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The Effect of Multiple Factors on Working Memory Capacities: Aging, Task difficulty, and Training

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***Abstract*— *Goal:* Working memory (WM) is a memory system with a limited capacity that can process and store information temporarily in the performing of cognitive tasks. Despite WM is known to be influenced by age, the difficulty of tasks and trained or not from behavior studies, little is known about their relationships from the aspect of the brain functional network. Our goal was to explore the factor of aging-related changes of WM with brain functional networks. *Methods:* In this study, 25 healthy elderly and 23 healthy young volunteers were recruited for electroencephalogram (EEG) recording during the visual WM task with four difficulty levels (1-4 backs). In each back, we repeat the experiment with four sessions, and we add training sections between session one and session two as well as between session two and session three. However, we remove any training section between session three and session four in order to evaluate the impact of forgetting on WM in different age groups. After the experiment, we utilized graph theoretical analysis to characterize the brain functional network in three frequency bands (alpha, beta, and theta). *Results:* From the well-designed experiment, we found that physiological aging influences brain network connectivity and makes the functional brain network less differentiated. Moreover, there is an inverse relationship between alpha activity and WM load for the elderly group, which is absent in the young group. At the same time, theta band activity will be correlated with behavioral performance for the elderly group with WM training between sessions, which is also absent in the young group. To further study the influence of difficulty of tasks and training on the WM, we distinguish the tasks with quantified topological characteristics, and the classification results manifest that the training is more effective for the young group. Finally, through the establishment of a brain map before and after training, we find that the right parietal lobe plays an important role in the training of WM for the elderly group whereas the beta band plays an important role in WM for both the elderly group and the young group. *Conclusion:* Taken together, our findings clarify the underlying mechanism of WM under different frequency bands in terms of physiological aging, the influence of training, and task difficulty. *Significance:* the working memory capacities can be uncovered in terms of the combination of three-way ANOVA and EEG-based graph theoretical analysis.**

***Index Terms*—Brain functional network, EEG, Working memory**

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I. Introduction

ALTHOUGH the development of medical and food safety has prolonged people’s life spans, aging is still an inevitable problem that we should face. Aging is often accompanied by neurodegenerative disorders such as Alzheimer’s disease, which cannot be cured at present [1]. Therefore, a long-period tracking method that can effectively differentiate physiological and pathological brain aging is essential. Specifically, EEG is a convenient and noninvasive method that can characterize neural functioning and be engaged in disease diagnosis [2]. By adding more electrodes to the EEG device, we can improve the spatial resolution of EEG. Despite still showing a less superior spatial resolution compared to other neuroimaging techniques such as functional magnetic resonance imaging (fMRI), EEG’s high temporal resolution is helpful to the task that requires multi-frequency analysis of brain activity.

Working memory (WM) is a cognitive process that can hold information temporarily [3, 4]. Such manipulation of stored information is very important to the guidance of decision-making and behavior [5]. The capacity of WM increases gradually in childhood but declines in old age [6-8]. Fortunately, cognitive abilities like WM can be improved by corresponding training [9]. However, aging-related studies of WM tend to focus on the behavioral aspect and the design of experimental protocols might be oversimplified, therefore cannot sufficiently delineate the phenomenon of aging in the brain. For example, Hou et al. proposed an n-back WM task with only a 0-back and 2-back paradigm [10]. Although a varying experimental protocol can explain the difference of the aging changes on WM, the extension of brain aging or the influence of a progressive experimental design on brain aging cannot be studied under such protocol. Moreover, the effect of training on brain aging is also not discussed. Nevertheless, a good experimental design can be beneficial to unravel the underlying mechanism of physiological aging in the brain.

The most prevalent experimental assessment of WM is the n-back task, a continuous performance task in cognitive neuroscience that can measure WM and its capacity. During the task, the participant will receive a sequence of stimuli and they are asked to match the current stimulus with the one from n steps earlier in the sequence. The combination of n-back tasks and brain tracking techniques like EEG and fMRI is commonly used to uncover the underlying mechanism of aging from brain activity [11-18]. However, EEG-based WM studies often focus on the regional properties of the brain as the analysis of EEG signals is in the view of the spectral power of different frequency bands (alpha, beta, theta, and gamma) or the event-related potentials (ERPs). For instance, Dong et al. found that WM capacity differences among individuals can be reflected by P300 wave, theta event-related synchronization (ERS), and alpha event-related desynchronization (ERD) at the most challenging level and lowest difficulty level [19]. And both P300 analysis and ERS/ERD results focus on the frontal and parietal regions of the brain. However, such EEG-based WM analysis neglects the global properties of the brain. In addition, in each block, n will be a constant and the WM task within a block will be more difficult with a higher value of n. The difficulty of age-related WM tasks usually does not go beyond 2-back and the 0-back paradigm is used for the control group [20]. In this study, we aim to find the influence of experimental difficulty on the WM performance of people from different age groups and thus performed a 4-back paradigm that varied n from 1 to 4. Furthermore, to evaluate the effect of forgetting on WM in different age groups, we incorporated a forgetting protocol between the 3-back and 4-back paradigms.

Arises from the brain's anatomical structure and neural circuitries, intricate interactions and cross talks of different brain regions further contribute to the functional processing of cognitive functions. For example, the acquisition of motor learning is contributed by the plasticity between the parallel fiber (PF) and Purkinje cell whereas the consolidation of motor learning may be stored within the plasticity between the PF and cerebellar nuclei site [21]. Evidence suggests that memory formation may be related to the interregional synchronization of neural activity [10, 22]. Therefore, the study of age-related WM should adopt a comprehensive approach that exploits the advantages of the brain functional connectivity network and the high temporal resolution of EEG signals.

Recently, EEG-based graph theoretical analysis (GTA) for functional connectivity networks has attracted many interests. In neuroscience, due to the anatomical morphology within the brain, GTA can build a model that contains regions of interest (nodes) and their connection (edges). As the brain network has a special topology organization, GTA can inform us characteristics of the brain based on the nodes and edges. For example, global efficiency is a feature that measures the overall information exchange capability of the network. In our previous work, global efficiency is a good property that can tell the driving state in most frequency bands (alpha, beta, and theta) [23]. Apart from analyzing the mental state of the brain, GTA can be also used for the diagnosis of degenerative disease and WM training [24, 25]. Although GTA has been applied to the age-related n-back WM task, we will use GTA to explore a more comprehensive mechanism with a well-designed training protocol for subjects of different ages [10].

