Altered EEG Theta and Alpha Band Functional Connectivity in Mild Cognitive Impairment During Working Memory Coding

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***Abstract*— Individuals with mild cognitive impairment (MCI), the preclinical stage of Alzheimer disease (AD), suffer decline in their visual working memory (WM) functions. Using large-scale network analysis of electroencephalography (EEG), the current study intended to investigate if there are differences in functional connectivity properties extracted during visual WM coding stages between MCI patients and normal controls (NC). A total of 21 MCI patients and 20 NC performed visual memory tasks of load four, while 32-channel EEG recordings were acquired. The functional connectivity properties were extracted from the acquired EEGs by the directed transform function (DTF) via spectral Granger causal analysis. Brain network analyses revealed distinctive brain network patterns between the two groups during the WM coding stage. Compared with the NC, MCI patients exhibited a reduced visual network connectivity of the frontal-temporal in θ (4-7Hz) band. A likely compensation mechanism was observed in MCI patients, with a strong brain functional connectivity of the frontal-occipital and parietal-occipital in both θ and α (8-13Hz) band. Further analyses of the network core node properties based on the differential brain network showed that, in θ band, there was a significant difference in the out-degree of the frontal lobe and parietal lobe between the two groups, while in α band, such difference was located only in the parietal lobe. The current study found that, in MCI patients, dysconnectivity is found from the prefrontal lobe to bilateral temporal lobes, leading to increased recruitment of functional connectivity in the frontal-occipital and parietal-occipital direction. The dysconnectivity pattern of MCI is more complex and primarily driven by core nodes Pz and Fz. These results significantly expanded previous knowledge of MCI patients' EEG dynamics during WM tasks and provide new insights into the underpinning neural mechanism MCI. It further provided a potential therapeutic target for clinical interventions of the condition.**

***Index Terms*— Alzheimer disease, mild cognitive impairment, electroencephalography, working memory, network patterns.**

Manuscript received 11 August 2023; revised 29 April 2024; accepted 22 May 2024. Date of publication 21 June 2024; date of current version 12 August 2024. This work was supported in part by the National Clinical Research Center for Geriatrics, West China Hospital, Sichuan University, under Grant Z2024YY002; in part by the National Natural Science Foundation of China under Grant 62206032; in part by the Fundamental Research Funds for the Central Universities under Grant 2024CDJXY017; in part by the Fundamental Research Funds for the Central Universities under Grant YJ202373; in part by the Science and Technology Major Project of Tibetan Autonomous Region of China under Grant XZ202201ZD0001G; and in part by the 1.3.5 Project for Disciplines of 1435 Excellence Grant from the West China Hospital under Grant ZYYC22001. *(Corresponding author: Ning Jiang.)*

This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Committee of West China Medical College, Sichuan University under Application No. 2021(1447), and performed in line with the Declaration of Helsinki.

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Digital Object Identifier 10.1109/TNSRE.2024.3417617

I. Introduction

MILD cognitive impairment (MCI) is a cognitive state between normal aging and clinically defined onset of Alzheimer's disease (AD). Epidemiological evidence showed that 10-15% of MCI patients would be converted to AD annually, while the conversion rate is only 1-2% for normal elderly people [2]. Individuals with MCI appear to have intact general cognitive function and unimpaired ability for activities of daily living (ADL), but their memory function is impaired, compared with age-matched normal controls. Deteriorated working memory (WM) maintenance and the impairment of visuospatial memory are early symptoms of MCI and AD [3], [4]. WM can be defined as a component of short-term memory with a restricted capacity that depends on central executive functions and attention, utilizing stored information and linking them to long-term memory, and can serve as a sensitive marker of early cognitive decline [5], [6].

The high temporal resolution of EEG makes it an appropriate tool to quantify the neuronal oscillation coupling process of the human brain, as signals with different frequencies are considered to have specific neural functions, implying different information processing mechanisms. Among them, θ (4)-7Hz) and α (8-13Hz) frequency bands have been identified in extensive studies as WM indicators [7], [8]. The θ neural oscillation was first discovered in the hippocampus entorhinal

