

Stochastic Fluctuation in EEG Evaluated via Scale Mixture Model for Decoding Emotional Valence

Shunya Fukuda¹, Akira Furui¹, Maro G. Machizawa², and Toshio Tsuji¹

Abstract—Electroencephalogram (EEG) analysis has garnered attention as a method for quantitatively decoding human emotions, and EEG amplitude values in specific frequency bands are typically used for this purpose. However, as brain states can fluctuate rapidly in response to external stimuli, accounting for temporal fluctuations in amplitude could enhance the accuracy of emotion decoding. In this paper, we investigate the relationship between pleasant/unpleasant emotions and fluctuations in EEG amplitude by utilizing a scale mixture model that assumes a hierarchical stochastic structure for EEG variance. This model focuses on the connection between the non-Gaussianity of the EEG amplitude distribution and stochastic fluctuation of the EEG variance (i.e., amplitude), which can be quantitatively evaluated by introducing a feature value. In the experiments, we used an EEG dataset obtained during the presentation of pleasant and unpleasant images and computed the proposed and conventional features, such as simple variance and approximate entropy values, for comparison. Statistical tests and receiver operating characteristic analyses of the calculated features indicated that the proposed feature, which reflects the stochastic fluctuation of variance, can distinguish between pleasant and unpleasant emotions more accurately than conventional features. These findings suggest that not only the conventional amplitude value but also its fluctuation, may be useful in assessing emotional valence.

I. INTRODUCTION

Accurate evaluation of human emotions is crucial for designing effective products and services. However, many current assessment methods rely on subjective measures, such as questionnaires, which can be prone to cognitive biases and lead to unreliable results. Thus, an objective method for assessing emotions would be valuable for mitigating these issues.

Quantitative and objective assessments of human emotions can be achieved via analysis of electroencephalogram (EEG). Several methods have been proposed for decoding emotions based on the spectral power values in specific EEG frequency bands [1], [2]. These spectral power values are indicative of the average amplitude of waveforms over a temporal analysis window; thus, they do not account for the amplitude fluctuations that occur within that window. Considering that the state of the human brain changes from moment to moment, the response to external stimuli is not constant, and

amplitude fluctuations are expected to differ depending on the type of stimulus. Consequently, studies have investigated the use of features that characterize amplitude fluctuations, such as entropy, which represents the signal complexity [3], [4]. However, no method has been developed to accurately decode diverse and complex human emotions in practical terms.

Furui et al. proposed a distinct approach for assessing amplitude fluctuations using an analysis method based on a scale mixture-based stochastic EEG model [5]. This model focuses on the non-Gaussianity of the EEG amplitude distribution, and assumes a hierarchical stochastic structure to represent it, enabling the evaluation of EEG amplitude fluctuations according to the magnitude of the stochastic fluctuation of the EEG variance. Based on this model, the EEG signals during epileptic seizures [5] and sleep [6], which are associated with amplitude fluctuations, were analyzed. However, this model has not been employed to analyze EEG signals linked to emotional valence. If the relationship between the amplitude fluctuations evaluated via this model and human emotions can be clarified, a novel method for decoding emotions based on EEG would be developed.

This paper analyzes EEG features related to emotional valences using a scale mixture model to evaluate stochastic fluctuations in EEG amplitude. The scale mixture models are fitted to the frequency-decomposed signals, and the features representing the stochastic fluctuations of the variance are calculated for each frequency band. The analysis employs a multi-channel EEG dataset obtained from 28 participants during the presentation of pleasant and unpleasant images. To assess the efficacy of utilizing the stochastic fluctuation of variance in emotion decoding, we compare the features calculated using the scale mixture model with conventional features.

II. METHODS

Fig. 1 shows an overview of the analytical approach adopted in this paper. The proposed approach encompasses a preprocessing phase that entails independent component analysis (ICA) and filter banks as well as feature extraction based on a scale mixture model.

