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ORIGINAL RESEARCH

EEG-Based Micro-Expression Recognition: Flexible Brain Network Reconfiguration Supporting Micro-Expressions Under Positive Emotion

Jiejia Chen[1,2,*], Xingcong Zhao[1,3,*], Zhiheng Xiong[4], Guangyuan Liu[1,2]

[1]School of Electronic and Information Engineering, Southwest University, Chongqing, People's Republic of China; [2]Key Laboratory of Cognition and Personality, Ministry of Education, Southwest University, Chongqing, People's Republic of China; [3]West China Institute of Children's Brain and Cognition, Chongqing University of Education, Chongqing, People's Republic of China; [4]School of Humanities, Southeast University, Nanjing, People's Republic of China

*These authors contributed equally to this work

Correspondence: Guangyuan Liu, Email liugy@swu.edu.cn

Purpose: Micro-expression recognition is valuable in clinical, security, judicial, economic, educational, and human-computer interaction fields. Electroencephalography (EEG)-based micro-expression recognition has gained attention for its objectivity and resistance to interference, unlike image-based methods. However, the neural mechanisms of micro-expressions remain unclear, limiting the development of EEG-based recognition technology.

Methods: We explored the brain reorganization mechanisms of micro-expressions (compared with macro-expressions and neutral expressions) under positive emotions across global networks, functional network modules, and hub brain regions using EEG, graph theory analysis, and functional connectivity.

Results: In global network, micro-expressions demonstrated higher network efficiency, clustering coefficient, and local efficiency, along with shorter average path lengths. In functional network modules, micro-expressions enhanced connectivity between the bilateral superior frontal gyrus (SFG), anterior cingulate cortex, and ventromedial prefrontal cortex (cognitive control), as well as between the left orbitofrontal cortex (OFC), temporal pole (TP), and inferior frontal gyrus (emotional processing). In hub brain regions, micro-expressions increased the hub centrality, information transmission efficiency, and local clustering of bilateral SFG, left OFC, left TP, and left Broca's area.

Conclusion: Micro-expressions require more efficient global communication and specialized emotion and cognitive control modules. Key hub regions supporting positive micro-expressions include the bilateral SFG (inhibitory control), left OFC and TP (emotion processing), and left Broca's area (language processing).

Keywords: macro-expressions, neutral expressions, electroencephalography, EEG, graph theory, functional connectivity

Introduction

Micro-expressions are fleeting, involuntary facial expressions that unconsciously reveal themselves when individuals attempt to suppress or hide their authentic emotions.[1–3] Micro-expressions provide insights into a person's genuine intentions, in contrast to macro-expressions, which can be deliberately disguised.[4,5] Hence, micro-expressions find broad applications across multiple domains, including deception detection in the legal sphere,[6,7] screening for suicidal tendencies and feigned illnesses in healthcare,[3] and the recognition of non-verbal indicators for national security purposes.[8]

Currently, micro-expression recognition heavily relies on image recognition technology based on facial expressions.[9] Chen introduces a novel Block Division Convolutional Network (BDCNN) with implicit deep feature augmentation, achieving state-of-the-art performance in micro-expression recognition with an accuracy of 84.32% on 3-class datasets and 81.82% on 5-class datasets across the CASME II, SMIC, and SAMM databases.[10] Building on this progress, Wei proposes a novel framework for micro-expression recognition by constructing a geometric two-stream graph network to aggregate low-

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order and high-order geometric movement information from facial landmarks, introducing a self-learning mechanism to model dynamic relationships between nodes, and proposing an adaptive action unit loss to correlate landmarks with facial action units, achieving an impressive recognition rate of 87.21% with significantly reduced computational costs.[11]

However, image-based micro-expression recognition is susceptible to environmental variations due to the brief duration and low intensity of micro-expressions.[12,13] Factors such as facial occlusion, fluctuations in lighting conditions, and changes in head posture can introduce errors, potentially compromising the accuracy of the recognition process.[14,15] However, identifying micro-expressions through electroencephalogram (EEG) signals may help overcome shortcomings in image-based studies, as EEG offers objectivity and resistance to interference. Zhao et al utilized electroencephalogram (EEG) signals for micro-expression recognition, achieving a remarkable recognition rate of 92.60% with their machine learning model.[16] This approach demonstrates the potential of integrating neurophysiological data to significantly enhance the accuracy of micro-expression analysis.

Nonetheless, the limited understanding of EEG-related neural mechanisms underlying micro-expressions may hinder the progress of EEG-based micro-expression recognition research. Micro-expressions of positive emotions, which occur more frequently than those of negative emotions, have attracted scholars' attention due to their encouraging and communicative roles in social interactions.[17] In this study, we employed functional connectivity and graph theory methods to analyze micro-expressions from the perspectives of global network, functional network modules, and hub regions. By comparing micro-expressions with macro-expressions and neutral expressions, we systematically elucidated the brain reorganization mechanisms underlying micro-expressions during positive emotional states. This work establishes a neuroscientific foundation for EEG-based micro-expression recognition applications.

Advantages of EEG in Studying Micro-Expression Neural Mechanisms

Investigating the neural mechanisms of micro-expressions through EEG offers three key advantages: (1) High Temporal Resolution: Compared to the relatively low temporal resolution of functional magnetic resonance imaging (fMRI), EEG provides millisecond-level temporal precision, enabling the rapid capture of brain activity during micro-expression events.[18–20] (2) Objectivity and Resistance to Interference: Unlike peripheral physiological signals, EEG directly captures central nervous system activity associated with micro-expressions. This ensures objectivity, as EEG signals are less susceptible to suppression or manipulation and are not affected by environmental changes.[21,22] (3) Convenience and Affordability: Among various neuroimaging technologies, EEG stands out as a highly promising brain-computer interface due to its low implementation costs, user-friendly design, and wearable advantages.[23–25] Research on the neural mechanisms of micro-expressions based on EEG demonstrates promising potential for the development of EEG-based micro-expression recognition technology. This technology is highly likely to be applied in real-world scenarios.

Previous Theories and Literature

Frank posits that micro-expressions arise from a tug-of-war between automatic and voluntary regulatory systems: the automatic system unconsciously triggers emotional expressions, while the voluntary system suppresses inappropriate emotional displays. The competition between these systems produces micro-expressions, reflecting extensive interactions among brain regions involved in cognitive control and emotional arousal.[26] However, the literature examines the neural mechanisms of micro-expressions primarily from the perspectives of regional activation and network efficiency, without clarifying the broad inter-regional interactions underlying micro-expression generation.[27,28] Systematic research on the brain reorganization mechanisms associated with micro-expressions remains limited. For example, Zhao et al used EEG source localization analysis to investigate differences in brain activation between micro-expressions and macro-expressions.[27] The study found that, compared to macro-expressions, happy micro-expressions showed increased activation in the motor cortex, supplementary motor area, and precentral gyrus, whereas fearful micro-expressions exhibited reduced activation in the somatosensory cortex and angular gyrus. Another study employed graph theory efficiency metrics to analyze differences in brain activity efficiency between micro-expressions and neutral expressions.[28] The results indicated that, compared to neutral expressions, micro-expressions exhibited significantly higher overall efficiency in the α, β, and γ frequency bands.