cortex system of animals. It originates from the interaction between glutamate and dopaminergic neurons and encodes spatial position information through phase precession [9], [10]. The θ neural oscillations played a crucial role in maintaining sequential memory items. Exactly as the spectrum and time-frequency analysis of EEGs acquired during the visual WM task showed that θ amplitude increased significantly at the beginning of WM [11]. In further EEG studies with more complex sequential memory tasks, researchers observed an increase in θ activity. And more importantly, the changes in memory load is monotonically correlated with the power change of θ [12]. The information processing of WM not only needs to consciously maintain task-related information, but it also needs to effectively eliminate the interference of task-unrelated information. And α neural oscillation plays a major role in interference suppression, which is mainly found in the parietal medial cortex. Many studies on WM reported that, in the memory maintenance stage, the power of α decreases with the increase of memory load, just as whether the information is text, number, object shape, face or spatial position. α oscillation t is considered to be the inhibition of visual cortex processing to help subjects maintain their existing memory better [13], [14]. These research on the WM mechanism have left a deep impression on the academic community, but a deeper understanding of the neural signal coupling mechanism between different brain regions in WM tasks is still missing.

Considering the spatiotemporal distribution of brain activities, our brain operates as a complex network, consisted of a large number interconnected cortical regions [15], [16], and the related information is constantly integrated and processed among those specialized, spatially distributed but functionally linked regions [17], [18]. Such interactions could be studied by the brain network analysis. Understanding the functioning of the neural connections at early stage of cognitive decline is important for the early diagnosis, accurate prognoses, and effective treatments, which allows one to slow down or even reverse the progress of cognitive decline towards dementia. In addition, changes in the interaction among regions of a network could precede changes in regional activations [19]. Structural and functional connectivity studies in AD have revealed a reduction in the connectivity between different regions of the brain, converging into a network disconnection hypothesis [20]. For example, a functional magnetic resonance imaging (fMRI) study revealed that in the early stages of AD, the connectivity of the default mode network (DMN) regions decreased, and after 2-4 years, the connectivity of all regions significantly decreased [21]. Another study on early stage of AD also showed that the medial temporal lobe and related cortex have atrophy, and the connectivity of the front and middle regions of the brain has decrease [20]. The pathways between these brain regions play important role in the understanding of the visual WM network. For example, the damage of the frontal-temporal pathway and parietal-temporal pathway will lead to the decline of individual WM ability and memory accuracy. This evidence is supported by Wang et al.'s study, which showed that, under WM state, the bilateral thalamic regions of NC patients had increased dynamic amplitude of low frequency fluctuation (ALFF), but MCI patients had decreased ALFF, as well as significant changes in functional connectivity (FC) related to memory behavior data [22]. While there were considerable literature focusing on the decreased functional connectivity of MCI and AD in the resting state within the θ and α frequency ranges [23], [24], [25], [26], [27], the changes in functional connectivity related to memory tasks have been rarely studied, and previous reports have shown mixed results [28], [29], [30]. Therefore, from a network perspective, visual WM in MCI is a particularly interesting topic, as the neural networks associated with this cognitive function are particularly influenced by the neuropathological processes of AD, especially the connectivity between the frontotemporal lobe [31]. In addition, performing visual WM tasks can accentuate the EEG abnormalities related to MCI and potentially improve the classification accuracy of healthy subjects and patients [32], [33]. Furthermore, WM is a complex dynamic memory processing process, which includes memory encoding, delay and memory retrieval process. Each of these stages involves the participation of different brain regions. For example, in memory encoding activation, the activation area of the dorsolateral prefrontal lobe mainly leans towards the posterior and lateral regions [34], while in the memory delay stage, the activation area of the dorsolateral prefrontal lobe mainly leans towards the anterior [34] and central regions [35], [36]. However, to the best of our knowledge, no research investigated the memory coding stage of visual WM task to explore the network connectivity patterns of MCI WM coding. Therefore, the purpose of this study is to analyze EEG functional connectivity and network differences in the θ and α frequency band during visual WM coding between MCI patients and healthy elderly, and verify whether pre-AD MCI also has abnormal brain functional connectivity during visual WM tasks.

II. Methods

A. Participants

A total of 41 community-dwelling elderly people were recruited in this experiment, including 21 MCI and 20 cognitively normal elderly people (NC). The detailed information of the participants was shown in table I. This study was approved by the Ethics Committee of West China Medical College, Sichuan University, and all participants provided written informed consent prior to their participation.

The neurocognitive scales used in the study were as follows: Mini Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA), ADL, Geriatric depression scale, Generalized Anxiety Disorder, and Ischemia Scale.