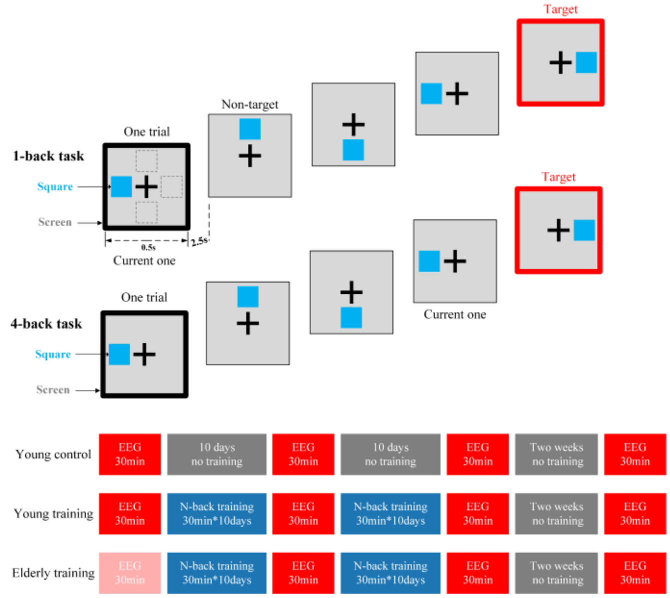

Fig. 1. Experimental protocol.

II. Material and Methodology

A. Participants

Twenty-three students (aged 24±1.2) from the National University of Singapore and twenty-five older adults (aged 60±3.1) were recruited.

All participants were right-handed with normal or corrected vision. All the selected participants were interviewed by a brief interview to ensure that they met all the inclusion criteria. For example, participants who admitted chronic physical or mental illness, a history of being diagnosed with a sleep disorder or hyperactivity disorder during childhood, or long-term medication were excluded. Before the experiment, participants were asked to have a full night (> 7 hours) sleep on two nights, avoid caffeine or alcohol, and refrain from strenuous exercise for 24 hours before the study. All participants signed the consent form before the experiment. The experiments were approved by the Institutional Review Board of the National University of Singapore, written informed consent was obtained from all subjects before the experiment and monetary compensation was given for their participation.

B. N-back task

In this experiment, a spatial n-back task was implemented in which a square would be randomly presented on one of four positions (up, down, left and right) specified on the screen (Fig. 1). Participants sit in front of the computer and avoid any interference from the external environment to the subject. At the beginning of the experiment, 5 pictures appeared on the screen in turn, each picture was displayed for 0.5 s, and nothing was displayed for an interval of 2.5 s. Each picture displayed a square, and there are 4 possible positions of the square. Each time, a random position was displayed. When the fifth screen is displayed, the top of the screen will prompt the back task. Participants recalled according to the back task. If the fifth screen is consistent with the previous back screens, then press the yellow button. If it does not match, press the white button. The response window last from the onset of the stimulus until the presentation of the next stimulus (3 s). Four difficulty levels of the task were created (1, 2, 3, 4-back). For each session, there were 240 trials. For both the training session and the testing session with EEG recording, participants received 1-, 2- ,3-, and 4-back levels in this order, with each level presented 60 trials, resulting in a total 240 trials. In the analysis, only the correct trials are selected. There was total four sessions for the whole experiment with training or no training between each two sessions. In the first three sessions, the time interval between two consecutive sessions was set to be 10 days whereas the last interval between session 3 and session 4 was set to be two weeks. For the training groups, participants received n-back task training for each day between sessions. As elderly cannot complete the experiment well without training in the first session, they only have the results of session 2, 3 and 4. In addition, we selected results for analysis from the participants who can complete all four phases of the experiment, so the final participants are 17 young people and 11 elderly people.

During the task, EEG signals from 64 channels were recorded with the ASALab system (ANT B.V., Netherlands) at a sampling rate of 256 Hz. EEG activity refers to the mean value of two mastoid processes. Two electrodes were placed above and below the left eye to record the vertical EOG. The recorded EEG signals were re-referenced to the average reference. The artifacts caused by eye movement or significant muscle activity were removed by independent component analysis (ICA). A bandpass filter (0.5~70 Hz) was used for antialiasing, and a 50 Hz notch filter was used to remove the main interference during the experiment.

C. Method

Three typical frequency bands (theta, 4~8 Hz, alpha, 8~12 Hz, and beta, 12~30 Hz) related to WM were extracted by wavelet packet decomposition with the wavelet basis function of db4 [26, 27]. Then the brain functional network is constructed by phase lag index (PLI) in each frequency band for graph theoretical analysis.

The PLI is computed by

$$PLI_{k,l} = \left|\left\langle sign\left[sin\left(\varphi_k(t) - \varphi_l(t)\right)\right]\right\rangle\right| \tag{1}$$

where *sign* stands for signum function and | | indicates absolute value function whereas *k* and *l* represent different channels.

PLI values are between 0 and 1. A value of 0 indicates no coupling and 1 indicates perfect phase locking. The stronger this nonzero phase locking is, the larger PLI values are. During the computation of the graph metric, a sparsity threshold was applied to the connection matrix. Since there is no definitive method to determine the sparsity threshold [28], we followed previous studies to utilize a series of thresholds to eliminate the bias due to only using one arbitrary threshold [28-30]. A series of thresholds ranging from 0.12 to 0.40 with an incremental step of 0.01 were used in our study and the metric values were obtained by taking the integral of all values corresponding to the thresholds.

The clustering coefficient describes the connection centralization of the connection network. The clustering coefficient for channel *i* is defined as:

$$C_i = \frac{\sum_{k\neq i}\sum_{l\neq i,l\neq k} w_{ik}w_{il}w_{kl}}{\sum_{k\neq i}\sum_{l\neq i,l\neq k} w_{ik}w_{il}} \tag{2}$$

where *w* stands for entries in the connection matrix, which was PLI values and *i*, *k*, *l* are channel indices.

L is the mean of the shortest path length, and is the path with the maximum total weight between vertices, as shown in follow:

$$L = \frac{1}{n}\sum_{i\in N}\frac{\sum_{j\in N,j\neq i} d_{ij}}{n-1} \tag{3}$$

where d_{ij} is the shortest path length between nodes *i* and *j*. *L* is a major indicator of global integration. The shorter the path length, the greater the functional integration intensity and the more direct connections between brain regions.

E_{global} measures the global information transmission ability, which is the reciprocal of the shortest path length, as shown in follow:

$$E_{global} = \frac{1}{n}\sum_{i\in N}\frac{\sum_{j\in N,j\neq i}\left(d_{ij}\right)^{-1}}{n-1} \tag{4}$$

E_{local} is a measure to evaluate the efficiency of information transmission in a network, as shown in follow:

$$E_{local} = \frac{1}{2}\sum_{i\in N}\frac{\sum_{j,h\in N,j\neq i}\left(w_{ij}w_{ih}\left[d_{jh}(N_i)\right]^{-1}\right)^{1/3}}{k_i(k_i-1)} \tag{5}$$

where w_{ij} is the connection weight between nodes *i* and *j*.