Graph Theory and Micro-Expressions

An increasing body of evidence suggests that brain function emerges from highly specialized and spatially segregated complex networks within the nervous system, which play a crucial role in shaping behavior, cognition, and emotional states.[29–31] The generation of micro-expressions requires the reorganization of functional brain networks to enhance communication between inhibitory control regions driven by suppressive motivation and emotion-processing areas driven by external stimuli. Traditional EEG methods cannot fully reveal these connections. As an advanced analytical tool, graph theory metrics have been increasingly applied in neuroscience, offering a unique opportunity to assess and quantify the complex brain networks involved.[32,33]

Therefore, this study employed functional connectivity and graph theory techniques to investigate the reorganization mechanisms of functional brain networks underlying micro-expressions from three perspectives: global network, functional network modules, and hub regions. The global network dimension focuses on the overall connectivity characteristics of brain networks, such as information processing efficiency and integration, which helps to reveal the brain's need for global information integration during micro-expression generation.[34,35] The functional network module dimension examines networks of brain regions and their functional properties to understand the interactions among these modules during micro-expression generation.[29,36] The hub regions dimension focuses on key nodes within the network that are responsible for information transmission and integration.[37] Hub regions serve as bridges between global and local networks, facilitating the coordination of connections and information flow among different modules.[38,39] By integrating these three dimensions, we can uncover the brain's global integration capacity, the coordination among functional modules, and the importance of key nodes in the brain network reorganization process, thereby providing a more systematic explanation of the neural mechanisms underlying micro-expression generation.

Aims of the Present Study

Based on this, the present study employed functional connectivity and graph theory methods to systematically elucidate the brain reorganization mechanisms underlying positive micro-expressions (compared to macro-expressions and neutral expressions) from three perspectives: global networks, functional network modules, and hub brain regions. This study provides a neuroscientific foundation for EEG-based micro-expression recognition applications. Given that the generation of micro-expressions involves a complex interplay between cognitive control and emotional arousal signals, we proposed the following three hypotheses based on previous literature. First, from a global network perspective, we hypothesized that, compared to macro-expressions (failure of emotion suppression) and neutral expressions (low emotional arousal), micro-expressions would require greater local and global information processing capacity. Second, from the perspective of functional network modules, we hypothesized that the generation of micro-expressions might enhance functional connectivity within inhibitory-related networks (prefrontal areas) and emotion-related networks (temporal lobe, orbitofrontal cortex, and amygdala). Third, from the hub regions perspective, we predicted that the dorsolateral prefrontal cortex (dlPFC), anterior cingulate cortex (ACC), and other inhibitory control centers, as well as the orbitofrontal cortex (OFC) and temporal lobe—key emotion-processing centers—would serve as hub regions during the generation of micro-expressions.

Materials and Methods

Participants

We recruited 70 university students for this study based on specific inclusion criteria. The selection criteria for participants included being right-handed, having normal or corrected vision, no history of mental illness, no use of psychotropic drugs, and no risk of depression, as indicated by a Beck Depression Inventory (BDI) score below 14. A total of 65 participants were included in the analysis after excluding five participants due to issues with EEG data quality or the absence of observable micro-expressions (mean age = 20.00 ± 1.54 years; 23 males and 42 females). Before the experiment, written informed consent was obtained from all participants, who agreed to the use and public sharing of their EEG and facial image data for scientific research purposes. The study was conducted in accordance with the Declaration of Helsinki and was approved by the Ethics Committee of the School of Electronic and Information Engineering at Southwest University (Ethics approval number: CEIE2022100501).

Materials

We selected videos that provide a rich blend of visual and auditory stimuli, given that the elicitation of micro-expressions often requires highly intense emotional arousal conditions. The main goal was to maintain the stimulation of happiness emotions, eliciting expressions of laughter. Moreover, cultural factors can influence emotional responses in experiments, so clips from Chinese comedy films and various shows were meticulously selected and employed. Stringent criteria were applied in selecting video materials: (a) content capable of eliciting a specific target emotion (ie, the urge to laugh), (b) easily comprehensible content that did not demand excessive cognitive processing, and (c) a duration less than 3 minutes to mitigate visual fatigue. Following these criteria, we manually curated 15 online videos as emotional stimuli and are recruiting 20 participants (not participating in the formal experiment) to assess their effectiveness. We set the criterion for selection as a score of ≥ 6 points on a 7-point Likert scale for the ratings. Subsequently, we edited three videos selected as the elicitation materials for experimentation to ensure a seamless and continuous emotional elicitation experience, specifically targeting laughter urges.

Experimental Design

We employed the real-time supervision and emotional expression suppression (SEES) experimental paradigm to elicit micro-expressions. This paradigm extended the classic ME paradigm by incorporating a "real-time monitoring and evaluation module." It presented several advantages, including heightened ecological validity and increased participant motivation to suppress facial expressions, resulting in a greater occurrence of micro-expressions. The experiment involved both participants and supervisors, creating a simulated social supervision scenario. Participants were instructed to maintain a neutral facial expression while exposed to emotionally charged videos. They were explicitly informed that their performance would be assessed by the supervisor, with their reward linked to their success level. Simultaneously, the role of the supervisor involved monitoring participants' facial expressions and documenting their performance in the experiment.

At the outset, a baseline of resting-state EEG data was meticulously recorded from each participant over a duration of 60 seconds. The central experiment comprised three carefully selected pleasant video clips, presented in a systematically balanced order. Throughout the video presentations, participants were explicitly instructed to suppress facial expressions and maintain a neutral emotional state. Subsequent to each video clip, participants were tasked with evaluating their emotional arousal levels using a 7-point Likert scale. To avoid fatigue, we incorporated a 60-second intermission between each video presentation.

EEG Data Acquisition and Preprocessing

The study recorded EEG signals from 128 active electrodes at a sampling rate of 1024 hz using a Biosemi Active system (Biosemi, Amsterdam, The Netherlands). We developed a synchronization system based on LabVIEW (National Instruments, Austin, TX, USA) to accurately synchronize the EEG acquisition device with the high-speed camera. We precisely synchronized the EEG signal with the acquisition of facial images by utilizing the same trigger simultaneously to generate timestamps on the camera recording and the Biosemi Active system (as shown in Figure 1). During the EEG preprocessing stage, we used the EEGLAB plugin for offline data analysis. After manually interpolating bad channels, a band-pass filter (0.5–60 hz) was applied. Independent component analysis (ICA) was used to correct for eye blinks, vertical/horizontal EOGs artifacts. To optimize the signal-to-noise ratio, EEG signals were referenced to the average reference.