The inclusion criteria for MCI that meet the criteria are as follows: 1) the 2018 Guidelines for the Diagnosis and Treatment of Dementia and Cognitive Disorder in China; 2) Complaint of memory impairment; 3) The MoCA score $<$26/30, and the MMSE score $>$ 24; 4) Daily Tool Activity Scale score$>$6/8, ADL $=$100; 5) Age: 65-75 years old; 6) no history of taking anti AD drugs; 7) no history of neurological or mental illness. 8) Willingness to provide informed consent form.

TABLE I
DESCRIPTIVE STATISTICS OF THE NC GROUP AND THE MCI GROUP REPRESENT AS MEAN (SD)

	NC group N= (20)	MCI group N= (21)	t/x^2	p
Sex	Female (N=12) Male (N=8)	Female (N=15) Male(N=6)	0.595	0.440
Age(years)	70.00(3.39)	70.33(2.85)	0.444	0.659
Education(years)	11.05(3.63)	9.52(3.50)	1.369	0.179
MOCA	26.70(1.38)	19.91(2.98)	9.284	<0.001*
MMSE	28.05(1.43)	26.76(2.02)	2.343	0.024*

SD: standard deviation; NC: cognitively normal elderly; MCI: mild cognitive impairment; MOCA: Montreal Cognitive Assessment; MMSE: Mini Mental State Examination. *p<0.05.

The inclusion criteria for the NC group are: 1) Not actively complaining about forgetfulness; 2) The MoCA score >26/30, and the MMSE score >24; 3) Age: 65-75 years old; 4) no mental diseases and central nervous system disease.

The current standard the 2018 Guidelines for the Diagnosis and Treatment of Dementia and Cognitive Disorder in China, with an appropriate level of complexity, is in line with the current national situation and is also reasonable.

B. Experiment Setup and Paradigm

The delayed sample-matching paradigm was used to examine the WM ability of elderly people. Before the experiment begins, each subject must practice the experimental task until they were familiar with the process and understood the purpose of the experiment before finally formally starting the experiment. The collection of EEG data was conducted between 9am and 6pm on weekdays. Participants sat in rooms with dim lighting and reduced sound. All elderly people have normal or corrected vision.

To remove the potential impact of image attributes such as color, familiarity and pleasure on participants' memory, all experimental materials were two-dimensional black and white images. At the beginning of each trial, the prompt symbol "+" would appear in the center of the screen for 1.5 seconds to remind the participant to direct his/her visual attention to the center of the screen at the beginning of a trial. Subsequently, four different stimulus images were randomly presented in the center of the screen, each with a presentation time of 1 second and a display interval of 13 ms between the images. After displaying four stimulus images, a fixation point "+" was displayed on the screen for 3 seconds. During this stage, the participant was asked to recall four stimulus images and maintain memory of them. After the "+" disappears, a fifth detection image (the detection image) would be displayed in the center of the screen for 2.5 s. The participant was asked to determine whether the fifth image was one of the previous four stimulus images. If so, the participant would be required to press the "Space" key on the keyboard, and press the "Right" key if not. The participant would have 2.5 s to make this decision and press the corresponding key. The fifth image in each trial was pseudo random, with a 50% probability of being one of the previous four stimulus images of the current trial and 50% probability of not. Each session consisted of 20 such trials, as shown in Fig.1. The behavioral data of the subjects, including reaction time and accuracy, would also be recorded.

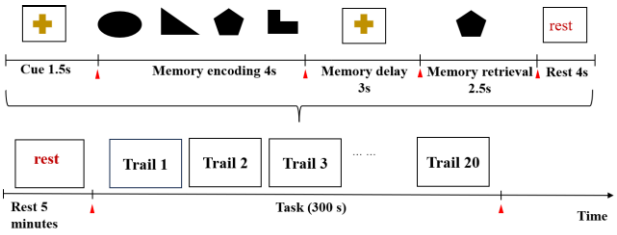

Fig. 1. Experiment setup and paradigm.