To quantify the extent to which a network displays small-world structure, we define the Small-World Propensity, φ, to reflect the deviation of a network's clustering coefficient, C_{obs} and characteristic path length, L_{obs} from both lattice (C_{latt}, L_{latt}) and random (C_{rand}, L_{rand}) networks constructed with the same number of nodes and the same degree distribution:

$$\varphi = 1 - \sqrt{\frac{\Delta_C^2 + \Delta_L^2}{2}} \tag{6}$$

where

$$\Delta_C = \frac{C_{latt} - C_{obs}}{C_{latt} - C_{rand}} \tag{7}$$

and

$$\Delta_L = \frac{L_{obs} - L_{rand}}{L_{latt} - L_{rand}} \tag{8}$$

The ratios Δ_C and Δ_L represent the fractional deviation of the metric (C_{obs} or L_{obs}) from its respective null model (a lattice or random network). Because it is occasionally possible for real-world networks to display path lengths or clustering coefficients that exceed that of a lattice or random network, we bound both Δ_C and Δ_L between 0 and 1. Thus, if Δ_C or $\Delta_L>1$, we set Δ_C or $\Delta_L=1$ and if Δ_C or $\Delta_L<0$, we set Δ_C or $\Delta_L=0$, which guarantees that φ is bounded in the range [0, 1]. Networks with high small-world characteristics (low Δ_C and Δ_L) will have a value of φ close to 1, while lower values of φ represent larger deviations from the respective null models for clustering and path length, and display less small-world structure.

To quantitatively describe the importance of a node, the most effective measurement method is to calculate the betweenness centrality. The betweenness centrality B_i of node i is defined as:

$$B_i = \sum_{j,k \in N} \frac{n_{jk(i)}}{n_{jk}} \tag{9}$$

where n_{jk} represents the number of shortest paths between nodes j and k; $n_{jk}(i)$ represents the number of nodes i in the shortest path between nodes j and k. Betweenness centrality reflects the role and influence of nodes in the whole network and is an important global geometric quantity.

III. Results

A. Behavioral analysis

The results were selected from the participants who completed all four phases of the experiment accurately, including 17 young participants and 11 elderly. Using ANOVA two-factor analysis test, the accuracies of N-back tasks were compared (Fig. 2).

As shown in Fig. 2A, excluding the age factor, task ac-curacies across different training sessions and difficulties are compared. The figure on the left shows that the accuracy comparison among sessions of the elderly group and no significant changes between sessions has been observed. However, for young participants, although there was no obvious significance throughout all sessions of the 1-back task, for the 2-back to 4-back difficulty levels, the performance during session 1 was significantly different from other sessions (training factor, $F(3,64) = 57.98$, $p<0.0001$). Hence, the n-back training produced more obvious effects on the WM performance of young people but not the elderly.

As shown in Fig. 2B, the training factor is neglected, while the impact of age and difficulty of tasks on the accuracy was compared. In session 2, there was little difference within both 1-back and 2-back tasks between elderly and young participants whereas the differences within 3-back and 4-back were significantly different (age factor, $F(1,26)=66.59$, $p<0.0001$). In session 3 and session 4, there were statistically significant difference in 3-back and 4-back between the elderly and young people (age factor, session 3: $F(1,26)=41.87$, $p<0.0001$; session 4: $F(1,26)=29.83$, $p<0.0001$). Such results suggest that young people can more flexibly adjust to the change in the difficulty of the n-back task. On the other hand, as the difficulty of tasks increases, the accuracy of the elderly group is gradually decreasing.

As shown in Fig. 2C, the impact of age and train stages on task accuracy was compared based on different difficulty levels. In the 1-back task, there was no significant difference between the elderly and young groups whereas in the 2-back task, a significant difference between the two groups was recorded. Similarly, in the 3-back and 4-back tasks, there were statistically significant differences. (age factor, 2-back: $F(1,26)=16.30$, $p=0.0004$; 3-back: $F(1,26)=73.42$, $p<0.0001$; 4-back: $F(1,26)=104.0$, $p<0.0001$) Such results demonstrate that with increasing task difficulty, while the accuracy of elderly participants gradually declined, that of young participants was not significantly affected.

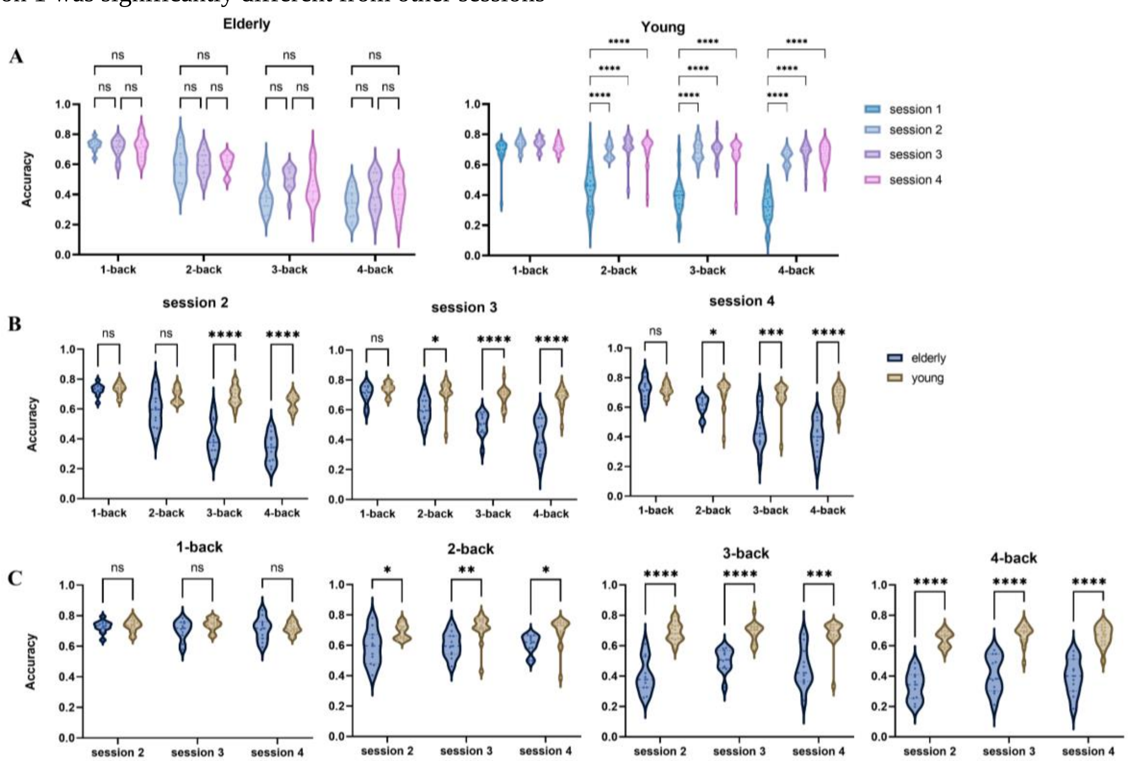

Fig. 2. Behavioral results with two-way ANOVA analysis. A, difficulty of task factor and training factor to the accuracy of n-back tasks. B, age factor and difficulty of task factor to the accuracy of n-back tasks. C, age factor and train factor to the accuracy of n-back tasks. (*: p<0.05, **: p<0.01, ***: p<0.005, ****: p<0.001, ns represents no significance)

