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Directed EEG Functional Connectivity Features to Reveal Different Attention Indexes Using Hierarchical Clustering

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ABSTRACT Functional connectivity related to familiarity has recently been investigated in the context of various stimuli (e.g., words, faces, pictures, music, and video). However, the directed functional connectivity patterns with different attention indexes as a response to familiar/unfamiliar stimuli remain unclear. In the current study, we employed the Directed Transfer Function (DTF) to estimate the information flow between brain areas. This method was reported to be practically robust to volume conduction. Furthermore, the hierarchical clustering approach was utilized to group subjects based on the attention index, i.e., the alpha/theta ratio of fronto-central (frontal to central and central to frontal) features. Three major findings were revealed from this study. First, all subjects had different attention indexes when they watched familiar/unfamiliar videos. Then, subjects were sorted into three groups: low index (LI), middle index (MI), and high index (HI). Second, a competition between two states (familiar/unfamiliar) showed that the information flows of familiar stimuli were greater than unfamiliar stimuli, which involved significant effects in the frontal, temporal, and parietal areas. Third, comparison between groups (LI/MI/HI) demonstrated that the frontal and central regions were the primary sources that distributed information flows to almost the whole brain, particularly during familiar conditions. This result indicates that these two regions may play an important role in attentional processing.

INDEX TERMS Attention index, Directed Transfer Function (DTF), Dunn Index, electroencephalograph (EEG), familiarity, fronto-central, hierarchical clustering.

I. INTRODUCTION

According to previous studies, watching video affects the human brain [1], [2]. For example, in an fMRI study, Anderson *et al.* investigated the distribution of the cortical network while watching standard video action sequences [2]. An EEG study observed that human emotion was elicited by viewing various music video clips as well [3]. Moreover, the brain's responses to the video could also be applied in the BCI (Brain–Computer Interface) and rehabilitation. For instance, Moon *et al.* proposed interval electroencephalograph (EEG) features with different band combinations to detect a viewer's attention being paid to video segments [4]. Mercado *et al.* developed a game of a BCI video for neurofeedback training for autism [5].

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Another central factor that affects audiovisual perception is familiarity. Familiarity is defined as the state of knowing something very well and is believed to have a critical role in our daily lives because it affects decision making [6], business [7], and social interaction [8]. It also contributes significantly to human–computer interaction (HCI) [9]. More recently, researchers have investigated familiarity effects using neuroimaging methods. To examine how the cortical response and familiar music are related, an EEG was used by Kumagai *et al.* [10]. They found that unfamiliar music activated a cortical response better than familiar music. The right hemisphere is triggered by an unfamiliar feeling, whereas the left hemisphere is activated by a familiar feeling for an odor or music, as confirmed by an fMRI study [11]. Thammasan *et al.* [12] investigated the correlation of brain activity and music familiarity in spectral power and connectivity based on EEG. They revealed that music familiarity has an impact on power and functional connectivity. Interestingly, many recent studies have demonstrated that familiarity can modify attention. Barenholtz *et al.* demonstrated that familiarity influences selective attention to a video [13]. In a face recognition study, less attention will be paid to unfamiliar faces than familiar faces [14]. Kumagai *et al.* [15] investigated the concept that familiarity and attention level affect the level of entrainment.

Attention is a state that is difficult to measure through self-assessment. EEG is an effective tool to evaluate changes in attention conditions. Some studies have utilized a Brain–Computer Interface to evaluate attention. For example, Patsis *et al.* [16] measured the attention states of Tetris players using BCI. Lim *et al.* [17] proposed a new system that monitored the attention of attention-deficit/hyperactivity disorder (ADHD) children during a Stroop task using a headband with dry EEG sensors. They suggested that a training game based on BCI can be used as an effective therapy for ADHD. Rosenberg *et al.* predicted performance variability across subjects using the strength of functional brain networks in a vigilance task [18]. Furthermore, several studies have evaluated the characteristics of the EEG with ADHD [19], [20]. They reported that the amplitudes of ADHD sufferers in the β1/theta ratio in the frontal regions were lower than in healthy children. One other study [21] examined the relation between EEG potential and attention indices in children between 12–13 years old and reported that children with good working ability exhibit a high spectral energy ratio between beta-1 and theta bands.