C. Instrumentation and Data Pre-Processing

A g.Nautilus active electrode EEG system was used to acquire 32-channel EEG, with the 10-20 international standard electrode positions. The EEG sampling rate was 250 Hz. During the acquisition process, the electrode impedance was kept below 10 kΩ. In the current study, the data pre-processing module mainly focused on acquiring the reliable WM task-memory state related trials. To ensure data quality for subsequent network analysis, the following preprocessing steps were performed: 1) common-average-reference (CAR); 2) 1-30 Hz band-pass filtering; 3) Independent component analysis (ICA) was completed to identify and remove artifacts such as eye-blink (>80%) and muscle artifacts (>80%); 4) data segmentation and baseline correction. All data processing was performed with the EEGLAB toolbox. And the Infomax algorithm of ICA in the toolbox was used in the third pre-processing step. In the process of data segmentation, the length of EEG data in the encoding stage is 4 seconds, where 0 second represents the onset of the four stimulus pictures.

D. The Directional Transfer Function (DTF)

The directional transfer function (DTF) is used to describe the size and direction of the information flow between multi-channel signals. The strength of the causal relationship between channels can be represented by the magnitude of the DTF value, which is based on Granger causality theory and can be extended to variables of any dimension. DTF method can effectively estimate the brain connection of cerebral cortex.

A multivariable autoregressive model (MVAR) is established based on the 32-channel EEG time series. Set the signal as:

$$X(t) = [X_1(t), X2(t), \ldots, Xi(t) \ldots, X32(t)] \quad (1)$$

where X_i is the time series of the i_th channel. The multivariable autoregressive model is as follows:

$$X(t) = \sum_{n=1}^{p} AnX(t-n) + e(t) \quad (2)$$

where A_n is 32 × 32 Coefficient matrix, $e(t)$ is white noise, and p is the order of MVAR model, determined by bayesian information criterion (BIC). In this study, the order of the model was 2, and a constant model order was used for all participant data to ensure that the data analysis results of different participants were compared and explained within the same model framework, which increased the consistency and interpretability of the results of the same group of participants.

BIC is used for model selection, particularly in the fields of statistics and machine learning. It has unique advantages in selecting the order of MVAR models and are widely used in modeling and prediction of practical problems [38]. BIC tends to choose concise models with fewer parameters when selecting models. This feature is very useful in preventing overfitting, especially in small datasets or complex model structures. BIC considers the posterior probability of the model and provides a more comprehensive method for model evaluation. This makes BIC more rigorous in theory and can better reflect the true performance of the model. In addition, in some practical applications, especially in scenarios that require high-precision prediction or strong interpretability, BIC is often able to select models with better performance. This may be because BIC's strict limitation on model complexity helps to avoid selecting overly complex models, thereby improving the model's generalization ability and interpretability.

Formula (1) can be transformed to frequency domain by Fourier transform:

$$X(f) = A^{-1}(f)e(f) = H(f)e(f) \tag{3}$$

where f is the frequency, H is the transfer matrix, A is the identity matrix. Finally, the directional transfer function DTF, which is also called $\gamma_{ij}^2(f)$, is defined by the transfer matrix $H(f)$ as:

$$\gamma_{ij}^2(f) = |H_{ij}(f)|^2 / \sum_{m=1}^{k} |H_{\mathrm{im}}(f)|^2 \tag{4}$$

In the formula, $\gamma_{ij}^2(f)$ represents the ratio of the influence of channel j on channel i over the influence of all channels on channel i, after normalization. The larger $\gamma_{ij}^2(f)$ is, the stronger the causal connectivity between channel j (cause) and channel i (effect) is, and *vice versa*. k represents the number of channels.

A non-zero $\gamma_{ij}^2(f)$ value indicates that there is a causal connectivity between channel j and channel i, but this connectivity may be a "pseudo connectivity". Therefore, the surrogate data method was used to test the significance of $\gamma_{ij}^2(f)$, screen out effective functional connectivity, and eliminate meaningless connectivity due to chance probability. This method was proposed by Kaminski [39] to test the significance of $\gamma_{ij}^2(f)$ in 1991. The core idea of this method is to generate an empirical distribution for significance testing. Firstly, shuffle the EEG signals of each channel, randomly arrange them to obtain new data, and then calculate the $\gamma_{ij}^2(f)$ of the reconstructed data; Repeat this process 1000 times to obtain the values of $\gamma_{ij}^2(f)$ in ascending order. Take the 950th data as the statistical test variable, which is a statistic with a confidence level of 0.05; When the $\gamma_{ij}^2(f)$ calculated from the real EEG signal is higher than 95% of the statistical test, the causal connectivity between channel j and channel i is true, DTF_{ij} is $\gamma_{ij}^2(f)$; When the $\gamma_{ij}^2(f)$ calculated from the real EEG signal is below 95% of the statistical test, the causal connectivity between channel j and channel i is false, and DTF_{ij} is 0.