TABLE I
THE RESULT OF THREE-WAY ANOVA : INTERACTION OF VARIOUS FACTORS IN DIFFERENT FREQUENCY BANDS

		aging*training*difficulty		aging*training		aging*difficulty		training*difficulty		aging		training		difficulty	
		F	p	F	p	F	p	F	p	F	p	F	p	F	p
Characteristic Path Length	theta	-	-	3.883	0.021	-	-	-	-	19.594	<0.001	6.815	0.001	-	-
	alpha	-	-	8.162	<0.001	-	-	-	-	299.607	<0.001	6.003	0.002	-	-
	beta	-	-	19.639	<0.001	-	-	-	-	80.391	s<0.001	46.829	<0.001	-	-
Global Efficiency	theta	-	-	23.971	<0.001	-	-	-	-	-	-	21.468	<0.001	-	-
	alpha	-	-	14.811	<0.001	-	-	-	-	334.149	<0.001	15.579	<0.001	-	-
	beta	-	-	37.483	<0.001	2.619	0.049	2.483	0.021	91.675	<0.001	42.76	<0.001	-	-
Clustering Coefficient	theta	-	-	12.738	<0.001	-	-	2.359	0.028	41.08	<0.001	-	-	3.199	0.022
	alpha	2.503	0.021	10.837	<0.001	-	-	-	-	612.71	<0.001	5.06	0.006	-	-
	beta	2.913	0.008	17.288	<0.001	-	-	-	-	420.096	<0.001	-	-	-	-
Local Efficiency	theta	-	-	9.488	<0.001	-	-	2.708	0.013	278.864	<0.001	13.298	<0.001	9.79	<0.001
	alpha	2.573	0.018	8.934	<0.001	-	-	-	-	1121.599	<0.001	-	-	8.438	<0.001
	beta	2.813	0.01	24.556	<0.001	-	-	-	-	655.944	<0.001	9.98	<0.001	7.933	<0.001
Small-world Propensity	theta	-	-	38.37	<0.001	-	-	-	-	198.115	<0.001	58.152	<0.001	5.331	0.001
	alpha	2.872	0.009	20.609	<0.001	-	-	-	-	161.222	<0.001	-	-	-	-
	beta	-	-	-	-	-	-	3.001	0.006	596.324	<0.001	48.638	<0.001	4.28	0.005

B. *Graph theoretical analysis* (*GTA*)

The brain topological characteristics of the cortical functional connectivity network in different WM tasks could be reflected in three factors, namely age, training, and task difficulty. We used three-factor ANOVA to analyze the effect of factors on different frequency bands. The analysis results are shown in TABLE I.

It was observed that there was a three-factor interaction between the alpha and beta frequency bands in the clustering coefficient, local efficiency, and the alpha frequency band of the small-world tendency, hence indicating that these characteristics are affected by the interaction of three factors. Also, brain topological features were affected by the interaction of aging and training stage, except the small-world propensity beta band. From a single factor perspective, aging had a great influence on the experimental results, with an exception that the theta frequency band of global efficiency was not significantly affected by age. The training stage had little effect on the local efficiency and clustering coefficient theta and beta bands, as well as small-world propensity alpha band, probably because of the lack of influence on the topological features of these bands by learning and memory. The difficulty of task also affected the local efficiency, small-world propensity theta and beta frequency bands and clustering coefficient theta frequency band.

Fig. 3 shows the influence of training on the brain topological characteristics under different frequency bands for the elderly group. The characteristic path length increased with training (session 2 vs session 3) and decreased without training (session 3 vs session 4) for 1 to 3-back especially in beta bands (session 2 vs session 3, 1 and 2-back, $p<0.001$; session 2 vs session 3, 3-back, $p<0.01$; session 3 vs session 4, 1 to 3-back, $p<0.001$). Accordingly, the global efficiency decreased with training and increased without training, and the statistical difference was significant in theta and beta frequency bands for 1-3 backs (session 2 vs session 3 and session 3 vs session 4, theta frequency band, 2 and 3-back, $p<0.001$; session 2 vs session 3, beta frequency band, 1 and 2-back, $p<0.001$, 3-back, $p<0.005$; session 3 vs session 4, beta frequency band, 1 to 3-back, $p<0.001$). It showed similar trends as in characteristic path length for clustering coefficient and local efficiency in 1 to 3-back. The small-world propensity decreased with training and increased without training for all backs. Moreover, in the 4-back task, the influence of training was less than that of in other WM tasks which might be attributed to the overload of WM for the elderly.

In contrast, Fig. 4 shows the influence of training on the brain topological characteristics under different frequency bands for young people, which was quite different from that of the elderly group. For example, the characteristic path length of the youth group decreased with training (session 1 vs session 3, beta band, 1-back, $p<0.001$, 3-back, $p<0.05$) and increased