We aimed to evaluate whether attention indexes varied across subjects when they watched a music video. To achieve this goal, we employed the Directed Transfer Function (DTF) to estimate the functional connectivity and then applied hierarchical clustering approaches to group subjects based on the attention index (alpha/theta ratio). DTF has been successfully implemented in previous research [22]–[24] and has been shown to be practically robust to volume conduction [19], [20]. DTF is an effective connectivity method based on the phase difference between channels that employs the Multivariate Autoregressive Model (MVAR).

Clustering analysis has been successfully used to evaluate individual variation based on the EEG feature. For example, Buckelmüller *et al.* [27] adapted a similarity measure and cluster analysis based on electroencephalogram spectra to investigate intra-individual and inter-individual variability in an EEG sleep study. Maksimenko *et al.* [28] applied a cluster analysis that employed the hierarchical clustering approach based on the subject's EEG features. In their research, they found that EEG activity during mental tasks varied from one subject to another.

In the present study, we investigated the relations between directed connectivity features and attention indexes. Based on [15], [29], [30], we present the following hypotheses:

1) Watching familiar/unfamiliar videos can generate different attention indexes across subjects.
2) Information flow in the fronto-central regions may relate to attentional processing.

Based on our information, this is the first research to demonstrate a clustering attention indexes using a directed functional connectivity feature.

II. METHODS

A. DATASET

In the current study, we used a public database for emotion analysis using physiological signals (DEAP) [31], a multimodal dataset collected using electroencephalograms, physiological, and video signals. Thirty-two subjects (16 females and 16 males with ages ranging from 19 to 37) participated in the data collection. EEG signals were acquired from 32 AgCl electrodes at a sampling rate of 512 Hz using the Biosemi ActiveTwo system while subjects watched 40 video stimuli displayed in the 17-inch screen. In the experiment process, 40 videos were displayed in 40 trials, with each trial consisting of a progress display of 2 s, baseline recording of 5 s, and a music video of 60 s, as displayed in Fig. 1. At the end of each video trial, some ratings were recorded from the subjects: valence, arousal, dominance, and liking on a continuous scale from 1 (low) to 9 (high), and familiarity to the music on a discrete scale from 1 (“never saw the video before the experiment”) to 5 (“knew it very well”).

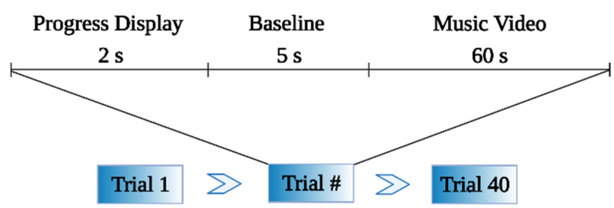

FIGURE 1. Experiment protocol.

B. EEG SIGNALS PREPROCESSING

The procedures of EEG signals preprocessing can be summarized as follows [31]: 1) EEG data were resampled at 128 Hz; 2) electrooculography (EOG) artifacts were removed using the blind source separation technique; 3) a bandpass filter (4–45 Hz) was applied to remove electromyography (EMG) artifacts in the high frequencies; and 4) EEG data were averaged to the common reference.

In this study, we investigated the correlation between directed functional connectivity features and attention indexes in familiar and unfamiliar states. Therefore, we used the familiarity rating that was recorded in the experiment. By following the procedure in [12], familiarity ratings were defined as follows: 3–5 as familiar and 1–2 as unfamiliar. Ratings of familiarity were not present in three subjects: subjects 2, 15, and 23. The standard of the familiar/unfamiliar ratio was set at 0.30, resulting in the data from subjects 4, 5, 25, and 27 being disregarded [12]. Thammasan *et al.* [12] also ignored EEG data from four subjects: subjects 9, 11, 22, and 24. These four subjects were identified to have more than 25% of bad channels (a power spectral density (PSD) value above 100 μV2/Hz) [12]. We then performed an analysis using only the data from the other 21 subjects. Illustration of the EEG data analysis is presented in Fig. 2.