A. Preprocessing

The following preprocessing is performed to remove artifacts from the EEG and extract the frequency components relevant to the emotion assessment. First, ICA, a method of blind signal source separation, is used to transform the EEG signal $\mathbf{x} \in \mathbb{R}^L$ measured by L channel electrodes, into

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¹S. Fukuda, A. Furui and T. Tsuji are with the Graduate School of Advanced Science and Engineering, Hiroshima University, Higashi-Hiroshima, 739-8527, Japan (email: shunyatafukuda@hiroshima-u.ac.jp).

²M. G. Machizawa with the Center for Brain, Mind and KANSEI Sciences Research, Hiroshima University, Higashi-Hiroshima, 739-8527, Japan.

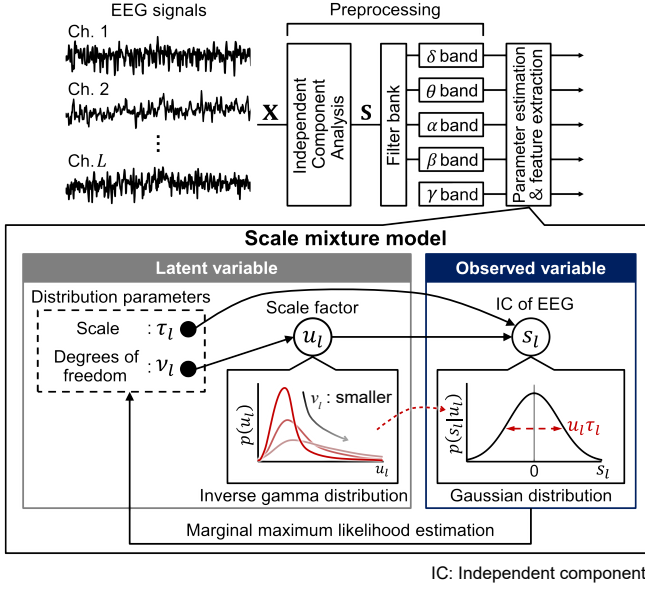


Fig. 1: Overview of the analysis method and graphical representation of the scale mixture model

independent components (ICs) $\mathbf{s} \in \mathbb{R}^L$, which are mutually uncorrelated.

$$\mathbf{s} = \mathbf{W}\mathbf{x}, \quad (1)$$

where $\mathbf{W} \in \mathbb{R}^{L \times L}$ is the weight matrix of the ICA estimated using the InfomaxICA algorithm [7]. The obtained L ICs are evaluated using the following criteria defined in [1] to identify and eliminate noisy components, and the remaining $\tilde{L}$ ICs are used for the analysis.

- Residual variance is greater than 50%.
- The estimated location of the signal source computed by dipole estimation is outside the brain.
- In the matrix $\mathbf{W}^{-1}$ that reconstructs the EEG from the independent components, when the vector corresponding to each independent component is extracted, the contribution to any one EEG electrode is greater than $\pm 5SD$ (standard deviation) of the whole.

The resulting IC vectors and weight matrices after removing noisy ICs are denoted by $\tilde{\mathbf{s}} \in \mathbb{R}^{\tilde{L}}$ and $\tilde{\mathbf{W}} \in \mathbb{R}^{\tilde{L} \times L}$, respectively.

Subsequently, third-order Butterworth bandpass filters are applied to the ICs by dividing them into five frequency bands: δ (1–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–20 Hz), and γ (20–40 Hz). These frequency bands are typically used to capture EEG features [8]. Using the aforementioned preprocessing steps, the noise components are diminished, and the brain activity within specific frequency bands can be extracted.

B. Feature Extraction Using Scale Mixture Model

1) *Model structure*: In the context of the scale mixture model, the EEG signal $\mathbf{x}$ measured by L -channel electrodes

is represented by a multivariate scale mixture distribution [5]. We apply this modeling framework to ICs, $\tilde{\mathbf{s}}$, obtained via the linear transformation of $\mathbf{x}$, that is, $\tilde{\mathbf{s}} = \tilde{\mathbf{W}}\mathbf{x}$. In this model, the distribution of $\tilde{\mathbf{s}}$ in each frequency band is expressed as follows:

$$p(\tilde{\mathbf{s}}) = \int p(\tilde{\mathbf{s}}|u)p(u)du. \quad (2)$$

For the conditional distribution $p(\tilde{\mathbf{s}}|u)$, we set a zero-mean multivariate Gaussian distribution with a mean vector of $\mathbf{0}$ and covariance matrix of $u\mathbf{\Sigma}$ as follows:

$$p(\tilde{\mathbf{s}}|u) = \mathcal{N}(\tilde{\mathbf{s}}|\mathbf{0}, u\mathbf{\Sigma}) = \frac{1}{(2\pi)^{\frac{\tilde{L}}{2}} |u\mathbf{\Sigma}|^{\frac{1}{2}}} \exp\left(-\frac{1}{2u} \tilde{\mathbf{s}}^T \mathbf{\Sigma}^{-1} \tilde{\mathbf{s}}\right), \quad (3)$$

where $\mathbf{\Sigma} \in \mathbb{R}^{\tilde{L} \times \tilde{L}}$ represents a scale matrix weighted by latent variable $u \in \mathbb{R}^+$. For the distribution of u , we set the following inverse gamma distribution.

$$p(u) = \text{IG}(u|\nu/2, \nu/2) = \frac{1}{\Gamma(\frac{\nu}{2})} \left(\frac{\nu}{2}\right)^{\frac{\nu}{2}} u^{-\frac{\nu}{2}-1} \exp\left(-\frac{\nu}{2u}\right), \quad (4)$$

where $\nu \in \mathbb{R}^+$ is a degree-of-freedom parameter that influences the stochastic fluctuation in the variance of ICs.

Because each element of the IC vector $\tilde{\mathbf{s}}$ is independent of the others, the off-diagonal elements of the scale matrix $\mathbf{\Sigma}$ are all set to 0. Specifically, let $\tilde{s}_l$ be the l th IC and τ_l be the diagonal element of the corresponding scale matrix; the following equation holds:

$$\mathcal{N}(\tilde{\mathbf{s}}|\mathbf{0}, u\mathbf{\Sigma}) = \prod_{l=1}^{\tilde{L}} \mathcal{N}(\tilde{s}_l|0, u\tau_l), \quad (5)$$

where $\mathcal{N}(\tilde{s}_l|0, u\tau_l)$ represents a univariate Gaussian distribution with mean zero and variance $u\tau_l$. While the latent variable u is shared across all dimensions, in this paper, we set a separate latent variable u_l for each dimension, with the aim of emphasizing the differences in the characteristics of each IC. Consequently, the scale mixture model of the ICs can be expressed as an independent model for each dimension, as follows:

$$p(\tilde{s}_l) = \int \mathcal{N}(\tilde{s}_l|0, u_l\tau_l) \text{IG}(u_l|\nu_l/2, \nu_l/2) du_l \quad (6)$$

$$= \frac{\Gamma(\frac{\nu_l+1}{2})}{\Gamma(\frac{\nu_l}{2})} \frac{1}{\sqrt{\pi\tau_l\nu_l}} \left(1 + \frac{\tilde{s}_l^2}{\nu_l\tau_l}\right)^{-\frac{\nu_l+1}{2}}. \quad (7)$$

2) *Parameter estimation*: Let $\tilde{S}_l = \{\tilde{s}_{ln}\}_{n=1}^N$ be the IC data with sample size N , the parameters τ_l and ν_l can be estimated by maximizing the marginal likelihood $p(\tilde{S}_l) = \prod_{n=1}^N p(\tilde{s}_{ln})$. We estimate these parameters based on the expectation maximization (EM) algorithm [9], an efficient optimization method for models with latent variables.

In the scale mixture model presented above, the parameter ν_l represents a characteristic for which a larger value implies a smaller stochastic fluctuation in the variance. This indicates that the distribution of ICs approaches a Gaussian distribution at $\nu_l \rightarrow \infty$. In this paper, we compute the inverse of ν_l ,

denoted by $1/\nu_l$, and utilize it as a feature value to describe the stochastic fluctuation of the variance, or non-Gaussianity, of the amplitude distribution of ICs. Hereafter, the subscript l is omitted, unless a specific IC element is mentioned.