Calculate the DTF matrix of 32 EEG channels in different frequency bands, DTF_{ij} represents the value of the directional transfer function from channel j to channel i, N is the number of electrodes, *i.e.* the node of the causal network, and the matrix value of the directional transfer function DTF_{ij} is used as the edge of the causal network. DTF_ Mean is the average value of the DTF matrix of multi-channel EEG in frequency range. DTF_mean as network parameters to quantitatively analyze the connectivity characteristics of the network can be directly used as an indicator to describe the causal connectivity strength of network.

E. Out-Degree

The outdegree index is one of the attributes of EEG networks calculated from the DTF matrix, and is often used to measure the characteristics of brain information sources and extensions [40]. A prominent node is often considered as the command center for distributing information to other nodes. Based on the constructed dynamic network, the outdegree of each node can be obtained as:

$$k_i = \sum\nolimits_{j \epsilon N} a_{ij}, \quad i \neq j \tag{5}$$

where N is the number of all nodes in the network, a_{ij} is the connectivity from node i to node j. If there is a significant connectivity, then a_{ij} = DTF_mean, otherwise $a_{ij} = 0$.

F. Statistical Analysis

The SPSS 22.0 software was used for statistical analysis. Independent sample t-tests were used to analyze the differences in neurocognitive scale scores, behavioral data, DTF_mean connectivity values, and important node network attributes (node degrees) between the two groups. The significant was $p < 0.05$ for all analyses.

III. Result

A. General Behavioral Results

The results showed that there were significant differences between the two groups in the scores of the behavioral data in WM tasks, there were significant differences between the two groups in accuracy ($p < 0.001$) and accuracy/reaction time ($p < 0.001$), but no significant difference in response time ($p = 0.745$). as shown in Fig. 2.

B. Dynamic Network Patterns

The WM memory encoding stage involves a series of complex neurocognitive processes such as attention, inhibition, and decision-making, which not only depend on the activation of a single brain region, but also involve information exchange among multiple brain regions. The brain network analysis method can objectively measure the relationships between brain regions, treating EEG electrodes positions as network

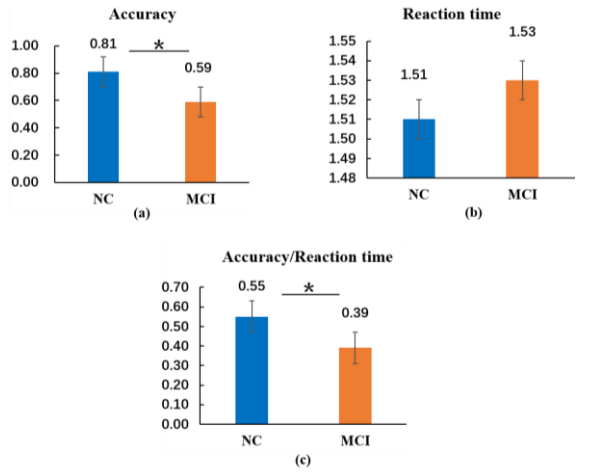

Fig. 2. Statistical analysis of behavioral results. (a) Statistical analysis of the accuracy of the two groups, (b) Statistical analysis of the reaction time of two groups, (c) Statistical analysis of the accuracy/reaction time of two groups. $^{*}p < 0.05$.

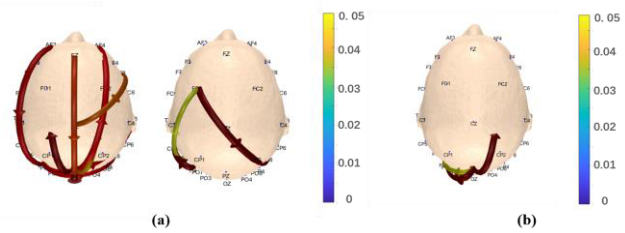

Fig. 3. The significant differences of brain functional connectivity between the two groups. (a) The differential Dynamic network patterns between two groups in the θ frequency band. Left: functional connectivity of MCI that have stronger information flow pattern than NC; right: functional connectivity of NC that have stronger information flow than MCI. (b) The differential Dynamic network patterns between two groups in the α frequency band, showing functional connectivity of MCI that have stronger information flow pattern than NC.

nodes and considering the connectivity between nodes as the edge of network, which can explore the network topology properties of different populations in WM memory states and reveal MCI-related abnormal mechanisms of information processing.