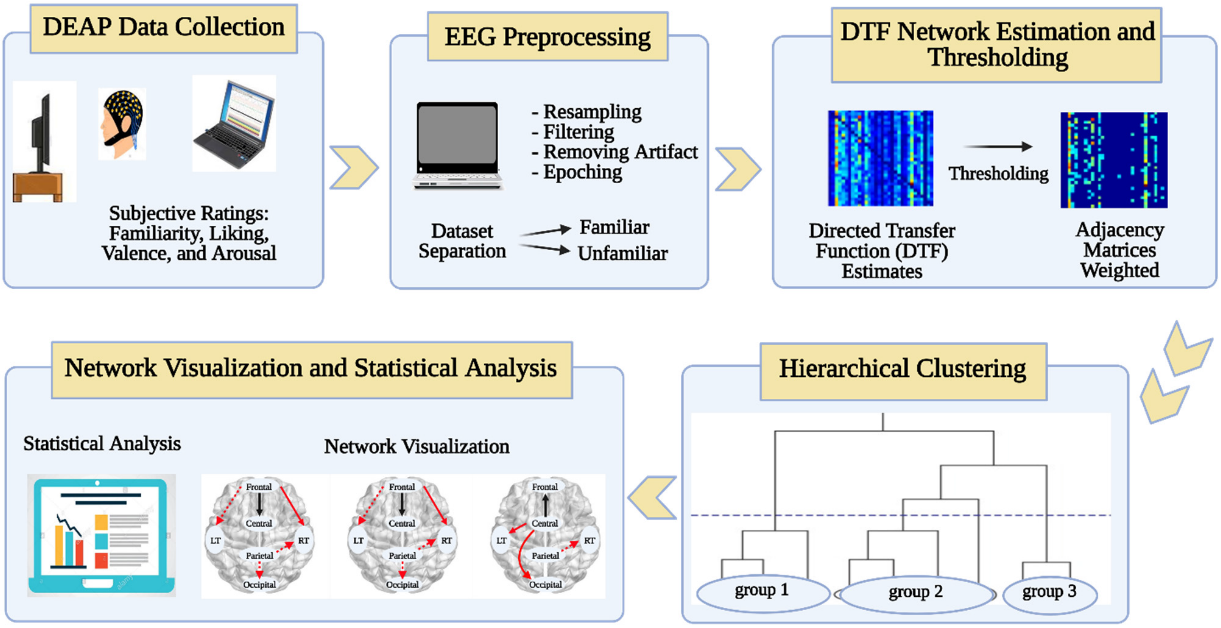

FIGURE 2. Flowchart of EEG data analysis.

C. DIRECTED TRANSFER FUNCTION

The Directed Transfer Function (DTF) was used for the calculation of effective connectivity in the relationships between cortical areas of the human brain. DTF is a connectivity metric based on multivariate autoregressive (MVAR) modeling, defined in the frequency domain [32]:

For a multivariate k-channel process, $X(t) = (X1(t), X2(t), \ldots, Xk(t))$, the multivariate autoregressive model takes the form in equation (1):

$$X(t) = \sum\nolimits_{m=1}^{p} \hat{A}(m) \cdot X(t-m) + E(t)\ or$$
$$= \sum\nolimits_{m=1}^{p} A(m) \cdot X(t-m) = E(t), \tag{1}$$

where E(t) is a k-dimensional vector and $\hat{A}$ is a square k × k matrix. Transforming the multivariate autoregressive model to the frequency domain, we obtain the following using equation (2):

$$\begin{aligned} A(f)X(f) &= E(f), \\ where\ A(f) &= -\sum\nolimits_{m=1}^{k} A(m) \cdot e^{-i.2\pi.f.m} \\ \rightarrow X(f) &= A^{-1}(f)E(f) \\ &= H(f)E(f), \end{aligned} \tag{2}$$

The matrix of coefficients H is called the transfer matrix. The Directed Transfer Function is stated as a normalized form of the transfer matrix using equation (3):

$$DTF_{j\rightarrow i}^{2}(f) = \frac{|H_{ij}(f)|^2}{\sum_{j=1}^{k} |H_{ij}(f)|^2}, \tag{3}$$

The following formula expresses the quality of the fitting of the model given in equation (4):

$$k \cdot d < 0.1 \cdot N, \tag{4}$$

where N is the window length, d is the model order, and k is the number of the EEG channels. The model order was estimated using the Akaike information criterion.

