The Effects of a Virtual Reality Rehabilitation Task on Elderly Subjects: An Experimental Study Using Multimodal Data

Jing Qu, Lizhen Cui, *Member, IEEE*, Wei Guo, Xipei Ren, and Lingguo Bu

***Abstract*— Ageing populations are becoming a global issue. Against this background, the assessment and treatment of geriatric conditions have become increasingly important. This study draws on the multisensory integration of virtual reality (VR) devices in the field of rehabilitation to assess brain function in young and old people. The study is based on multimodal data generated by combining high temporal resolution electroencephalogram (EEG) and subjective scales and behavioural indicators reflecting motor abilities. The phase locking value (PLV) was chosen as an indicator of functional connectivity (FC), and six brain regions, namely LPFC, RPFC, LOL, ROL, LMC and RMC, were analysed. The results showed a significant difference in the alpha band on comparing the resting and task states in the younger group. A significant difference between the two states in the alpha and beta bands was observed when comparing task states in the younger and older groups. Meanwhile, this study affirms that advancing age significantly affects human locomotor performance and also has a correlation with cognitive level. The study proposes a novel accurate and valid assessment method that offers new possibilities for assessing and rehabilitating geriatric diseases. Thus, this method has the potential to contribute to the field of rehabilitation medicine.**

***Index Terms*— EEG, multimodal data, rehabilitation assessment, virtual reality.**

I. Introduction

THE ageing population is a universal phenomenon that has profound implications for all aspects of human life. According to the 2019 World Population Prospects report released by the United Nations, the world's population will enter an unprecedented stage of ageing owing to the combined effects of declining global fertility and increasing average life expectancy, while population growth will experience a general slowdown in the next decade. Overall, it is expected that by 2050, the global proportion of people aged 65 years or above will rise from 9% in 2019 to 16% [1]. According to statistical data from China's National Bureau of Statistics, by the end of 2021, China's population will be composed of 20.56 million people aged 65 and above, accounting for 14.2% of the country's population [2]. As population ageing intensifies, medical insurance systems for the elderly face serious challenges. Of the 293 diseases covered by the Global Burden of Disease (GBD), 92 (31.4%) are identified as age-related, including a variety of infectious diseases, trauma-based diseases, non-communicable chronic diseases (cardiovascular diseases, cancer, neurological diseases, etc.) and others [3]. Population ageing has multiplied the number of elderly people suffering from related diseases, putting enormous pressure on the state, society and families in various aspects such as medical expenses and daily care. To reduce the multiple pressures caused by an ageing population, more accurate methods and tools are needed to assess diseases, provide help at different stages of the diseases, reduce the prevalence of diseases and mitigate the diseases as much as possible.

Nowadays, virtual reality (VR) is widely used in the field of rehabilitation medicine, both in assessment and treatment [4]. The use of VR for the timely and accurate evaluation of a subject's condition allows for the phased adjustment of rehabilitation training tasks, leading to better treatment outcomes. The rehabilitation process is often long and arduous for patients [5]. They need to make reasonable arrangements in terms of time, while trained therapists are required to assist them from the sidelines to achieve better rehabilitation results. This puts an increased burden on both families and society. Computer-based VR environments cannot only respond to different scenarios of rehabilitation but also provide timely feedback [6]. Saposnik *et al.* found that rehabilitation training incorporating VR helps stroke patients regain arm movement [7]. VR is a form of rehabilitation that is not only of benefit to the body but also to brain function and cognitive levels. Tan *et al.* found that the use of specific stimulus scenarios enhances the effectiveness of memory training in rehabilitation [8]. Park *et al.* observed that VR-based cognitive-motor

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Human Ethics Committee of Shandong University, and performed in line with the Declaration of Helsinki.

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rehabilitation could improve cognitive function in older adults better than traditional cognitive rehabilitation [9]. Riaz *et al.* found that VR-based environmental enrichment could stabilise cognitive function in patients [10]. The immersive interaction that VR provides by creating a multisensory simulation environment can improve patient focus, motivation and initiative when undergoing rehabilitation training. Hence, training outcomes tend to be better with immersive VR compared with other interventions, and multi-sensory engagement may be a potential reason for this [11]. Given the multisensory integration of VR, the simultaneous involvement of multiple brain regions in the study task, the ease of use and the strong interactivity, VR technology was chosen for our experimental design. With the increasing demand for specific and personalised rehabilitation, more accurate appraisal tools are needed. Therefore, combining VR technology with other methods can allow better assessment and interpretation of the physiological and psychological changes patients undergo during rehabilitation.