III. EXPERIMENTS

To investigate the relationship between emotional valence and EEG amplitude fluctuations, we conducted EEG analysis using a dataset curated by Machizawa et al. [1]. The Hiroshima University Ethics Committee approved all the experiments (registration number: E-965).

A. Dataset

The dataset includes data from 28 healthy subjects (12 males and 16 females; mean age: 22.17 ± 1.79 years) with normal vision and hearing. The full experimental procedures were explained verbally to the participants and written consent was obtained prior to the experiment. EEG was measured at a sampling rate of 2,000 Hz via 64-channel electrodes arranged according to the international 10–20 system, and then downsampled to 512 Hz. Fig. 2 presents a schematic diagram of a single trial of the experimental task, which included 0.25 s of auditory stimulation, 3.75 s of image anticipation, 4 s of visual stimulation, and 1 s of subjective rating. Each participant completed 240 trials in the task sequence.

During auditory stimulation, participants were presented with three types of tones: low frequency (500 Hz), medium frequency (1,000 Hz), and high frequency (1,500 Hz). Pitch differences were used as cues to anticipate whether the subsequent visual stimulus would be pleasant or unpleasant. The reason for presenting these auditory stimuli is that the original paper [1], which created this dataset, aimed to elucidate emotions in the anticipation phase. A high frequency auditory stimulus guarantees the presentation of a pleasant image, whereas a low frequency auditory stimulus guarantees an unpleasant image. The allocation of high and low frequencies was counterbalanced across the participants. The medium-frequency auditory stimulus had a 50% chance of presenting a pleasant or unpleasant image as a visual stimulus. Therefore, the experimental task was divided into three types (80 trials for each task): expected pleasant images, expected unpleasant images, and unpredictable images. In this paper, only data from unanticipated tasks were included to exclude the effects of anticipation-related expectancies.

During the image anticipation task, the participants were instructed to imagine a picture that would appear in the subsequent visual stimulus. For the visual stimuli, pleasant and unpleasant images were presented for 4 s, which were selected from the International Affective Picture System (IAPS) dataset [10] based on their emotional valence ratings. The IAPS is a commonly used dataset in studies of pleasant and unpleasant emotions elicited by visual stimuli. Images that evoked excessively unpleasant emotions or that could be interpreted in multiple ways were excluded from this presentation [1]. For the subjective rating, the participants were asked to rate the images on a 4-point Likert scale

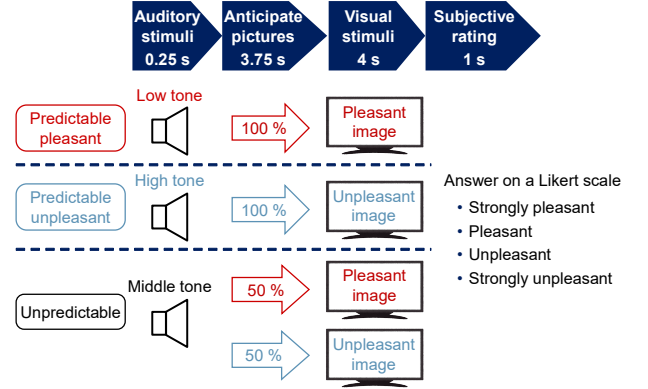


Fig. 2: Schematic representation of the experimental task for a single trial. In this paper, the analysis included only data from the unpredictable task.

(strongly pleasant, pleasant, unpleasant, and strongly unpleasant). However, the results obtained from subjective ratings were not utilized in this paper. The analysis in this paper is based on the general pleasantness defined in the IAPS dataset.

B. Feature calculation

We analyzed the EEG data obtained during 4 s of visual stimulation. Following preprocessing of the EEG data under unpredictable task conditions, we calculated feature $1/\nu$ based on the scale mixture model. To facilitate comparison, we calculated the variance σ^2 as an amplitude feature, which is equivalent to the spectral power employed in previous studies, and the approximate entropy (ApEn) [11], which is a measure of the complexity of the amplitude.