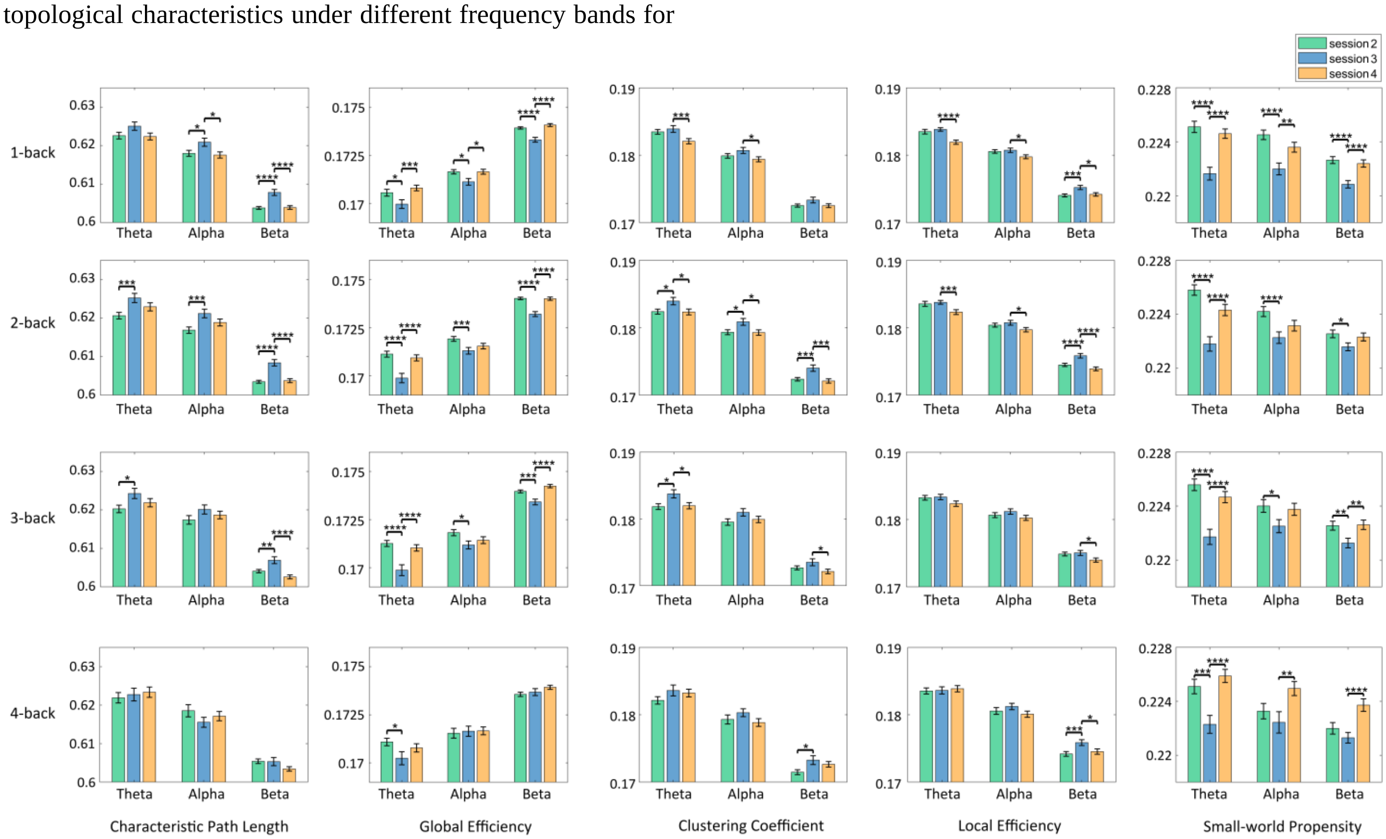

Fig. 3. The graph theoretical analysis under different frequency bands for elderly people with and without training. Each column stands for different properties for n-back tasks and each row is the difficulty of the WM task. In each sub-figure, three kinds of frequency bands (theta, alpha, and beta) are used for the comparison. The three colors of bars stand for three sessions (cyan: session 2, blue: session 3, and orange: session 4). The elder participants received training of WM tasks between session 2 and session 3 whereas no training was conducted between session 3 and session 4. (*: $p<0.05$, **: $p<0.01$, ***: $p<0.005$, ****: $p<0.001$)

without training (session 3 vs session 4, alpha band, 2-back, $p<0.05$, 3-back, $p<0.01$). And other indexes like clustering coefficient and local efficiency had similar trends with and without training for the young group. However, the trend for global efficiency for the young group was opposite to that of the elderly group, which increased with training (session 1 vs session 3, beta band, 1 and 4-back, $p<0.001$, 2-back, $p<0.005$, 3 back, $p<0.01$) and decreased without training (session 3 vs session 4, beta band, 1-back, $p<0.005$, 2 and 4-back, $p<0.05$). The small-world propensity of the young group decreased with training and increased without training in which the trend is the same as the elderly group. In the young group, the improvement of working memory performance was accompanied by an improvement of global efficiency as well as a decrease of local efficiency, which suggests that a more dispersed network rather can promote better working memory performance than a dense network.

Fig. 5 shows the influence of training difficulty on brain topological characteristics for both elder and young people in session 3. In the comparison of the 1-back and 4-back tasks, the local efficiency increased for young people (1-back vs 4-back, theta frequency, $P<0.05$) whereas the characteristics path length increased (1-back vs 4-back, alpha frequency, $P<0.005$) and the small-world propensity decreased (1-back vs 4-back, beta frequency, $P<0.05$) with the increasing difficulty of the task for elderly people.

Betweenness centrality refers to the ability of a given node that transmits information along the shortest path between node pairs in the network. Fig. 6 shows the comparison BC of the CP1 node in WM in terms of aging (Fig. 6A) and training (Fig. 6B) under the alpha band. There are significant differences between the elder group and the young group in the completed

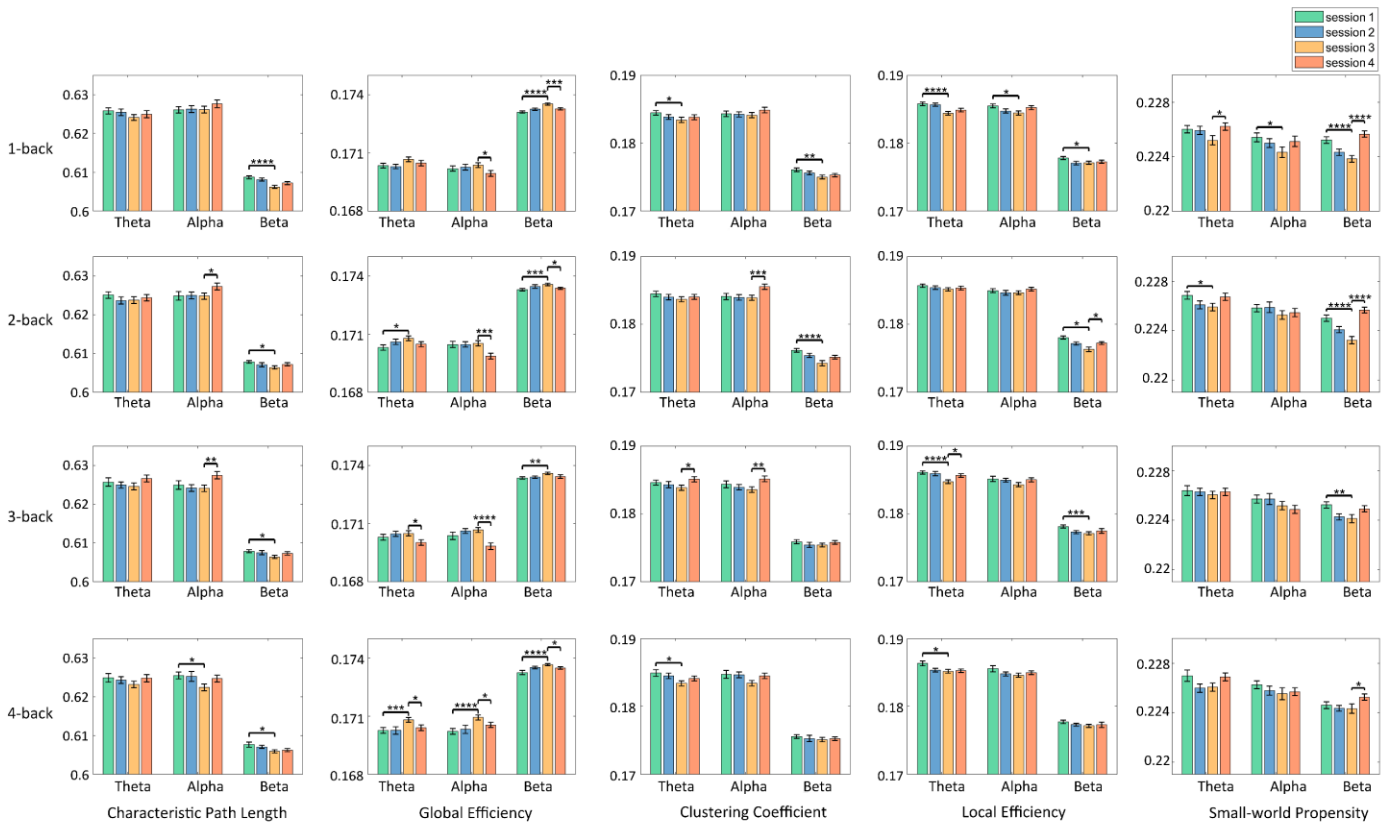

Fig. 4. The graph theoretical analysis under different frequency bands for young people with and without training. Each column stands for different properties for n-back tasks and each row is the difficulty of the WM task. In each sub-figure, three kinds of frequency bands (theta, alpha, and beta) are used for the comparison. The four colors of bars stand for four sessions (cyan: session 1, blue: session 2, earthy yellow: session 3, and orange: session 4). The young participants received training of WM tasks between session 1 and session 2 as well as between session 2 and session 3 whereas no training was conducted between session 3 and session 4. (*: p<0.05, **: p<0.01, ***: p<0.005, ****: p<0.001)