For each participant, we first calculated the DTF using eConnectome toolbox [33] from 32-channels EEG data for the window length of 10 s at time course of 0–10 s and a median model order of O = 10. As a result, the 32 × 32 adjacency matrix of DTFij (Δf) denotes the sensor space of the "information flow" from electrode j to electrode i, at frequency f. By taking the median over frequency bands of interest, we obtained a 32 × 32 matrix of the DTF values, calculated using equation (5):

$$mDTFj \rightarrow i(f) = median(DTFj \rightarrow i(\Delta f)), \tag{5}$$

This value was considered separately in the following frequency bands: theta (4–7 Hz) and alpha (8–12 Hz).

Second, we applied a threshold for each subject's DTF matrix. The threshold was set to one standard deviation after the median [34]. Then, the ratio between alpha and theta was calculated with the following equation (6):

$$mDTF^{k} = mDTF_{j\rightarrow i\,alpha}/mDTF_{j\rightarrow i\,theta}, \tag{6}$$

The ratio between alpha and theta band is often used as the index of attentional processing [29], [35].

We divided the DTF adjacency matrix (32 × 32) into six regions of interest (ROIs) as follows: frontal (FP1, FP2, AF3, AF4, Fz, F3, F4, F7, F8), central (FC5, FC6, FC1, FC2, Cz, C3, C4), left temporal (T7, CP5), right temporal (T8, CP6), parietal (CP1, CP2, Pz, P3, P4, P7, P8), and occipital (PO3, PO4, Oz, O1, O2).

Finally, mDTFk values were calculated for both familiar and unfamiliar conditions. Then, we averaged the $mDTF^{k}$

between two ROIs—for example, between frontal and central areas—which was computed according to equation (7):

$$\mathrm{mDTF}^{\mathrm{k}}_{\mathrm{central}\rightarrow\mathrm{frontal}} = \frac{1}{xy}\sum_{x}\sum_{y} mDTF_{j(x)\rightarrow i(y)}, \quad (7)$$

where x represents electrodes in the central region and y represents electrodes in the frontal region. As a result, for each participant, we achieved a 6 × 6 DTF adjacency matrix.

D. ANALYSIS OF CLUSTERING

The aim of the clustering approach, when evaluating individual variability, is to partition the subjects' EEG features into groups according to their similarity. One widely used clustering algorithm is hierarchical clustering. Hierarchical clustering has several advantages compared to other methods: 1) it results in informative visualization and exploration, where the result is presented in the form of trees—namely a dendrogram—thus, the number of clusters can be decided by looking at the dendrogram [36]; and 2) it is easy to implement for small datasets. In this part, we applied hierarchical clustering [37], [38] to group participants based on their connectivity features, specifically the information flow of alpha/theta ratio from frontal to central and from central to frontal areas. The clustering procedure for our proposed method is described below:

1) We computed connectivity features, which employed the Directed Transfer Function (DTF) based on equations (1–7) for both familiar and unfamiliar conditions.
2) We applied hierarchical clustering based on the Euclidean distance matrix.
3) We determined the number of groups using the Dunn Index, an index of cluster validity for clustering proposed in [39] which attempts to identify "compact and well-separated clusters". Dunn's Index, DIm, for m clusters is given by equation (8):

$$DI_m = \min_{1\le j\le m}\left\{\min_{1\le i\le m, j\ne i}\left\{\frac{\delta\left(C_i, C_j\right)}{\max_{1\le k\le m}\Delta_k}\right\}\right\}, \quad (8)$$

where $\delta(C_i, C_j)$ is the inter-cluster Euclidian distance between clusters Ci and Cj, Δ_k = max, d(x,y), and d(x,y) is the Euclidian distance between the points x and y in cluster Ci.