C. Clustering of independent component

Owing to the uniqueness of ICs in each participant, performing a statistical analysis across participants is difficult. Therefore, we used clustering based on the Gaussian mixture model (GMM) to aggregate similar ICs across participants into common IC clusters. The input to the GMM was scalp topography $\hat{\mathbf{W}}^{-1}$, which represented the contribution of the ICs at each electrode placement. Because the polarity of IC scalp topographies is arbitrary, the polarity is inverted, if necessary, to ensure that all scalp topographies are positively correlated. In addition, each scalp topography was standardized to have a mean of 0 and standard deviation of 1.

In the GMM, the off-diagonal elements of the covariance matrix for each cluster were fixed at zero to enhance computational efficiency. Additionally, a regularization constant of 0.05 was added to the diagonal components to suppress overfitting. To determine the number of clusters to be extracted, we varied the number of mixtures in the GMM from 0 to 60 and selected the value that minimized the Bayesian information criterion (BIC) [1].

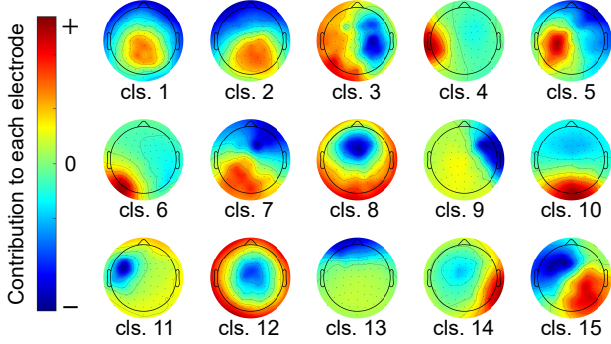


Fig. 3: Scalp topographies of IC clusters averaged over all included ICs

D. Analysis

Statistical tests and receiver operating characteristic (ROC) analyses were conducted to examine the association between the proposed features and emotional valence. Specifically, we employed the Wilcoxon signed-rank test (significance level: 5%) to compare feature values between emotional valences (i.e., pleasant and unpleasant conditions) within each IC cluster obtained. To adjust for multiplicity between frequency bands, we corrected p values using the Benjamini-Hochberg method. Furthermore, we calculated the probability of superiority p_{sdep} [12], which is a type of effect size that reflects the degree of difference between the conditions. p_{sdep} ranges from 0 to 1, with values closer to either extreme indicating a greater difference between the conditions. Subsequently, ROC curve analysis was performed to evaluate the classification performance of each feature within the IC clusters and frequency bands that showed significant differences. The area under the ROC curve (AUC-ROC) was computed as an accuracy metric. The ROC-AUC value reflects the relationship between the false positive rate and true positive rate, with values closer to 1.0 indicating better classification performance.

IV. RESULTS

The results showed that the BIC was smallest when the number of clusters was 15. Fig. 3 depicts the scalp topographies of the obtained 15 IC clusters, which were averaged over all included ICs. Statistical and ROC analyses were performed on these clusters.

Fig. 4 shows an example of the calculation results of $1/\nu$, σ^2 , and ApEn for an IC within cluster 1. The top panel (a) shows the waveforms during pleasant image presentation, and the bottom panel (b) shows the waveforms during unpleasant image presentation. The original ICs are shown on the left, whereas the waveforms and density histograms of the extracted θ band are shown on the right, accompanied by their corresponding features (i.e., $1/\nu$, σ^2 and ApEn). The shaded area in the waveform represents the analyzed portion, which entails a visual stimulus. During unpleasant image presentation, the θ band waveform exhibited immediate amplification following image presentation, which then rapidly decreased, implying a fluctuation in amplitude after

the visual stimulus. The value of $1/\nu$ was higher than that during pleasant image presentation, and the distribution of the IC exhibited a non-Gaussian shape.