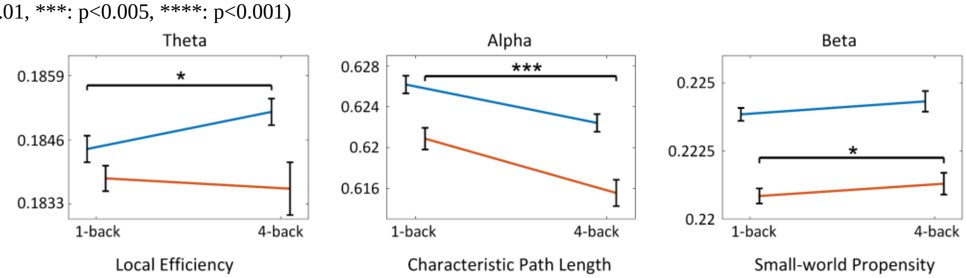

Fig. 5. The influence of training difficulty on brain topological characteristics for both elder (orange) and young (blue) participants. EEG signals with three kinds of frequency bands are used for the comparison and the difficulty of the WM task only contains two distinctive stages (1-back and 4-back). (*: p<0.05, **: p<0.01, ***: p<0.005, ****: p<0.001)

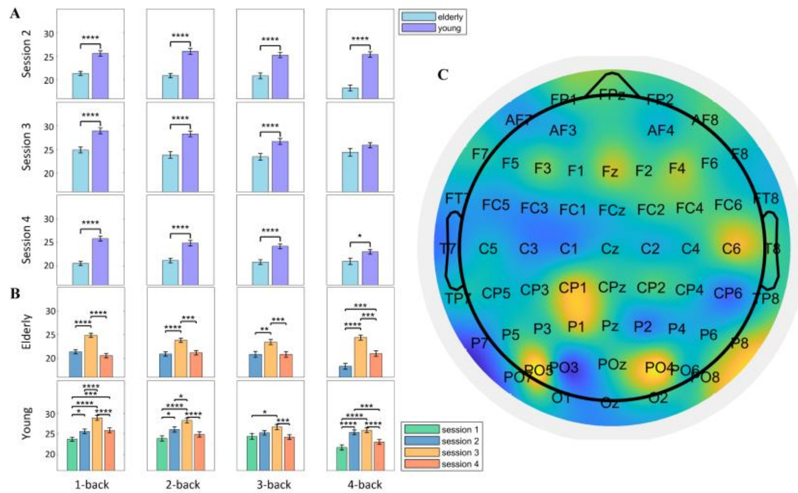

Fig. 6. The comparison of BC of CP1 node in WM in terms of aging and training under the alpha band. A, the influence of aging to BC of CP1 node. The two color bars stand for different groups of participants. (aquamarine: elder group, purples: young group). B, the influence of training to BC of CP1 node. The color bars stand for different sessions of the WM experiment (cyan: session 1, blue: session 2, earthy yellow: session 3, and orange: session 4). The elder participants received training of WM tasks between session 2 and session 3 whereas no training was conducted between session 3 and session 4. The young participants received training of WM tasks between session 1 and session 2 as well as between session 2 and session 3 whereas no training was conducted between session 3 and session 4. (*: $p<0.05$, **: $p<0.01$, ***: $p<0.005$, ****: $p<0.001$) C, the influence of training on the BC of the elderly. There are 62 leads in total, and the value of each lead is the difference between session 3 and session 2. Yellow represents the lead with an increased value of the BC after training, and blue represents the lead with decreased value after training.

WM task. Interestingly, with the increase of the task difficulty, the discrimination decreases in session 3 and session 4 of the 4-back task. On the other hand, the BC of the CP1 node is also influenced by the training process as there is a gradual increase of BC with training and a decrease of BC with the distinction process for both the elder group and the young group. As a result, the decline of WM caused by aging may be related to the disconnection of the CP1 node and training may be helpful to the recovery of disconnection. We also intuitively show an example of the BC for the elderly group that the training improves the BC of node CP1 in Fig. 6C.

To further explain the influence of the difficulty of the task on the WM, we used the quantified topological characteristics to classify the tasks (TABLE II). The input feature of the classifier was graph metric features of each frequency band with different numbers for each feature (clustering coefficient: 62, the characteristic path length: 1, global efficiency: 1, local efficiency: 62, small world propensity: 1). If there are three frequency bands, then there are 127 * 3 features in total. And the random forest was selected as the classifier. We observed that if the topological characteristics were used for four-category, the accuracy was low for both the young and the elderly groups. The highest classification accuracy was in 1, 2, 3 vs 4-back task which means that 4-back task can be relatively easily separated from other tasks. After training, the accuracy in the classification of 1 vs 2, 3, 4-back increased, indicating that the 1-back task (the simplest task) is easier to distinguish after training. However, the accuracy in the classification of 1, 2, 3 vs 4-back decreased, indicating that the 4-back task (the most difficult task) is more difficult to distinguish after training. In other words, for all age groups, the difficulty of the 4-back task decreased and become close to 1, 2, 3-back tasks. In the second case (the classification of 1 vs 2, 3, 4-back), the accuracy of young people was higher than that of old people, whereas in the fourth case (the classification of 1 vs 2, 3, 4-back), the accuracy of young people was lower than that of old people. Such findings showed that compared to young people, the 1, 4-back for the elderly was still difficult, with the training for young people being more effective.

IV. Discussion

In this study, we analyzed the variation of the network topology in EEG-related WM tasks for both young and elderly participants. We conducted multi-channel recording during the 1 to 4-back WM tasks across four sessions. In addition, we added WM training into the period between the 1st session and the 2nd session as well as the period between the 2nd session and the 3rd session. And during the period between the 3rd session and the 4th session, we revoke the training. Therefore, the whole experiment comprised the influence of difficulty of the task, aging, as well as forgetting on WM in terms of different frequency bands, which will be discussed below.