Detecting Facial Expressions and Capturing EEG Signals

It is difficult to induce complete micro-expressions in a laboratory setting, and often only partial facial expressions can be detected, such as a raised mouth or frown.[40,41] In this study, whole or partial facial expressions lasting 500 milliseconds or less were categorized as micro-expressions, while those lasting more than 500 milliseconds were considered macro-expressions.[40] Two coders were engaged in the examination of micro-expressions, following a three-step technique.

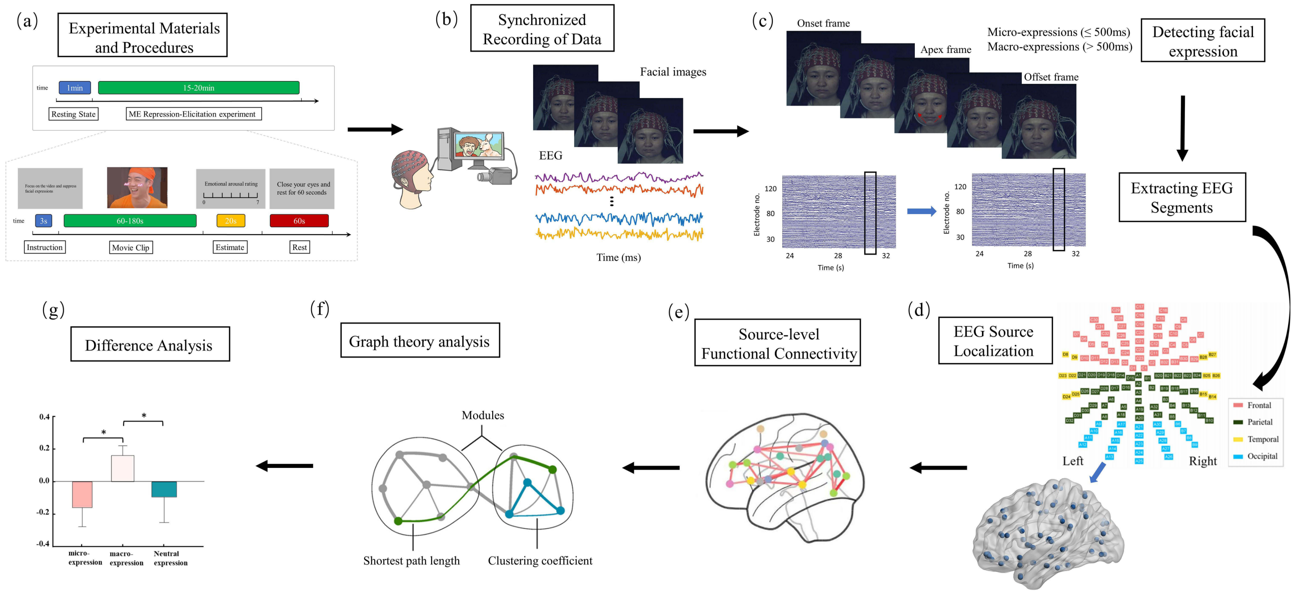

Figure 1 Graph theory analysis schematic representation for micro-expressions. (**a**) Experimental materials and procedures; (**b**) Synchronized recording of data; (**c**) Detecting facial expression and extracting EEG segments. The red arrows indicate the regions of facial expression changes, and the black boxes mark the EEG segments that are temporally synchronized with the facial expressions.; (**d**) EEG source localization; (**e**) Source-level functional connectivity; (**f**) Graph theory analysis; (**g**) Difference analysis. **p*<0.05.

Step 1: Rough selection of facial movements. The aim of this step is to streamline the facial movement dataset for analysis, ensuring a focused examination without overlooking pertinent expressions. Coders played the recordings at half speed, pinpointing segments showcasing facial movements. Subsequently, these segments underwent thorough scrutiny, with the systematic exclusion of non-emotion-related sections. Examples include general head movements or habitual actions like lip pressing during saliva swallowing or nose wiping.

Step 2: Frame-by-frame coding. The objective of this step is to establish the start, apex, and offset frames of the micro-expression based on the preceding step. To correctly identify these frames, the coders continuously looked for tiny variations between neighboring frames that were close to the micro-expression onset, apex, and offset and the length of the micro-expression was determined.[42,43] For result reliability, both coders independently determined the onset, apex, and offset frames for each expression, taking the average in cases of coding discrepancies. The start frame was the first frame that displayed changes of AU6, AU12, or both. The apex frame gave the fullest possible representation of this facial expression. The offset frame comes right before the face's expression returns to its original state.

Step 3: Capturing EEG Signals. EEG signals were extracted with the vertex frame moment of each expression as the midpoint, encompassing a 1-second duration. Based on the duration of the expressions, they were categorically labeled as micro-expressions (≤500ms) or macro-expressions (>500ms). To reduce the impact of subject-related errors on the result analysis, we selected neutral expression segments from participants who exhibited facial expressions (if a participant did not produce any facial expressions, their data were excluded from the subsequent analysis).

Ultimately, this experiment induced 168 micro-expression trials. To prevent subsequent statistical errors due to varying quantities, 168 trials were randomly selected from macro-expressions and neutral expressions to align with the micro-expression trials.

Computation of Functional Connectivity in the Source Space

This study employed source-level functional connectivity analysis to investigate the neural mechanisms underlying differences in micro-expressions, macro-expressions, and neutral expressions. Recognizing challenges such as volume conduction effects and limited interpretability in sensor-level EEG functional connectivity analysis,[44] researchers have proposed leveraging source-level functional connectivity to mitigate these issues effectively.[45,46] Source-level functional connectivity was evaluated in theta (4–7 hz), alpha (8–13 hz), beta (13–30) and gamma (30–60) bands.

We utilized a beamforming method known as Dynamic Imaging of Coherent Sources,[47] implemented using the open-source MATLAB toolbox FieldTrip,[48] to locate the origins of micro-expressions resulting from changes in brain oscillations. This method generated a cross-spectral density matrix and a spatial filter-based leadfield matrix (ie, a matrix of coefficients mapping the current sources to prospective differences in the scalp). The leadfield matrix was computed for a three-dimensional (3D) grid with a 1-cm resolution, employing a realistically constructed three-shell boundary-element volume conduction model. This model was based on the automated anatomical labeling template (AAL-90).[49] In addition, we employed a multi-taper frequency transformation to construct the cross-spectral density matrix for theta, alpha, beta and gamma bands. Subsequently, the brain was parcellated into 90 anatomical regions, with these regions defined by a single centroid voxel each. The functional connectivity between these regions was quantified using the Phase Locking Value (PLV),[50] which ranges from 0 (indicating no synchronization) to 1 (indicating perfect synchronization). Hence, for each trial involving micro-expressions, macro-expressions, and neutral expressions, we constructed a 90*90 matrix representing source-level functional connectivity.