Considering that the wide range of neural oscillations in the encoding stage of WM are distributed in the θ and α frequency band, in order to explore the differences of brain dynamic functional connectivity patterns between the two groups during the encoding stage of WM tasks, we calculated the significant differences of brain functional connectivity DTF_mean between the two groups in these two frequency bands ($p < 0.05$), as shown in Fig. 3. (Color represents the size of the p-value).

Evidently, during the WM task encoding stage, there were significant differences in brain network connectivity patterns between the two groups in both θ and α frequency bands, especially θ. Overall, stronger differential functional connectivity in the θ frequency band was found in MCI, involving a significantly wider range of brain regions (16 nodes vs 5 nodes) and higher number of brain network connectivity (13 vs 3). Meanwhile, in the α band, only MCI has stronger

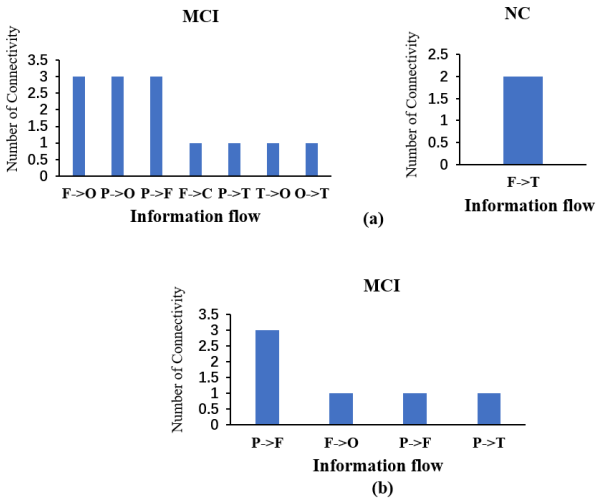

Fig. 4. Statistics on the numbers of connectivity with significant differences between different brain regions. (a) In the θ band, the difference in network pattern between MCI and NC corresponds to the statistics of the number on the connecting edges of five brain regions. (Left: MCI, right: NC); (b) In the α band, the network pattern of MCI differences corresponds to the statistics of the number on the connecting edges of five brain regions. F: frontal lobe; O: Occipital lobe; P: Parietal lobe; T: Temporal lobe; C: Central District.

differential brain network connectivity, where the number of nodes was 8 and the number of significant connectivity was 6. The more complex functional network structure means that MCI patients have lower processing efficiency than NC when completing the same WM task, resulting in mobilization of more brain functional connectivity when memorizing the same pictures.

C. Dynamic Network Properties

Then we further explored the abnormal brain functional connectivity of MCI brain regions during the WM processing stage, and calculated the numbers of brain connectivity with significant differences between different brain regions. Our research results showed that, for NC group, there was a significant connectivity from prefrontal lobe to bilateral temporal lobe (The numbers of the significant connectivity =2) in θ frequency band, while MCI did not. This indicated MCI patients had a significantly reduced brain functional connectivity from frontal lobe to temporal lobe than NC. However, MCI patients recruited a much stronger information flow from the frontal lobe and the parietal lobe to the occipital lobe in θ and α band, as shown in the Fig. 4, indicating that the brain connectivity of some brain regions related to visual WM in MCI patients have changed.

The changes in brian functional connectivity is derived by the functional abnormalities in brain regions, so exploring the core nodes in WM tasks may provide potential targets for the clinical interventions of MCI. Based on the different brain network patterns between the two groups, it was found that the core nodes were located in FZ and Pz, which indicated that Fz and Pz may be overactivated during the WM coding phase in MCI, and they served as the command center and sequentially control the activation of other nodes. The