E. STATISTICAL ANALYSIS

First, a one-way analysis of variance (ANOVA) and Bonferroni correction post hoc test for multiple comparisons ($\rho < 0.05$) were performed to evaluate significant differences between groups and between conditions, separately. Then, a two-way multivariate analysis of variance (MANOVA) with $\rho < 0.05$ was conducted to determine the significance for interaction between group and condition. All statistical analyses were performed using SPSS version 22.

III. RESULTS

In this study, we analyzed the DEAP dataset that recorded EEG signals from 21 participants while they were watching 40 emotional videos. Furthermore, the dataset was separated into familiar and unfamiliar datasets corresponding to a familiarity rating (see Methods).

A. CLUSTERING RESULT

The dendrogram in Fig. 3 displays the result of clustering. Furthermore, the Dunn Index was calculated to evaluate the performance of the hierarchical clustering technique, which ranged from 0 to 1, where a higher value indicated a more appropriate cluster framework [40]. It can be noticed from Table 1 that the Dunn Index obtained the highest value for the three clusters. Based on this, all participants were categorized into the following three clusters (groups): group I (subjects #1–#12), group II (subjects #13–#16), and group III (subjects #17–#21). Table 2 presents the information flow from the frontal to central and from the central to frontal areas ($\mathrm{mDTF^k}$) for both familiar and unfamiliar conditions for each of the 21 participants.

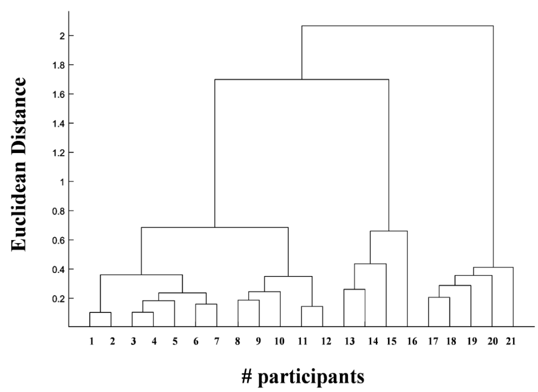

FIGURE 3. The clustering result.

B. FUNCTIONAL CONNECTIVITY

1) GROUP COMPARISON

In this study, the resulted DTF adjacency matrix (32 × 32) was then defined into six regions of interest (ROIs). To evaluate the changes of information flows between ROIs, we performed a one-way ANOVA between attention index groups (LI vs MI, MI vs HI, and LI vs HI), and between conditions (LI, MI, and HI groups, of familiar vs unfamiliar). Bonferroni correction was applied for multiple comparisons. Fig. 4a-4c demonstrate the statistical comparison of the directed connectivity of the three groups in the familiar condition. In Fig. 4a, compared with the MI group, the LI group showed significant connections from frontal to central ($\rho < 0.001$), frontal to right temporal ($\rho < 0.01$), and frontal to parietal ($\rho < 0.01$). As can be seen in Fig. 4b, MI vs HI groups shows a significant information flow from frontal to central ($\rho < 0.001$), frontal to right temporal ($\rho < 0.05$), from central to frontal ($\rho < 0.001$), central to left temporal ($\rho < 0.001$), and central to occipital ($\rho < 0.01$). In the comparison of the LI group and the HI in Fig. 4c, we found that the significant directed connectivity between

TABLE 1. Performance evaluation.