Fig. 5 shows the boxplots of the features within the IC clusters and frequency bands that indicated statistical significant differences between pleasant and unpleasant conditions, as well as their corresponding scalp topographies. For $1/\nu$, the two clusters/frequency bands exhibited significant differences. Because no clusters/frequency bands presented significant differences in σ^2 , we presented clusters/frequency bands that showed suggestive differences ($p \leq 0.1$). For ApEn, three clusters/frequency bands showed significant differences. Furthermore, we indicated the probability of superiority p_{sdep} of each result.

Fig. 6 shows the calculated values of ROC-AUC for the IC clusters and frequency bands that showed statistical significant differences. The highest AUC values were 0.616, 0.509, and 0.589 for the proposed $1/\nu$ in the θ band of Cluster 1, the variance σ^2 in the α band of Cluster 12, and ApEn in the β band of Cluster 7.

V. DISCUSSION

The proposed feature $1/\nu$ reflects the temporal fluctuation of the variance value (i.e., amplitude) within the analysis window. Waveform examples shown in Fig. 4, the amplitude tends to show greater temporal fluctuations following the presentation of unpleasant images compared to pleasant images. The conventional feature σ^2 averages out the temporal fluctuation within the window; thus, cannot completely capture the feature differences between pleasant and unpleasant conditions. A comparison of the feature values in the θ band in this example reveals that σ^2 has the same value during pleasant and unpleasant image presentation. In contrast, $1/\nu$, which represents the fluctuation of the variance, has varying values when pleasant images are presented and unpleasant images are presented, indicating that the characteristics of the amplitude fluctuation are captured. These results suggest that $1/\nu$ may be useful for assessing the emotional valence evoked by visual stimuli.

The IC cluster and frequency band that show significant differences at $1/\nu$ have been conventionally reported to be associated with emotional valence [13], [14], [15] (Fig. 5(a)). In particular, a significant difference was observed in the θ band in Cluster 1, where the contribution to the electrodes near the parietal region was prominent, resulting in a larger $1/\nu$ under unpleasant conditions. Similarly, Muñoz et al. reported a greater power fluctuation in the θ band of the parietal region during unpleasant image presentation than during pleasant image presentation [13]. Furthermore, relatively slow rhythmic waveforms, such as the θ band wave are believed to play an important role in the interactions between distant brain regions [16], and may be associated with emotion-related brain networks [17]. Therefore, $1/\nu$, which reflects the amplitude fluctuations, may capture the activity of the brain network for emotional valence.

ROC analysis revealed that $1/\nu$ and ApEn had higher AUC values than σ^2 (Fig. 6). Because ApEn theoretically