Functional Connectivity Differences Analysis

In order to investigate the neural mechanisms underlying micro-expressions, source-level functional connectivity matrices were subjected to independent samples t-tests using the GRETNA toolbox.[51] This analysis aimed to compare the functional connectivity differences between micro-expressions and macro-expressions, as well as between micro-expressions and neutral expressions. Subsequently, a cluster-based correction method using a non-parametric approach was employed for multiple comparison correction. The cluster-extent-corrected p-value is calculated by comparing observed cluster size (number of links) against a null distribution of maximal supra-threshold sizes created via permutation (5000 randomizations), resulting in an overall corrected $\alpha < 0.05$.

Graph Theoretical Analysis

The GRETNA toolbox (a graph theoretical network analysis toolbox) was used to identify graph properties that differed by facial expression condition (micro-expression, macro-expression and neutral expression).[51] The computation yielded 6 global graph properties: Average Path Length, Global Efficiency, Clustering Coefficient, Local Efficiency, Small-world and Assortativity. Additionally, 5 node-based graph properties were obtained: Nodal Degree Centrality, Nodal Betweenness Centrality, Nodal Efficiency, Nodal Local Efficiency, Nodal Clustering Coefficient.

These properties were chosen based on research related to emotion arousal and inhibition control.[38,39] And their relevance to understanding how the overall structure of a network functions and how individual regions change their relationship to the network in response to changing task demands, a primary aim of the present study. Global Efficiency and Average Path Length are used to determine the network potential for global information processing. Global Efficiency provides the capacity of the global information processing of the entire cerebral network.[34,35] High global efficiency and short Average Path Length reflect the use of short indirect neural pathways to transfer information across distributed brain regions. Moreover, the Clustering Coefficient and Local Efficiency are metrics designed to assess the potential capacity of local information processing.[36,52] They provide insights into the overall network segregation and the degree of aggregation among network nodes.[53] The high Clustering Coefficient and Local Efficiency indicate that nodes tend to form dense regional cliques, demonstrating high efficiency of local information transmission. Small-world reflects the ratio of functional specialization and integration of a network.[54,55] High small-world is linked to a well-designed and effective network, with high global and local efficiency. Assortativity measures the degree to which highly connected nodes are linked to other highly connected nodes.[52,56] Higher assortativity indicates that the network is more resilient to disruptions.

The remaining nodal graph properties assess the relationship that a particular node has to other nodes in its cluster, characterize the movement of information across the network, and provide important information about how the role of a region and its relationship to neighboring structures change dynamically with task demands.[34] Similar to their global counterparts, Nodal Efficiency, Nodal Local Efficiency, Nodal Clustering Coefficient assess the efficiency of communication for individual nodes within the global network and among their neighboring nodes, respectively.[53,57] Similarly, Nodal Degree Centrality and Nodal Betweenness Centrality assess the hub nodes by denoting the number of edges directly attached to a node and the degree to which a given node mediates the number of shortest paths from all other regions, respectively.[34] These measures provide insights into the importance of core brain regions within the entire brain network.

Firstly, to mitigate bias introduced by threshold processing, we utilized the GRETNA toolbox to calculate graph properties for micro-expressions, macro-expressions, and neutral expressions across a range of thresholds.[51] A minimum density of 0.10 was selected as it represented the lowest threshold ensuring connectivity across all nodes in a set of mean matrices. A maximum density of 0.60 was used along with a step size between densities of 0.05, resulting in 17 density thresholds examined.[58] After obtaining the graph property results for the 17 thresholds, the area under the curve was computed as a metric for cross-threshold graph property. For the calculation of graph theory node-based metrics, to minimize the number of comparisons, properties were specifically assessed for nodes identified in the functional connectivity differences analysis as having the highest number of connections in that differences network.[39] Five nodes were chosen for the node-based graph property analysis.

One-way analysis of covariance (ANOVA) models were used to compare the micro-expressions, macro-expressions, and neutral expressions groups on measures of graph properties. Subsequently, to interpret the group differences, post-hoc t-tests were conducted for micro-expressions versus macro-expressions, micro-expressions versus neutral expressions, and macro-expressions versus neutral expressions.

Results

Global Graph Properties Associated with Micro-Expression

The analysis of global graph properties reveals that, compared to macro-expressions and neutral expressions, micro-expressions exhibit higher Network Efficiency, Clustering Coefficient, and Local Efficiency, along with lower Average Path Length (see Figure 2 for details). Specifically, for the Network Efficiency (Figure 2b), micro-expressions were significantly higher than macro-expressions and neutral expressions in the alpha and gamma bands, and significantly higher than neutral expressions in the theta and beta bands (*ps* < 0.05). For the Average Path Length (Figure 2c), micro-expressions were significantly lower than macro-expressions and neutral expressions in the alpha and gamma bands, and significantly lower than neutral expressions in the theta and beta bands (*ps* < 0.05). For the Clustering Coefficient (Figure 2d), micro-expressions were significantly higher than macro-expressions and neutral expressions in the theta and