Number of Cluster	Dunn Index
2	0.33
3	**0.47**
4	0.28
5	0.42
6	0.42

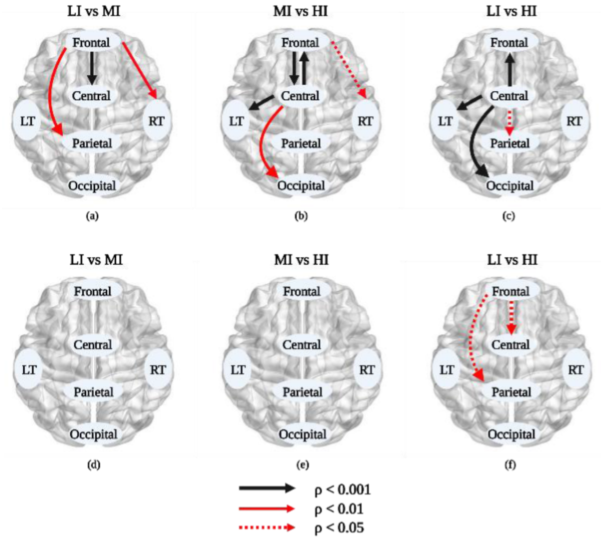

FIGURE 4. Comparison of connectivity strength between groups from all regions of interest (ROIs) during familiar conditions (a-c) and unfamiliar conditions (d-e). LT and RT represent left temporal and right temporal areas, respectively. A one-way ANOVA was used to calculate significant differences with ρ values of $\rho < 0.001$, $\rho < 0.01$, and $\rho < 0.05$ (Bonferroni corrected), indicated by line color and line thickness.

ROIs was almost the same as MI vs HI with some differences; i.e., a significantly enhanced level of difference from central to occipital ($\rho < 0.001$), an additional information flow from central to parietal ($\rho < 0.05$), and flows from frontal to central and frontal to right temporal did not exist.

Fig. 4d-4f show information flows between groups in an unfamiliar state. For the LI vs MI groups and the MI vs HI groups, we found there was no significant information flow between ROIs. Significant connections were found only in the LI vs HI; i.e., from frontal to central ($\rho < 0.05$) and frontal to parietal ($\rho < 0.05$).

2) STATES COMPARISON

Comparisons between familiar and unfamiliar conditions for each of three groups are shown in Fig. 5, in which familiar state was higher than unfamiliar state. In the LI group, we found significant information flow from frontal central ($\rho < 0.01$), frontal to left temporal ($\rho < 0.05$), frontal to right temporal ($\rho < 0.01$), frontal to parietal ($\rho < 0.05$), and from frontal to occipital ($\rho < 0.01$). We also found significant connections from parietal to frontal ($\rho < 0.01$), parietal to central ($\rho < 0.01$), parietal to left temporal ($\rho < 0.01$), parietal to right temporal ($\rho < 0.05$), and from parietal to occipital areas ($\rho < 0.05$). Similarly, in the MI group, statistically significant connections were found from frontal to central ($\rho < 0.001$), frontal to left temporal ($\rho < 0.01$), and frontal to right temporal ($\rho < 0.01$). Significant information flows were found also from parietal to right temporal ($\rho < 0.05$) and from parietal to occipital areas ($\rho < 0.05$). Lastly, information flows from central to frontal ($\rho < 0.001$), central to left temporal ($\rho < 0.01$), central to occipital ($\rho < 0.01$), and from parietal to right temporal ($\rho < 0.05$) were observed in the HI group.

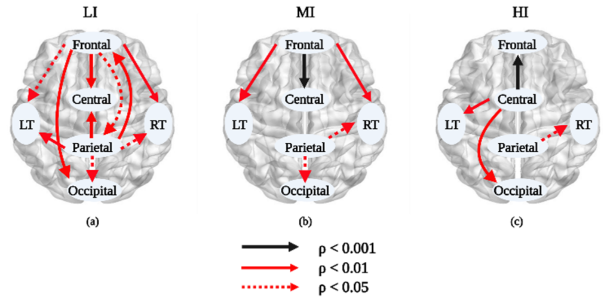

FIGURE 5. Comparison of connectivity strength between conditions (familiar vs unfamiliar) from all ROIs: (a) low index (LI) group, (b) middle index (MI) group, and high index (HI) group. The significant connection is indicated by line color and line thickness with ρ values of $\rho < 0.001$, $\rho < 0.01$, and $\rho < 0.05$, where the familiar conditions are higher than the unfamiliar conditions.