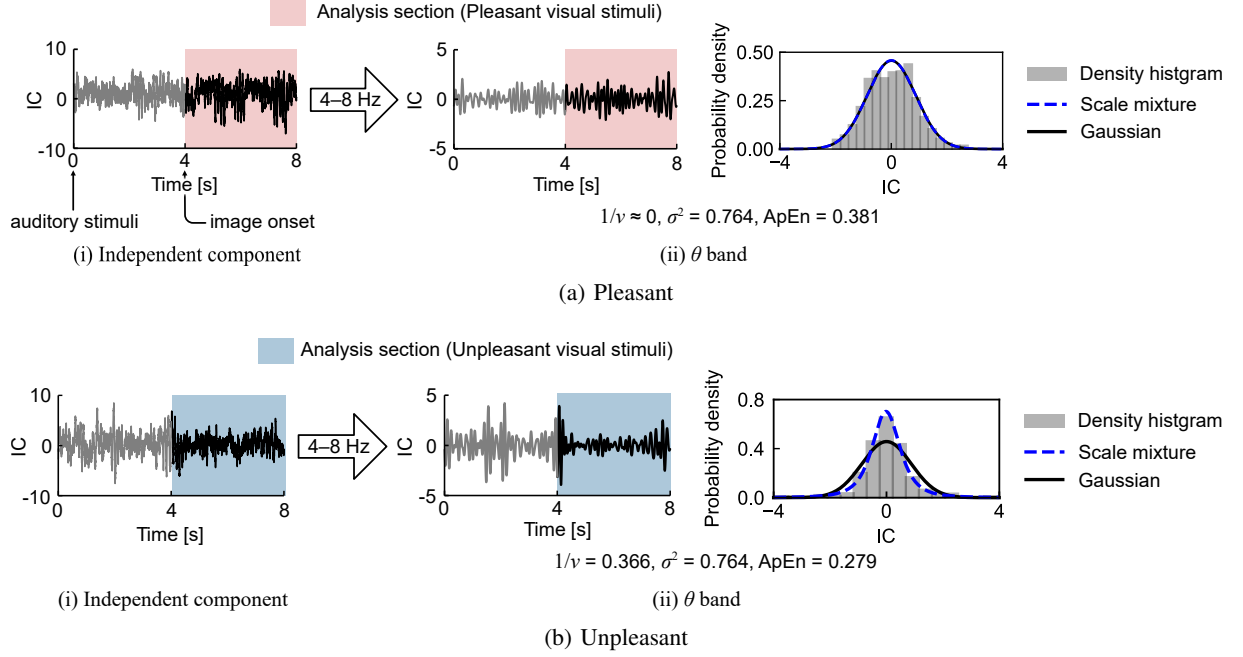


Fig. 4: Examples of original and filtered IC waveforms, their density histograms, and computed features

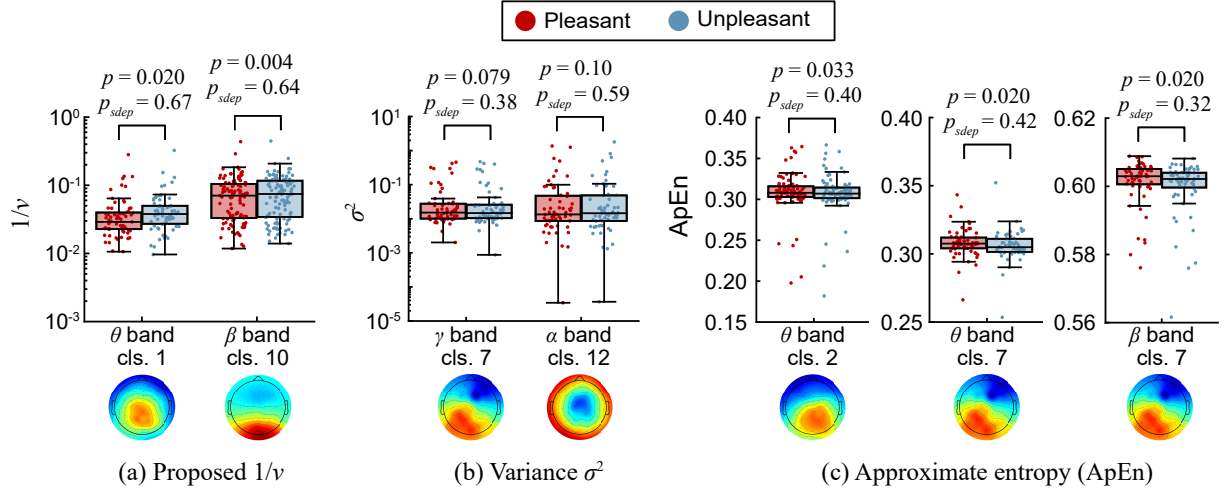


Fig. 5: Boxplots and scalp topographies of IC clusters and frequency bands showing significant/suggestive differences between pleasant and unpleasant. The vertical axis of the graph was converted to a logarithmic scale to facilitate visualization. Error bars extend to points within 1.5 interquartile ranges of the lower and upper quartiles, and then points outside this range are plotted independently. p_{sdep} represents the probability of superiority, a type of effect size, ranging from 0 to 1, with values closer to either extreme indicating a greater difference between the conditions.

maximizes when the data follow a Gaussian distribution [11], it is a feature that captures non-Gaussianity as well as $1/\nu$. Therefore, assessing the non-Gaussianity (i.e., $1/\nu$ or ApEn) resulting from amplitude fluctuations, rather than the simple variance value in the amplitude distribution, may prove useful in assessing emotional valence.