A. *The influence of aging on the WM*

The influence of aging on WM intuitively lies in the degree of task completion. For both the elderly group and the young group, we experimented with four tasks with four difficulties across four sessions. However, without training, the elderly group cannot complete the WM task and thus we do not have the complete data of session 1 for elderly people. Performance of cognitive function has been found to decline with aging in various aspects [31, 32]. There is evidence that the decline of performance in the WM tasks is related to changes in communication between different regions of the brain. Aging not only affects functional connectivity within specific functional networks but also alters the communication between different functional networks [33-35]. In this study, the elderly group has a lower clustering coefficient and local efficiency, which indicates that with the increase of age, the network connectivity decreases, and the functional brain network becomes less differentiated or specific. Previous studies have shown that the function of brain regions is dedifferentiated with age [36-38]. The decrease of network connectivity in the elderly may lead to an over-recruitment of brain regions to process the overwhelming incoming information, resulting in a decrease in local efficiency. In addition, we observed that the characteristic path length of the elderly group was lower than that of the young group, which may be attributed to the fact that the proportion of long-distance connections decreased with aging. High clustering (i.e. high local efficiency) and sparse long-range connection in brain networks can achieve the minimum metabolic cost. Although the cost of sparse long-range connections is higher, the information transmission speed can be improved. Despite the global efficiency of the elderly group was slightly higher than that of the young group, the small-world propensity was lower than that of the young group. The reason may be that aging is more obvious in local areas of the brain [39].

B. The influence of difficulty of tasks on the WM

In the functional connectivity network of the alpha band, the characteristics path length of the 4-back task decreased significantly compared with that in the 1-back task for the elderly group (Fig. 7), which indicates the decrease of functional segregation and local connection density. However, the alteration of alpha-band amplitude was not statistically significant for the young group. In recent years, many studies have shown that the amplitude of alpha activity is negatively correlated with the number of cortical resources used to perform cognitive tasks [20, 40-42]. Therefore, we speculate that the inverse relationship between alpha activity and WM load may be related to the weakening of local functional clustering in the alpha band in WM tasks. On the other hand, with the increasing difficulty of the task, the influence of training on the alteration of features was not evident for the elderly group. For example, in the 4-back task, the alteration of global efficiency and the characteristic path length (beta frequency) with training for the elderly group changed less than that in the 1,2,3-back tasks (Fig. 4). In contrast, the difficulty of a task made less impact on the young group than the elderly group (Fig. 5). Such phenomenon may be related to WM overload. In other words, if the cognitive requirements of the 4-back task are too high for the elderly, the decrease of cortical resource recruitment during the task may be related to the decrease of global efficiency and thus the effective connection involves relatively few cortical areas for the task.

C. The influence of difficulty of tasks on the WM

In the current study, compared with the young group, the EEG metrics in the theta band were significantly influenced by training for the elderly group when the WM training was included between sessions. In the 2-back or 3-back task, the characteristic path length of the theta band and the clustering coefficient increased with training for the elderly group (session 2 vs session 3). Nevertheless, if the elderly group returned to the state of no training and carried out the experiment, the EEG metrics in the theta band for both the characteristic path length and the clustering coefficient would recover to the corresponding state similar to that of before training. In contrast, there was no significant change in the characteristic path length of the theta band for the young group before and after training. At the same time, in the theta band, the global efficiency and the local efficiency were inversely correlated with and without training. Such alterations mean that the training can improve the information processing efficiency of local brain regions and thus reduce the overall efficiency of information integration for the elderly group. However, for the young group, the overall efficiency of information integration for WM tasks is improved with training, especially with the increase in task difficulty. Such a result is consistent with our previous findings [43] that the theta band is enhanced for more efficient propagation of information with the increase of task difficulty [20].

D. The influence of the BC of CP1 nodes on the WM

The BC is used to describe the importance of key nodes which own large numbers of the shortest path for pairs of nodes within a network. In this study, we calculate the BC of 62 nodes in terms of the aforesaid three factors and hereby find that the CP1 node possesses an important role in the WM considering the aging factor and the training factor. The CP1 node is located at the inferior parietal lobule. The latest work showed that repetitive (4-day) transcranial alternating current stimulation (tACS) on the scalp of the inferior parietal lobule (9 nodes) with non-invasive electrodes can improve the auditory-verbal WM of aging people [44]. Their experiment also implies that a certain memory function can be improved through the modulation of specific brain rhythms in a selective brain region [44-46].Therefore, our results demonstrate the existence of plasticity of key nodes from the view of graph theoretical and such plasticity can be modified by training regardless of aging and task difficulty. There remains a question does exist a network in a specific area of the brain that supports a certain

TABLE II
CLASSIFICATION RESULTS OF WM TASKS WITH THE QUANTIFIED TOPOLOGICAL CHARACTERISTICS

Group	Young (Accuracy: %)				Elderly (Accuracy: %)		
	session 1	session 2	session 3	session 4	session 2	session 3	session 4
1 vs 2 vs 3 vs 4	40 .71	33.05	30.36	31.43	37.39	32.82	36.65
1 vs 2, 3, 4	64.07	73.89	74.73	74.45	66.21	68.15	67.78
1, 2 vs 3, 4	62.99	58.26	56.39	58.03	61.86	60.91	60.84
1, 2, 3 vs 4	83.04	77.36	74.54	74.96	82.82	81.86	81.72

1 vs 2 vs 3 vs 4 means that it will be classified into four categories in accordance with 1,2,3,4-back. 1 vs 2,3,4 represents a binary classification in which the 1-back is a category whereas the rest backs will be in the same category. 1,2 vs 3,4 means 1-back and 2-back tasks will be in the same category whereas 3-back and 4-back tasks are in the other category.

memory function? Maybe the graph theoretical method can be potential guidance for clinical applications of ameliorating WM in aging adults and can be a method to find the network to support a specific memory function.

We also show the distribution of differences of the clustering coefficient between sessions for both the young and elderly groups. In the theta band, the clustering coefficients of the central and right parietal regions increased significantly with training and decreased significantly after revoking training. In the alpha and beta bands, the clustering coefficient of the right parietal lobe increased significantly after training and decreased significantly after revoking training. In conclusion, the training and non-training process of the elderly is accompanied by a significant change in the clustering coefficient of the right parietal lobe (Fig. 7). The results show that the right parietal lobe plays an important role in the training of WM in the elderly group. It has been proven that the right posterior parietal cortex is involved in spatial short-term memory [47], and the damage of the right posterior parietal cortex leads to the general defect of WM [48]. In addition, right parietal lobe dysfunction may be a manifestation of Alzheimer's disease [49]. Nonetheless, for the young group, there is no obvious alteration of the clustering coefficient in different brain regions for the theta band. On the other hand, more significant changes occurred in the beta band for both the elderly group and the young group. Recent studies also show that the beta band plays an important role in WM [50] (Fig. 8). Moreover, the active beta band may help to protect the current WM content from interference [51]. The change of the beta frequency band of young people is significant, which may help to carry out WM tasks more smoothly. By comparing the distribution of difference of clustering coefficient between the young and elderly groups for all sessions, the clustering coefficient of the right parietal lobe of the elderly was significantly higher than that of the young (Fig. 9). In a study on emergency awareness, compared with young people, the elderly showed excessive activation of the parietal lobe, which proved that the age-related destruction of the parietal lobe was enough to weaken consciousness [52]. And as mentioned earlier, the initial manifestation of Alzheimer's disease may appear in the right parietal lobe. These findings may indicate that the right parietal region has a significant impact on the working memory of the elderly. Through indepth study of the right parietal region, it may provide a new research direction for Alzheimer's disease and other diseases.