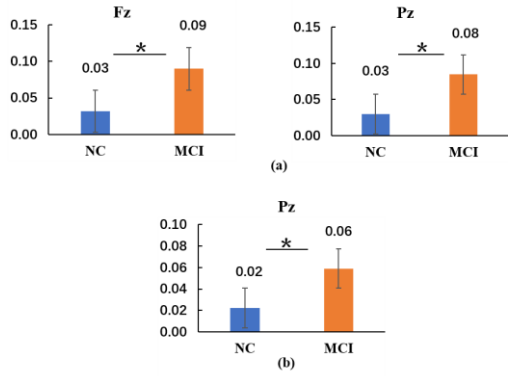

Fig. 5. Statistics of the outdegree information of core nodes between two groups (a) Statistics of electrode FZ and Pz outdegree information in MCI and NC among θ band. (b) Statistics of electrode Pz outdegree information in MCI and NC among α band.

outdegree measurement values of Fz and Pz were calculated, and the results showed that, in θ band, there was a significant difference in outdegree information of Fz (frontal lobe) and Pz (parietal lobe) between MCI and NC. On the other hand, in α band, there was a significant difference in the outdegree information between the two groups located in the Pz (parietal lobe) ($p < 0.05$), as shown in Fig. 5.

IV. Discussion

To our best knowledge, the current study was the first EEG-driven study of brain network connectivity patterns during the memory coding stage of WM tasks in MCI patients. In this study, we validated that functional connectivity abnormalities and disconnection of brain region occur in the early stages of MCI, as MCI patients exhibit significant changes in brain network connectivity patterns related to memory coding compared to NC. For differential brain network connectivity, this study found that, under WM encoding, MCI patients have reduced visual memory coding connectivity from the prefrontal lobe to the bilateral temporal lobe compared to NC, while significantly increasing compensatory connectivity from prefrontal and parietal lobes to the occipital lobe. More importantly, the result indicated that the more complex and diverse brain connectivity patterns are driven by the core node Fz (frontal lobe) and Pz (parietal lobe).

Memory is a core component of human cognitive function, involving multiple processes such as encoding, storing, and extracting information. In daily life and work, memory ability plays a crucial role in learning new knowledge, solving problems, and making decisions. The main clinical manifestation of MCI is the decline of memory function, including episodic memory [41] and WM [42]. Therefore, understanding the activity mechanism of the brain based on memory tasks is of great significance for understanding the essence of human cognitive function, revealing the pathological mechanisms of MCI diseases, and developing effective treatment methods.

WM depends on structures related to executive control, such as prefrontal cortex (PFC) and posterior parietal cortex (PPC), which are important nervous base of WM, the prefrontal cortex controls the screening of information that can be maintained in the parietal lobe region [43], [44], [45], and their neural activities persist in the process of maintaining the representation of WM [46], [47], [48]. Our study showed that the difference in activity of the prefrontal lobe between the two groups is mainly manifested in changes in the θ band of EEG, and this was also consistent with previous research findings [12], [49]. Therefore, during the encoding phase of MCI's WM task, the strong neural oscillation in the prefrontal lobe in the θ band may be an indicator of the decline of its WM ability. Based on the neural mechanism of the representation of visual WM storage accuracy, the posterior parietal cortex is an important brain region involved in the representation of visual WM accuracy. However, research on the involvement of the parietal lobe in the "information retention" moment is more focused on the analysis and processing of α band EEG signals. For example, Roberts et al. used an object memory information experiment and found that there was an energy increase in the θ band of the left prefrontal lobe, while there was an energy increase in the α band of the left parietal lobe. Our research shows that MCI excessively activates the parietal lobe region and exhibits stronger neural oscillations at not only in α but also in θ band. In conclusion, our research results show that MCI displays dysfunction of prefrontal and parietal lobes in brain regions related to visual WM coding, which further leads to changes in brain network patterns. At the same time, changes in these brain regions (such as the network outdegree information of the parietal and prefrontal lobes) can be identified as pre changed targets in the degenerative process leading to dementia. Current research has shown that non-invasive stimuli such as transcranial alternating current stimulation have a significant curative effect in memory function [50]. However, there is still no unified standard for the treatment parameters of MCI, including frequency and target selection. Therefore, the differential targets in different frequencies in current research can serve as important references for subsequent MCI interventions.