3) GROUP AND STATE INTERACTION

A two-way multivariate analysis of variance (MANOVA) was applied to evaluate the significance of group and state interaction. Two independent variables were group (LI/MI/HI) and state (familiar/unfamiliar), whereas the dependent variables were the information flows between ROIS. Fig. 6 shows significant information flows from frontal to central ($\rho < 0.001$), frontal to right temporal ($\rho < 0.01$), and frontal to parietal ($\rho < 0.01$). There were also flows from central to frontal ($\rho < 0.001$), central to left temporal ($\rho < 0.001$), and from central to occipital ($\rho < 0.001$).

IV. DISCUSSION

Previous studies have shown that visual stimulation can be an effective way to engage attention [33], [41], [42]. Furthermore, attention can be generated by familiarity [15]. For example, familiarity was reported to be able to affect selective attention to audiovisual speech cues [13]. In this study, we evaluated the attention index of subjects when they were watching familiar/unfamiliar videos. Hierarchical clustering was employed to cluster the attention index based on directed connectivity features. In the current study, we found that connectivity strengths from the central area to other regions (frontal, parietal, and occipital) were enhanced with an increased attention index during familiar conditions, as demonstrated in Fig. 4 (a-b). As we previously explained (see Methods), the attention index was obtained by the alpha/theta ratio averaged from frontal to central and from central to frontal areas. Our result is in line with Palva *et al.*, who reported that alpha-band amplitude increased in attention-demanding tasks [43]. Alpha-band power increased after the training period of a video game in a paired-task presentation that forced the subjects to extend attentional switching [44]. This result was supported by

TABLE 2. Functional connectivity features from the frontal to central and the central to frontal areas for both familiar and unfamiliar conditions for each of the 21 participants.

Group	Participant	Information flow from frontal to central		Information flow from central to frontal		Total	Median	Index Category
		Familiar	Unfamiliar	Familiar	Unfamiliar			
I	1	0.22	0.08	0.00	0.18	0.47	0.69	Low Index (LI)
	2	0.34	0.18	0.16	0.10	0.79		
	3	0.28	0.05	0.10	0.07	0.50		
	4	0.00	0.00	0.35	0.15	0.51		
	5	0.18	0.00	0.41	0.16	0.75		
	6	0.11	0.00	0.29	0.31	0.71		
	7	0.11	0.00	0.17	0.39	0.67		
	8	0.40	0.06	0.27	0.18	0.91		
	9	0.29	0.13	0.12	0.25	0.80		
	10	0.05	0.14	0.22	0.15	0.56		
	11	0.42	0.04	0.21	0.09	0.77		
	12	0.19	0.06	0.10	0.16	0.50		
II	13	0.75	0.08	0.24	0.15	1.22	1.21	Middle Index (MI)
	14	1.17	0.13	0.54	0.08	1.92		
	15	1.03	0.05	0.08	0.03	1.19		
	16	0.67	0.23	0.07	0.24	1.21		
III	17	0.35	0.19	1.09	0.08	1.71	1.64	High Index (HI)
	18	0.06	0.13	1.09	0.10	1.38		
	19	0.31	0.15	0.97	0.24	1.67		
	20	0.20	0.13	0.76	0.05	1.13		
	21	0.43	0.21	0.81	0.19	1.64		

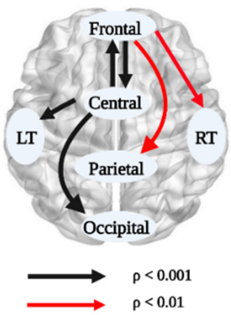

FIGURE 6. The significant information flows between ROIs for group x state interactions, indicated by line color with ρ values of $\rho < 0.001$ and $\rho < 0.01$.