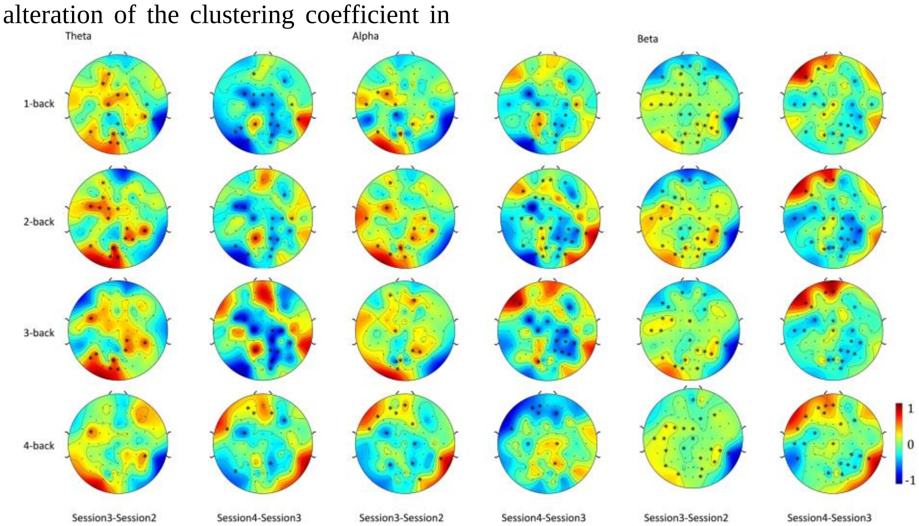

Fig. 7. The distribution of difference of clustering coefficient between sessions for elderly people. There was training between session 3 and session 2, but there was no training between session 4 and session 3. The asterisk represents the channel with a significant difference (P < 0.001).

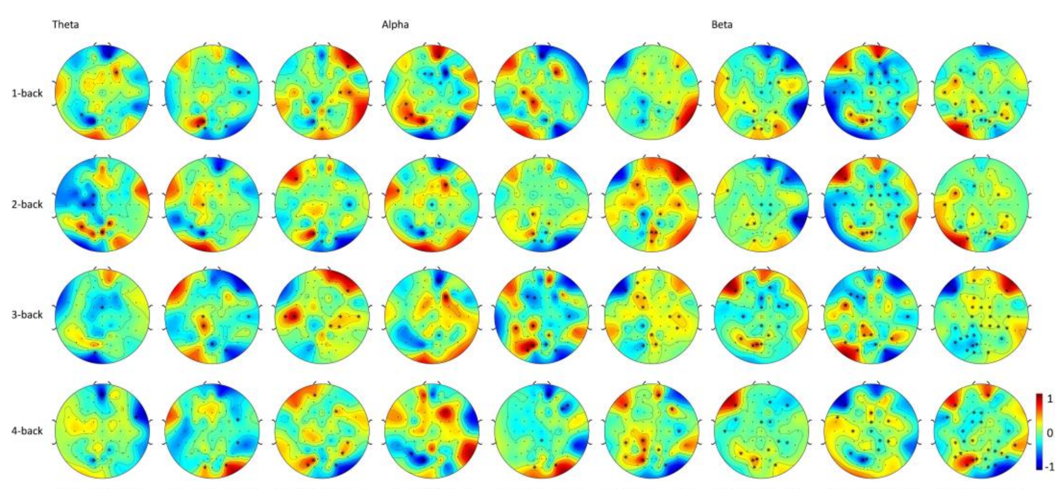

Fig. 8. The distribution of difference of clustering coefficient between sessions for young people. There was training between session 2 and session 1 as well as session 3 and session 2, but there was no training between session 4 and session 3, The asterisk represents the channel with significant difference (P < 0.001).

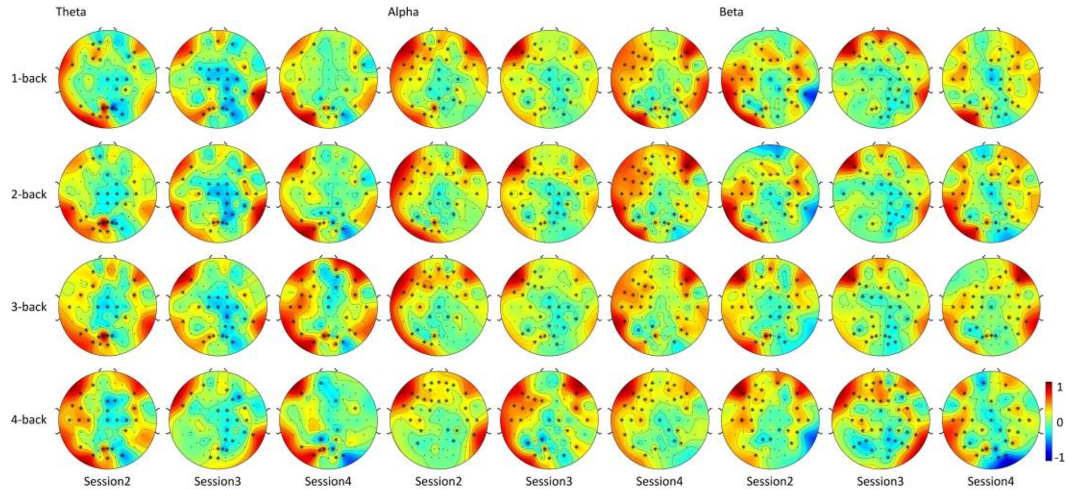

Fig. 9. The distribution of difference of clustering coefficient between the young and elderly group for all sessions. The asterisk represents the channel with a significant difference (P < 0.001).

V. Conclusion

In this study, we proposed an experiment of WM in terms of the effect of aging, task difficulty, and inclusion of training between sessions of the task on performance. Then we used the graph-theoretical method to characterize the brain functional network in three frequency bands. First of all, we found that physiological aging influenced brain network connectivity and led to a less differentiated functional brain network. Secondly, the interaction of aging and training influenced all the topological characteristics over all bands. Thirdly, we observed that there is an inverse relationship between alpha band activity and WM load whereas topological characteristics in the theta band were significantly influenced by WM training for the elderly group. Fourthly, training-induced improvement in performance was more evident in the young group whereas the BC of CP1 for both groups show plastic changes before and after training. At the same time, lateralization of beta frequency is obvious for the elder group with the extinction effect of training. Finally, the right parietal lobe plays an important role in the training of WM for the elderly group whereas the beta band plays an important role in WM for both the elderly group and the young group. Our findings may shed light on the EEG frequency-based analysis of WM and may promote the study of degenerative disorders from an aspect of the brain functional network.

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