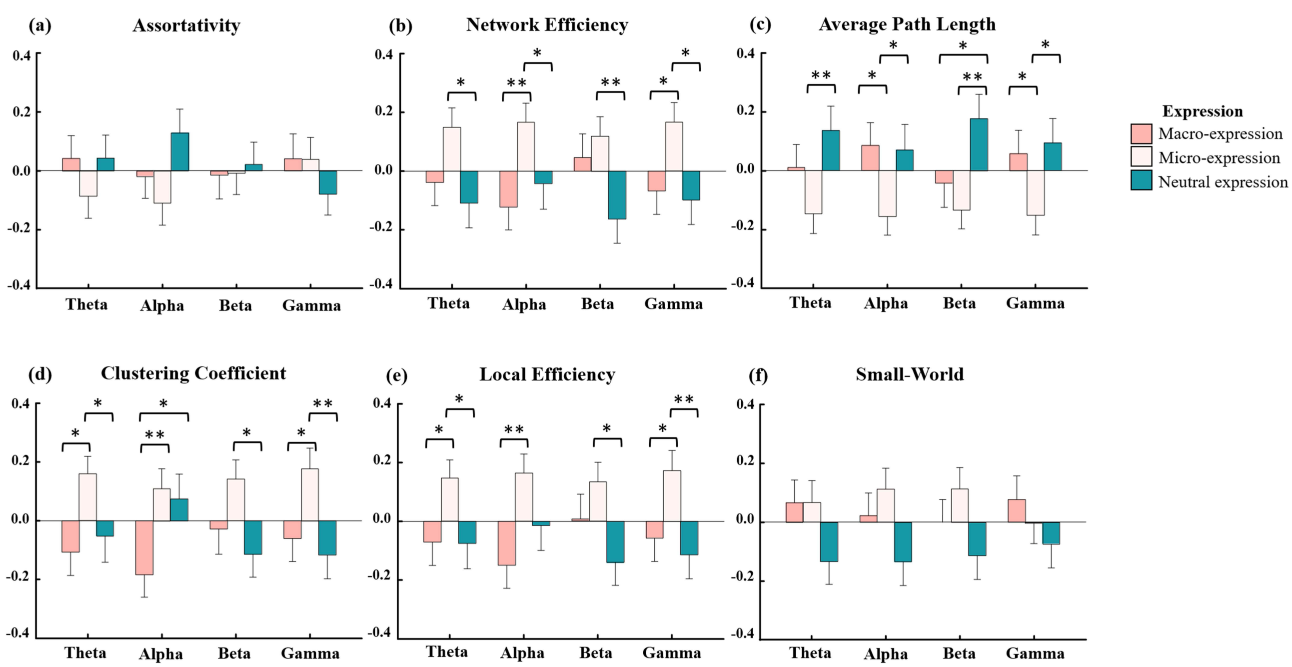

Figure 2 Differences in global graph properties between micro-expressions, macro-expressions, and neutral expressions. (**a**) Assortativity; (**b**) Network Efficiency; (**c**) Average Path Length; (**d**) Clustering Coefficient; (**e**) Local Efficiency; (**f**) Small-World. **p*<0.05; ***p*<0.01.

gamma bands, significantly higher than macro-expressions in the alpha band, and significantly higher than neutral expressions in the beta band ($ps < 0.05$). For the Local Efficiency (Figure 2e), micro-expressions were significantly higher than macro-expressions and neutral expressions in the theta and gamma bands, significantly higher than macro-expressions in the alpha band, and significantly higher than neutral expressions in the beta band ($ps < 0.05$). However, for the Assortativity and Small-World indices (Figure 2a and f), there were no significant differences between micro-expressions, macro-expressions, and neutral expressions across all four frequency bands ($ps > 0.20$).

Functional Connectivity Differences Analysis Associated with Micro-Expression

The analysis revealed differences in the functional connectivity between micro-expressions and macro-expressions, as well as between micro-expressions and neutral expressions across the theta, alpha, beta, and gamma bands. As illustrated in Figure 3a, in the alpha and beta bands, the functional connectivity of micro-expressions was significantly higher than that of macro-expressions in the bilateral superior frontal gyrus (SFG), bilateral anterior cingulate gyrus (ACC), and bilateral ventromedial prefrontal cortex (vmPFC) ($p < 0.05$). As shown in Figure 3b, in the theta, beta, and gamma bands, the functional connectivity of micro-expressions was significantly higher than that of neutral expressions in the left orbitofrontal cortex (OFC), left heschl's gyrus, left temporal pole (TP), left inferior frontal gyrus (IFG), and left amygdala ($p < 0.05$).

Nodal Graph Properties Associated with Micro-Expression

To examine the roles of influential nodes in network changes associated with micro-expression, the most highly connected nodes in these differential networks (as described in the Global graph properties associated with micro-expression section) were selected for further analysis. Ultimately, we selected five brain regions: bilateral SFG, left IFG (Broca's area), left OFC, and left TP. The results showed that in the left SFG, micro-expressions exhibited significantly higher Nodal Efficiency in the alpha and beta bands compared to macro-expressions (see Figure 4) ($ps < 0.05$). In the beta band, micro-expressions also showed significantly higher Nodal Local Efficiency and Nodal Clustering Coefficient compared to neutral expressions and macro-expressions ($ps < 0.05$). In the alpha band, micro-expressions had significantly higher Nodal Degree Centrality and Nodal Betweenness Centrality compared to macro-expressions ($ps < 0.05$). In the right SFG, micro-expressions exhibited significantly higher Nodal Efficiency, Nodal Local Efficiency, Nodal Clustering Coefficient, and Nodal Betweenness Centrality in the theta, alpha, and beta bands compared to macro-expressions ($ps < 0.05$). However, for Nodal Degree Centrality, neutral expressions showed significantly higher values in the theta, alpha, and beta bands compared to macro-expressions ($ps < 0.05$).

In the IFG (Broca's area), micro-expressions and macro-expressions were generally significantly higher than neutral expressions across all frequency bands for the Nodal Efficiency, Nodal Local Efficiency, Nodal Clustering Coefficient, Nodal Degree Centrality, and Nodal Betweenness Centrality indices ($ps < 0.05$). In the left OFC, both micro-expressions and macro-expressions showed significantly higher values than neutral expressions across all frequency bands for the Nodal Efficiency, Nodal Local Efficiency, Nodal Clustering Coefficient, Nodal Degree Centrality, and Nodal Betweenness Centrality indices ($ps < 0.05$). In the left TP, micro-expressions and macro-expressions were also generally significantly higher than neutral expressions across all frequency bands for the Nodal Efficiency, Nodal Local Efficiency, Nodal Clustering Coefficient, Nodal Degree Centrality, and Nodal Betweenness Centrality indices ($ps < 0.05$). However, for the Nodal Local Efficiency and Nodal Clustering Coefficient in the alpha band, no significant differences were observed among the three expression types ($ps > 0.20$).

Overall, compared to macro-expressions, micro-expressions exhibited higher nodal efficiency, nodal local efficiency, nodal clustering coefficient, nodal degree centrality, and nodal betweenness centrality in the bilateral SFG, which is associated with cognitive control. Compared to neutral expressions, both micro-expressions and macro-expressions showed higher nodal efficiency, nodal local efficiency, nodal clustering coefficient, nodal degree centrality, and nodal betweenness centrality in the left IFG (Broca's area), left OFC, and left TP, which are associated with language and emotional processing.