Sadaghiani *et al.*, who found a positive correlation between the alpha band and blood oxygen level-dependent (BOLD) signal [45]. Similar to this, Dosenbach *et al.* reported that brain regions in the inferior frontal, insular, and cingulate cortices played an important role in cognitive function [46]. In addition, a fronto-central theta band has been observed in healthy subjects and the ADHD population [47]–[49]. For instance, Mann *et al.* reported an increased frontal and central theta in ADHD children during drawing conditions [48]. An enhanced activation has been reported in dorsal anterior cingulate cortex (dACC) in attention to neutral stimuli [50]. During the selective attention task, an increase of activity was founded in the ventrolateral prefrontal cortex (vlPFC) [51]. The anterior cingulate cortex (ACC), dorsolateral prefrontal cortex (dlPFC), inferior frontal gyrus, and amygdala have been reported as brain areas that are related to attention [52]. Taken together, our results confirm and magnify the results of previous studies that the frontal and central regions have an important role in attentional processing.

Furthermore, we also observed significant connectivity from the central to occipital areas in familiar states (Fig. 4b and Fig. 4c). Our results were supported by a previous study of event-related potentials (ERP). This study suggested that the earliest response amplified by attention at 75 ms was recorded from the dorsal occipital areas in a visual task in which a subject was asked to notice the position of a target (vertical or reversed) in flashes that were randomly displayed to each field [53]. Pantazatos *et al.* found specific interactions between the ventromedial prefrontal cortex (vmPFC) and lateral occipital cortex (LOC) in a natural and complex search task [54]. These results support the notion that the occipital lobe has a primary role in examining visual information and attentional modulation.

In comparison between familiar and unfamiliar conditions, our results demonstrated that familiar states were dominant over unfamiliar states for all groups (Fig. 5). An fMRI study reported that the medial frontal lobe neurons were more activated in response to personally familiar people (mother or colleague) compared to unfamiliar faces in normal subjects [55]. Another fMRI study also revealed that the medial frontal lobe, insula, middle temporal, and inferior parietal were more active in response to a well-known face when contrasted to an unknown face [56]. Platek *et al.* reported that familiar faces invoked some areas in the medial frontal and parietal lobes reflecting that these areas may play a significant role in face familiarity and that recognition of familiar faces are localized to lateral frontal, temporal, and parietal areas [56]. In this study, we found significant familiar information flow from parietal to right temporal, which was greater than unfamiliar. This result is in agreement with the result reported by Sugimoto *et al.* in an fMRI study that the right temporo-parietal junction (rTPJ) was significantly greater in the competition with familiar friends than with unfamiliar others [57]. In addition, the functional connectivity of the rTPJ and reward-linked regions, composed of the striatum and substantia nigra, was larger in response to familiar friends compared to unfamiliar others [57]. Another fMRI study reported the familiarity effects with well-known people were observed in the left supra-marginal gyrus, the bilateral angular gyri, the left precuneus, and the middle part of the bilateral posterior cingulate cortices [58]. They also observed brain activation of the bilateral temporo-parietal, the right anterolateral temporal cortices, posterior middle temporal gyrus, posterior cingulate cortex, and the left precuneus when responding to personally well-known people [58]. In a study of spatial locations (photographs of the building), Elman *et al.* reported the activation of the posterior regions in the ventral PPC (posterior angular gyrus, LOC) and anterior regions in the medial PPC (anterior precuneus and retrosplenial cortex) when viewed familiar locations [59]. Generally, our results agree with previous studies that the frontal, temporal, and parietal were the most active brain regions in response to familiar stimuli (Fig. 5).

V. CONCLUSION

In this study, by using hierarchical clustering based on information flows of frontal to central and central to frontal, subjects were clustered into three groups: low index (LI), middle index (MI), and high index (HI). The altered topological properties between regions of the attention index groups were demonstrated using a directed connectivity approach that identified the importance of the frontal and central regions regarding attentional processing. In addition, our results also reveal the dominance of familiar stimuli compared to unfamiliar stimuli, which evoked significant effects in the frontal, temporal, and parietal areas. Our findings also show that frontal and central regions were the main sources in the interaction between group and state. In future studies, data analysis with a high-density setup is required to obtain a more accurate result and to corroborate our findings.

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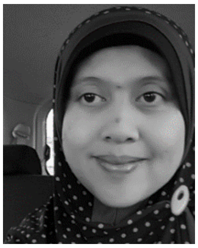

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