The difference between $1/\nu$ and ApEn is that $1/\nu$ estimates the non-Gaussianity parametrically by assuming a specific probability distribution for the background data, whereas ApEn estimates the non-Gaussianity non-parametrically. Furthermore, there are several aspects of

non-Gaussianity (e.g., heavy tail or left-right asymmetry of the distribution); however, the difference is that $1/\nu$ measures non-Gaussianity with respect to the tail weight, whereas ApEn is a comprehensive evaluation of various non-Gaussianities. Meanwhile, with respect to the maximum value of ROC-AUC, $1/\nu$ demonstrated a higher value than ApEn. Hence, focusing on the non-Gaussianity of the probability distribution with respect to the tail weight may be crucial for assessing emotional valence.

One limitation of this study is that, although $1/\nu$ achieved the highest AUC, its value was approximately 0.6, which is

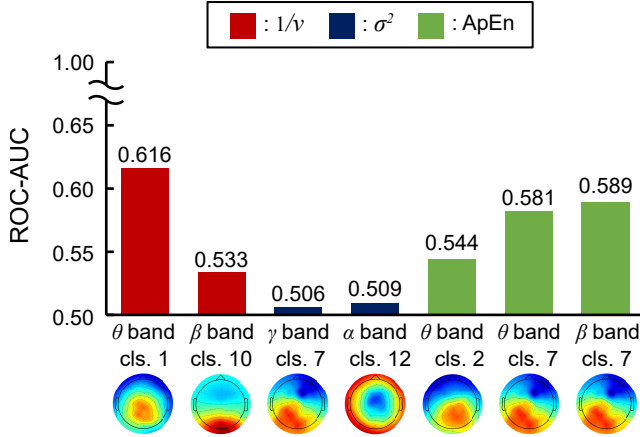


Fig. 6: Results of ROC-AUC for the IC clusters and frequency bands that showed significant differences in statistical tests. The abbreviation ApEn denotes approximate entropy.

relatively low for the classification accuracy of emotional valence. Therefore, $1/\nu$ alone does not have enough classification ability to replace conventional features in emotion assessment. However, since the brain regions and frequency bands that showed significant differences were different from those of the conventional features, the combination of the conventional features and $1/\nu$ may lead to an increase in the accuracy of emotion assessment. We analyzed the relationship between feature values and emotional valence in a single IC; however, future studies should explore multivariate approaches that combine features from multiple IC clusters with frequency bands.

VI. CONCLUSIONS

In this paper, we examined the relationship between emotional valence and fluctuations in EEG amplitudes using a scale mixture model. By modeling ICs of the EEG based on scale mixture models, the stochastic fluctuation of the variance in each dimension of the ICs can be quantitatively evaluated using the non-Gaussianity feature, $1/\nu$. Previous studies have reported the efficacy of scale mixture models in analyzing EEG signals during epileptic seizures [5] and sleep EEG [6], and our study is the first attempt to apply this approach to EEG signals linked with emotional valence.

In this experiment, we used an EEG dataset featuring image stimuli that elicited pleasant and unpleasant emotions. The results revealed that the proposed $1/\nu$ showed statistically significant differences between pleasant and unpleasant emotions in the IC clusters contributed by the electrodes near the parietal and occipital regions. Although significant or suggestive differences were obtained in the clusters with high contributions to regions similar to the $1/\nu$ case for the conventional features, the detailed characteristics, such as frequency bands, were different, suggesting that $1/\nu$ captures the responses linked to emotional valence from a different aspect than the conventional features. Furthermore, the results of ROC analysis indicated that the evaluation of the variance fluctuation, rather than the variance value

itself over a certain time range, enabled a more accurate classification of emotional valence. These findings suggest that $1/\nu$, which characterizes the stochastic fluctuation of the EEG (IC) variance, may be a novel index that increases the accuracy of pleasant and unpleasant emotion assessment when combined with conventional features.

In future research, we plan to investigate the validity of $1/\nu$ in more detail through validation using a more diverse dataset. Additionally, we aim to enhance the scale mixture model to obtain a structure that is more suitable for emotion assessment and apply it to an emotion decoding system.

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