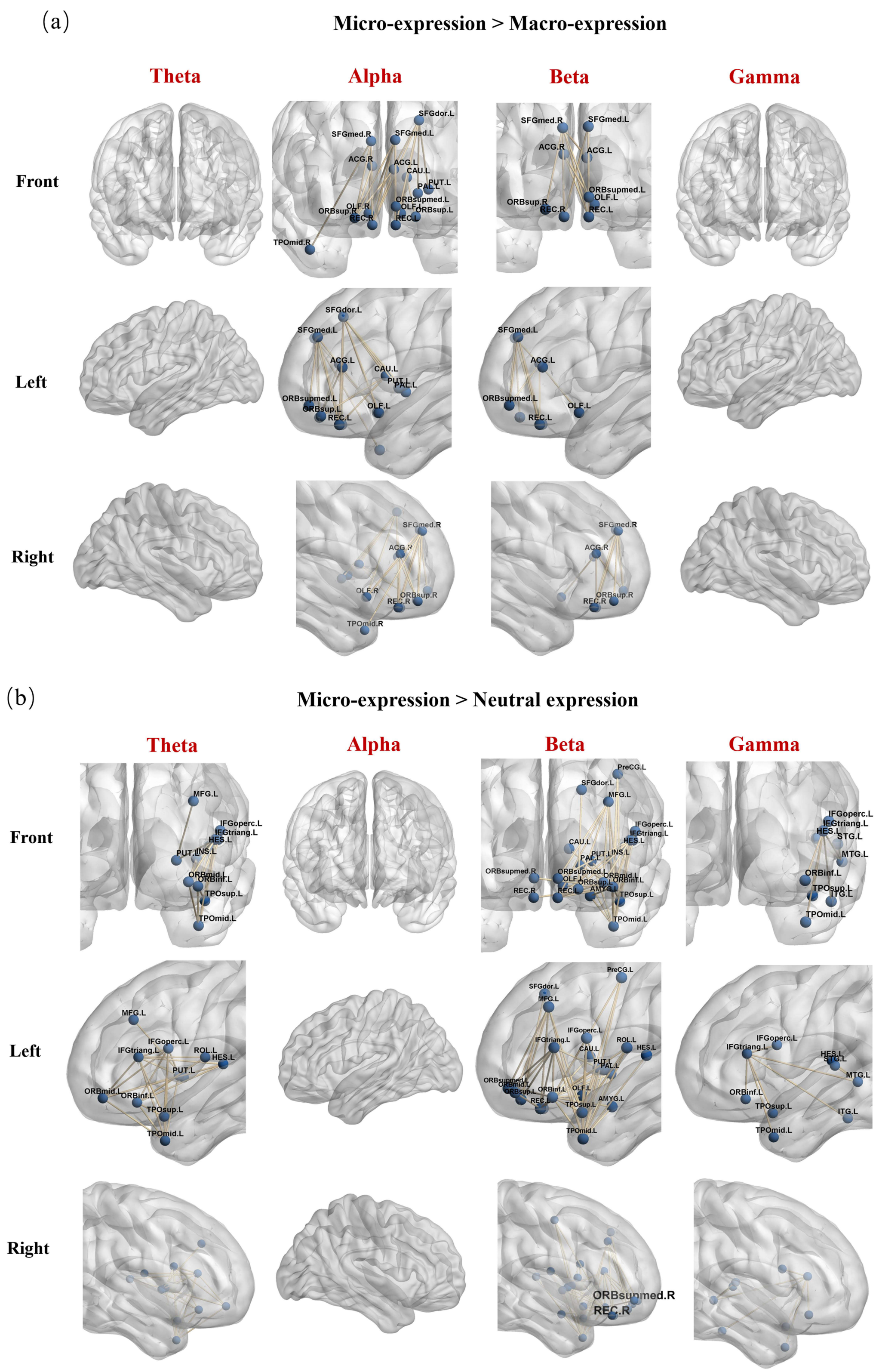

Figure 3 Enhanced connectivity of micro-expressions in the theta, alpha, beta, and gamma bands compared to (**a**) macro-expressions and (**b**) neutral expressions.

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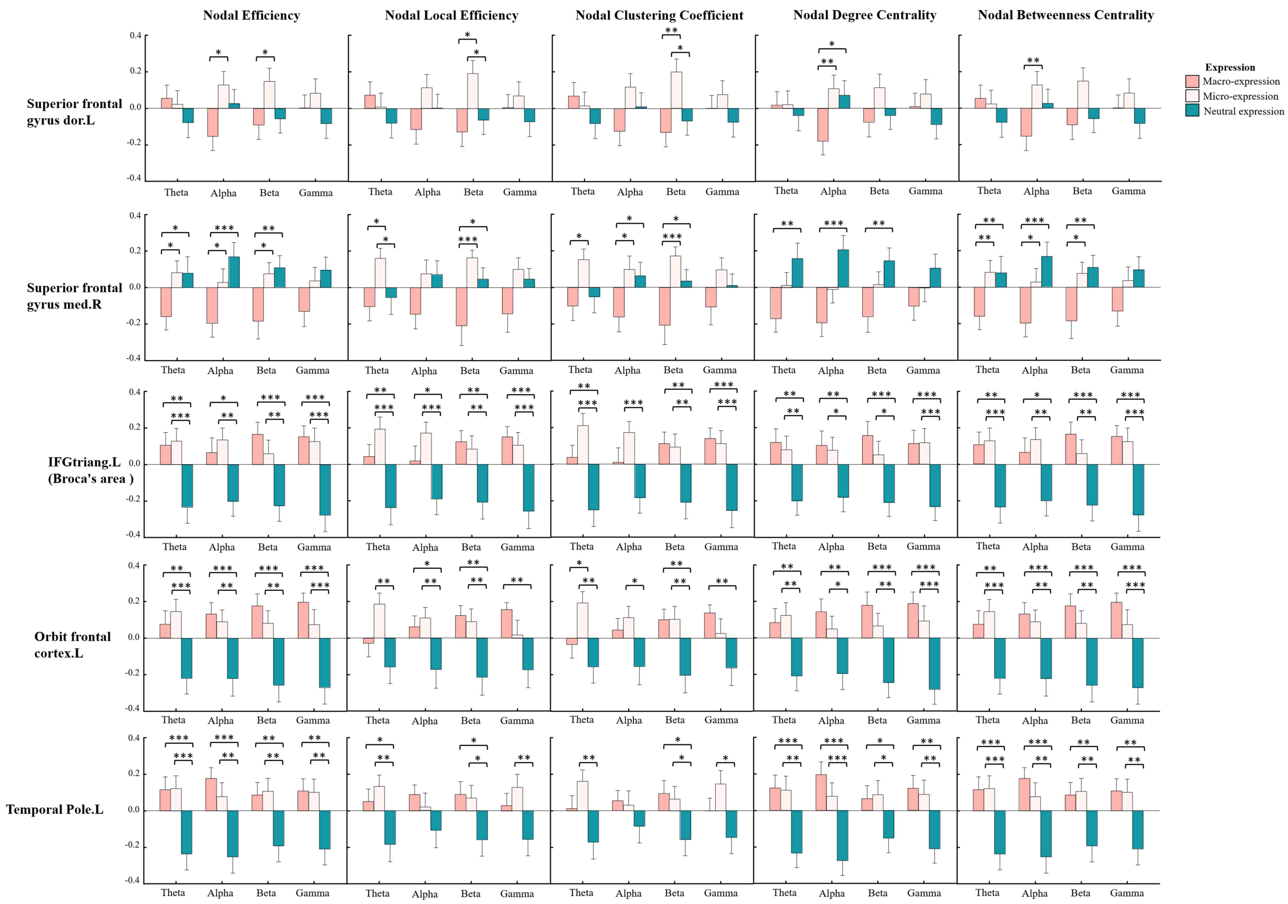

Figure 4 Differences in nodal graph properties between micro-expressions, macro-expressions, and neutral expressions. * p<0.05; ** p<0.01; *** p<0.001.