The next question involves the connectivity between brain regions and the relationship between this and behavior performance during WM tasks. Previously, most studies were based on resting state EEG to explore the brain connectivity of MCI, and some preliminary results were obtained, but there was still controversy [51], [52], [53], [54], [55], [56]. For example, in a previous brain network study based on resting state tasks, it was found that in the θ frequency band, the connectivity between the frontal and occipital lobes, as well as the connectivity between the central and occipital lobes, showed significant differences between MCI and NC. But in the α frequency band, there was no significant difference in the functional connectivity between the two groups [55]. However, in a review study, it was observed that the α synchronous specificity of the temporal parietal lobe (as well as the frontal parietal lobe) was reduced in MCI patients [56]. On the one hand, the use of different methods in research leads to an increase in the comparative complexity of the results. On the other hand, resting state EEG signals have characteristics such as susceptibility to interference, significant individual differences, and limited sensitivity to specific diseases, which can easily lead to a lack of authenticity in the data. Therefore,

for the elderly population who are difficult to cooperate with and have cognitive impairment characteristics, memory related cognitive paradigms are more likely to obtain specific electrophysiology and reveal the electrophysiological mechanisms of cognitive impairment. For example, when using WM tasks in functional neuroimaging, research reports suggest that changes in cortical connectivity related to memory are associated with increased deposition of CSF AD biomarker markers of Aβ and pTau burden in the brain [57]. In their other study, it was shown that there was a difference in the left visual WM task related potential values between NC and amnestic MCI, and it even can serve as a predictive factor of 5 years follow-up [58].

Based on WM task, our results indicated that differences in network differential patterns occur more frequently in the θ band, this is slightly different from previous results based on resting state. In resting state EEG network research, the differences between the two groups are mostly concentrated in the α frequency band [55], [56]. But these results were similar to EEG studies based on memory task states [59], [60]. However, research on task states almost only focuses on the frequency domain energy of brain regions, neglecting the dynamic interaction processes between brain regions, resulting in important information in the α frequency band is lost [61], [62], [63]. In our research, MCI has reduced brain connectivity from prefrontal lobe to bilateral temporal lobe, showing more abnormal brain connectivity in the prefrontal occipital and parietal occipital directions in θ band, as well the abnormal brain network connectivity also occurred in α band. Compared with previous resting state brain network results, the similarity was that there were abnormal connectivity in the frontal and occipital lobes of the brain in the θ frequency band [55], there was a significant abnormality in the connectivity between the frontal and parietal lobes in the α frequency band [56]; The difference was that the results based on the WM task state showed there was a significant difference in connectivity between the frontal and temporal lobes in the θ frequency band. The temporal lobe mainly contains the hippocampal structure, which plays an important role in the implementation of WM task [64]. The most direct cause of progressive learning and memory impairment in AD patients is brain damage, especially in the hippocampus, where synaptic structures are damaged or even disappear, and synaptic activity or transmission efficiency is reduced [65], [66], and age-related memory problems may be related to a decrease in the participation of hippocampal prefrontal cortex synergy [67]. Therefore, our study suggests that in the early MCI stage of AD, the functional connectivity between the hippocampus and prefrontal cortex may have decreased and may further affect the patient's WM ability, resulting in lower accuracy.

In the coding stage of WM, the sensory cortex and primary visual cortex will represent the content of memory and receive feedback regulation from the frontoparietal network. With the memory load, more attention resources are directed towards the frontal and parietal lobes of continuous activation, and the intensity of activation increases with the increase of memory load [68], [69], on the contrary, the primary visual cortex will show less activation with the increase of memory load [70]. Under higher WM load, the weakening of functional coupling and the stronger activation of the frontal lobe in this case mean that the high internal processing load may occupy limited nerve resources and prevent the frontal lobe from adjusting the visual area of the posterior occipital lobe from top to bottom. In our research, abnormal brain connectivity in the prefrontal and parietal to occipital lobes of the visual cortex in MCI patients may be the gain signal is regulated by enhancing task related information or suppressing task independent information. In addition, in MCI, there is a stronger visual pathway from the parietal lobe to the frontal lobe, which is an important part of the spatial template in the executive element, and also a basic neural pathway effectively representing WM. Therefore, these increased information interactions may compensate for the degradation of brain function, and these compensatory functional connectivity in θ and α band could be serve as early indicators of cognitive decline.

V. Conclusion

The WM deficit of MCI patients maybe the dysconnectivity of brain derived from the prefrontal lobe to bilateral temporal lobes. In addition, the discrepancy brain connectivity pattern of MCI is larger and more complex driven by core nodes Pz and Fz. These results provide a new perspective on the neural mechanism of WM deficiency in MCI patients, thus expanding previous research and providing a potential therapeutic target for subsequent clinical intervention.

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