis of alpha activities by multidimensional directed coherence. *Inst. Electrical Eng. Jpn C.* 118. 1016-1025. doi: 10.1541/ieejeiss1987.118.7-8_1016

T. Kamitake, H. Harashima, H. Miyakawa and Y. Saito (1982). Directed Coherence Analysis of Time Series and Its Application to Biological Signal Processing. *Inst. Electron. Inform. Comm. Eng.*. J-65-A(8). 779-786 https://search.ieice.org/bin/summary.php?id=j65-a_8_779

Beran, J., Y. Feng, S. Ghosh, and R. Kulik (2013). Long-Memory Processes: Probabilistic Properties and Statistical Methods. NewYork: Springer. doi: 10.1007/978-3-642-35512-7

Kasdin, N.J. (1995). Discrete Simulation of Colored Noise and Stochastic Processes and 1/fα Power Law Noise Generation. *Proceedings of the IEEE.* 83(5). 802-827. doi: 10.1109/5.381848