Discussion

Micro-expressions involve a restructuring of functional brain networks to enhance communication between inhibition-control regions driven by motivation and emotion-processing regions driven by external stimuli. However, the lack of systematic research on this complex brain network restructuring process has hindered progress in EEG-based micro-expression recognition research. Based on this, the present study employed functional connectivity and graph theory approaches to systematically investigate the brain network reorganization mechanisms underlying positive micro-expressions. This was explored from three dimensions: global network, functional network modules, and hub brain regions, through comparisons with macro-expressions and neutral expressions. The findings provide a neuroscientific foundation for EEG-based micro-expression recognition applications.

The present study found that: (1) In the global network, positive micro-expressions, compared to neutral and macro-expressions, exhibited higher Network Efficiency, Clustering Coefficient, and Local Efficiency, as well as a lower Average Path Length. These findings suggest that micro-expressions require more specialized modules and more efficient global information integration. (2) Regarding functional network modules, compared to macro-expressions (which reflect a failure of expression suppression), micro-expressions primarily showed enhanced connectivity in the bilateral SFG, ACC, and vmPFC, regions associated with cognitive control. In contrast to neutral expressions (successful expression suppression), micro-expressions primarily showed enhanced connectivity in the left OFC, TP, and IFG, which are involved in processing positive emotions. These findings suggest that micro-expressions result from enhanced connectivity within emotion-processing and cognitive control networks. (3) From the perspective of hub brain regions, micro-expressions, compared to macro-expressions, enhanced the hub centrality of the SFG, improved information transmission efficiency, and increased local clustering with surrounding regions, thereby better supporting facial movement inhibition. In contrast to neutral expressions, micro-expressions increased the hub centrality of the left OFC, TP, and Broca's area, with improved information transmission and local clustering, supporting emotional and linguistic processing. These findings highlight the bilateral SFG (cognitive control), left OFC and TP (emotion processing), and left Broca's area (language processing) as key hub regions for positive micro-expressions.

Positive Micro-Expressions: Specialized Modules and Efficient Global Communication

The research findings indicate that, compared to macro-expressions and neutral expressions, the global network reorganization associated with positive emotional micro-expressions involves more specialized modules. These modules are characterized by tighter clustering of nodes into specialized groups (higher Clustering Coefficient and Local Efficiency), as well as enhanced global communication efficiency (higher Network Efficiency and lower Average Path Length). This may suggest that processing micro-expressions entails a greater cognitive load as a challenging task, necessitating enhanced module specialization and global communication efficiency. Previous studies have found that higher cognitive loads during tasks increase network specialization and global communication efficiency.[38,39] For instance, Spielberg et al discovered that higher demands for inhibitory control were associated with global network reorganization, including enhanced module specialization and communication efficiency within the global network. Similarly, the demand for emotional suppression also increases clustering and overall communication efficiency.[39]

Specifically, the generation of micro-expressions involves a 'tug-of-war' between the automatic and voluntary regulation systems for the control of the facial muscles. The control of facial muscles is related to the facial nucleus, which consists of four distinct subnuclei (medial, lateral, dorsolateral, and intermediate subnuclei), each responsible for different muscle groups.[59,60] It is evident that the generation of micro-expressions is a high-cognitive-load process, involving not only the direct activation of the facial nucleus to produce expressions following emotional arousal but also active cognitive control to suppress these already activated signals from the facial nucleus. Such a demanding process, compared to macro-expressions resulting from failed expression suppression and neutral expressions with lower emotional arousal, reasonably requires enhanced module specialization and global communication efficiency to cope. Moreover, relevant studies have also found that micro-expressions exhibit higher global communication efficiency in the α, β, and γ frequency bands compared to neutral expressions.[28]

Positive Micro-Expressions: Network Module Specialization in Emotion Processing and Cognitive Control

The previous section discussed that positive micro-expressions, which involve a high cognitive load, require enhanced module specialization. Building on the functional connectivity results, the study found that this enhanced specialization is reflected in increased functional connectivity within networks associated with cognitive control and emotion processing. Specifically, compared to macro-expressions, micro-expressions showed enhanced functional connectivity in the frontal regions, primarily the bilateral SFG, ACC, and vmPFC, in the alpha and beta frequency bands. This likely reflects an increase in the specialization of cognitive control-related network modules during the generation of micro-expressions. The SFG plays a role in various cognitive and motor control tasks and is recognized as a crucial brain area for cognitive regulation and impulse control.[61] Additionally, it forms an essential component of the fronto-parietal network.[62] The ACC plays a crucial role in conflict monitoring and adaptive top-down control, and is a core region of the cingulo-opercular control network.[63] The vmPFC is vital for various aspects of social cognition, including theory of mind, self-related information processing, and emotion regulation.[64] Abnormal connectivity in these brain regions among patients with obsessive-compulsive disorder and depression frequently results in impaired executive function.[30,65]

Compared to neutral expressions, micro-expressions show enhanced functional connectivity in brain regions such as the left OFC, IFG, TP, and amygdala across the theta, beta, and gamma frequency bands. This likely reflects an increase in the specialization of emotion processing-related network modules during the generation of micro-expressions. Dalgleish and colleagues introduced the concept of the "emotional brain", proposing that the recognition and generation of emotions rely on the ventral system, which includes key brain regions such as the amygdala, insula, ventral striatum, and orbitofrontal cortex.[66,67] These emotion-processing brain regions not only have direct anatomical connections within the system,[68,69] but are also extensively connected to sensory cortical areas.[67] Therefore, during the perception and recognition of emotions, the sensory system first transmits information to emotion-related regions (eg, the amygdala), enabling rapid emotional processing through automated subcortical pathways.[70] Moreover, research has found that the functional connectivity of the emotion-processing network associated with micro-expression generation shows a leftward bias. This aligns with the concept of emotional laterality, which suggests that positive emotions are associated with enhanced activation and functional connectivity in the left hemisphere, resulting in leftward lateralization, while negative emotions are linked to activation and enhanced functional connectivity in the right hemisphere, leading to rightward lateralization.[71]

In summary, the generation of micro-expressions may result from the interaction between emotion processing and cognitive control networks. First, the pleasant video induces positive emotions in the individual (show enhances functional connectivity in emotion-related areas such as the vmPFC and amygdala). Secondly, positive emotions can then directly influence the facial nuclei through automated subcortical pathways to generate facial expressions (show enhanced functional connectivity in the OFC and primary motor cortex in the central precentral gyrus).[60,72] If there is no immediate suppression at this point, macro-expressions may occur, resulting in a complete leakage of facial expressions. However, if the individual suppresses the already activated facial nuclei signals, micro-expressions may emerge (show enhanced functional connectivity in the SFG and ACC). The ACC plays a key role in integrating environmental cues during the initiation of voluntary movements and learning processes, and may provide top-down control signals to other regions.[73,74]

Hub Brain Regions of Positive Micro-Expressions: Bilateral SFG, Left OFC, Left TP, and Left Broca's Area

To examine the role of hub brain regions in the network reorganization associated with micro-expressions, we selected the brain regions with the highest connectivity (degree centrality) within these differential networks. The results indicated that the left OFC and left TP, which are involved in emotion processing, the bilateral SFG associated with cognitive control, and the left Broca's area related to language processing, are hub brain regions supporting the generation of positive micro-expressions. The following sections will elaborate on these findings from the perspectives of emotion processing, cognitive control, and language processing.

The results of graph theory indicate that the left OFC and TP are crucial brain regions involved in emotional processing of micro-expressions. Specifically, compared to the neutral expression, micro-expressions enhance the hub centrality of the left OFC and TP (increased Nodal Degree Centrality and Nodal Betweenness Centrality), improve the efficiency of information transmission with other brain regions (improved Nodal Efficiency), and increase the local clustering with surrounding brain regions (enhanced Nodal Local Efficiency and Nodal Clustering Coefficient), thereby facilitating more effective processing of emotion-related information. Numerous neuroimaging studies have shown that the OFC plays a crucial role in the encoding of positive emotions, with the anterior regions likely serving as the primary area for encoding pleasant subjective experiences.[69,75,76] Additionally, the OFC has extensive and direct neural connections with various brain regions, including the amygdala, striatum, and inferior temporal cortex. It rapidly receives feedback from the amygdala through the large-cell pathway and is an integral part of the reward system.[67,68] The TP serves as a third region between the OFC and amygdala, receiving and transmitting signals between these two areas.[77] It is one of the key brain regions involved in emotional processing, particularly in social emotion processing.[77,78] In conclusion, the left OFC and TP support the emotional processing of micro-expressions by enhancing their hub centrality.

The results of graph theory indicate that the bilateral SFG are important brain regions supporting the cognitive control of micro-expressions. Specifically, compared to macro-expressions, micro-expressions enhance the hub centrality of the SFG (increased Nodal Degree Centrality and Nodal Betweenness Centrality), improve the efficiency of information transmission with other brain regions (improved Nodal Efficiency), and increase the local clustering with surrounding brain regions (enhanced Nodal Local Efficiency and Nodal Clustering Coefficient), thereby better supporting facial motor inhibition. The SFG, located at the top of the frontal lobe, is involved in various cognitive and motor control tasks, including regulating inhibitory responses, participating in goal-directed processes, and activating or generating actions.[61,79] The SFG serves as the "central" brain region for executive functions and is a core node within the executive control network, with extensive reciprocal connections to other cortical areas, including the ACC, inferior frontal cortex, and insula.[80,81] In conclusion, the bilateral SFG supports the cognitive control processing of micro-expressions by enhancing its hub centrality.

The results of graph theory indicate that the left Broca's area is a crucial brain region involved in the linguistic processing of micro-expressions. Specifically, compared to the neutral expression, micro-expressions enhance the hub centrality of the left Broca's area (increased Nodal Degree Centrality and Nodal Betweenness Centrality), improve the efficiency of information transmission with other brain regions (improved Nodal Efficiency), and increase the local clustering with surrounding brain regions (enhanced Nodal Local Efficiency and Nodal Clustering Coefficient), thereby facilitating more effective processing of linguistic information from video materials. It is well known that Broca's area is one of the core brain regions involved in language comprehension and production.[82,83] Given that the positive emotion induction materials in our study were derived from comedy films and various comedy programs, the clips that elicited laughter often contained humorous, ironic, punning, or exaggerated linguistic content. Compared to neutral language segments, laughter-inducing clips may require more cognitive resources for language processing. Furthermore, previous studies have found functional connections between Broca's area, which is involved in language processing, and the orbitofrontal cortex, which is involved in emotional processing.[68,84] In conclusion, the left Broca's area supports the processing of linguistic information in micro-expressions by enhancing its hub centrality.

Conclusion

EEG-based micro-expression recognition has significant application value in various fields, including clinical treatment, national security, judicial practice, economic activities, learning and communication, and human-computer interaction. However, the complex brain reorganization mechanisms underlying micro-expressions remain unclear, which limits the development of EEG-based micro-expression recognition technologies. Therefore, we systematically elucidated the brain reorganization mechanisms underlying micro-expressions in positive emotional states from three dimensions: global network, functional network modules, and hub regions. The global network results indicate that micro-expressions require more specialized modules and more efficient global communication. The functional network module results suggest that micro-expressions may result from enhanced connectivity within emotion and cognitive control networks. The hub region results show that the bilateral SFG, which is associated with inhibitory control, the left OFC and left TP, which are involved in emotion processing, and the left Broca's area, which is related to language processing, are key hub regions supporting the generation of positive micro-expressions. The study not only broadens our understanding of the neural mechanisms of positive micro-expressions from a brain network reorganization perspective but also clarifies their distinctions from macro-expressions and neutral expressions. This contributes to laying the psychological foundation for EEG-based micro-expression recognition research.

This study also has some limitations. First, it only explored the brain network reorganization of micro-expressions in the context of positive emotions, and future research should extend this investigation to other emotional categories, such as fear and sadness. Second, this study did not examine the causal connectivity of core brain regions during the generation of micro-expressions, and future studies should further explore this using directed connectivity techniques such as dynamic causal modeling (DCM).

Data Sharing Statement

The data can be obtained by contacting the corresponding author for reasonable requests.

Ethical Approval

The study was conducted in accordance with the Declaration of Helsinki, and approved by the Ethics Committee of School of Electronic and Information Engineering at Southwest University (Ethics approval number: CEIE2022100501).

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors report no conflicts of interest in this work.

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