Cognitive abilities can be classified into several specific domains such as attention, memory, executive cognitive function, language and visuospatial ability, each of which declines significantly with age [12]. The diminishing of sensorimotor functions, such as coordination difficulties, reduced motor speed and balance difficulties, also occurs widely with age [13]. Existing assessment methods include both subjective assessment and objective measures. As a simple, easy-to-understand and convenient method, scales are suitable for individual and group diagnosis and facilitate the collection of large amounts of data. They enable the quantitative measurement of the subjective state of people, which would be difficult to observe directly. Commonly used cognitive scales include the Mini–Mental State Examination (MMSE), Montreal Cognitive Assessment (MoCA) [14], the Trail Making Test (TMT) and Wechsler Memory Scales (WMS). These methods of appraisal using subjective scales are simple and quick, but differences in education, cultural background, examiner's skill and experience in using the scales, the examination setting, and the emotional and mental state of the subject can all have an impact on the scores. Qualitative assessment is not possible using scales only and is subject to subjective influences.

Objective measures are mainly based on various techniques of brain imaging, such as positron emission tomography (PET) [15]. This is an imaging technique that captures cerebral blood flow activity by measuring perfusion emission and uses radioactive material to identify abnormalities in organ function. The method can be used to measure deeper parts of the brain with high sensitivity and precise localisation, but the imaging process is long, the required system is expensive, and, although largely harmless, it is limited by the dose of radioactive material and should not be used frequently on the same subject. Functional magnetic resonance imaging (fMRI) [16] and functional near-infrared spectroscopy (fNIRS) [17] are both functional brain-imaging techniques based on the principle that neural activity in the brain causes local haemodynamic changes. fMRI assesses brain activity by detecting changes in blood flow [18]. Compared with PET, fMRI does not use radioactive substances, involves less risk and can be used multiple times on the same subject over a short period. fMRI delivers high spatial resolution but low temporal resolution, mainly owing to the physiological changes that accompany the neural activity [19]. It also has the disadvantage of being expensive, noisy, bulky and not easily mobile and is not suitable for patients with claustrophobia. fNIRS reflects brain activity by measuring changes in oxyhaemoglobin (HbO_2) and deoxyhaemoglobin (HbR). Its advantages include high spatial localisation, low cost and portability. It is not noisy, it is non-invasive and not particularly sensitive to the subject's movements during the experiment. It can be used across all kinds of populations, including infants and bedridden patients. Due to the slow and delayed changes in blood oxygen metabolic activity, the temporal resolution of fNIRS is approximately 100 milliseconds.

Electroencephalogram (EEG) offers new possibilities for evaluation as a non-invasive, easily accessible method providing high temporal resolution [20]. EEG measures the electrical activity generated by the brain through electrodes placed on the scalp and allows easy visualisation of brain activity in the form of electrical signals, enabling the observer to visualise the real brain activity behind human behaviour [21]. EEG is cost-effective, easy to use, portable and non-invasive and suitable for subjects of all ages. It is widely used in cognitive-related neurological disorders such as dementia [22] and Parkinson's disease [23], as it directly reflects the electrical activity of the central nervous system and offers a higher temporal resolution than the other techniques mentioned previously. However, the aforementioned methods, whether subjective or objective, only derive results from a single source of data and do not allow for a comprehensive multi-faceted appraisal. The treatment of geriatric diseases is a long-term process, and more timely and accurate assessment methods are needed to gain insights into the patient's current rehabilitation status to improve rehabilitation planning. The main challenge with current multimodal data–based rehabilitation assessments arises in the collection and analysis of data. Indicators that are more representative of the condition to be assessed must be selected and integrated to make the best use of their strengths.

This study uses VR to create immersive and interactive virtual environments for the test subjects, drawing on the multisensory integration of VR as much as possible, combined with a Kinect device, to obtain behavioural data that allow a visual representation of the subjects' motor abilities. These behavioural data are integrated with EEG data to obtain objective measures. At the same time, this study also includes the results of the scale used in the subjective appraisal. The result is a combination of quantitative and qualitative, objective and subjective data, aggregating information from multiple sources to form multimodal data, thus providing a comprehensive, accurate and valid evaluation method from a variety of perspectives. Based on the results of the multimodal data, it is hypothesised that cognitive levels decline with age, as does motor ability, represented by behavioural indicators, and that brain function is also affected by age. These findings provide evidence for cognitive decline and offer a new method of assessment. Using this assessment method, multiple data are used to accurately assess the subjects' current condition and

TABLE I
SUBJECTS' PERSONAL INFORMATION

Parameter	Elderly Group	Young Group	P-value
Female sex	37.5%	50%	/
Age (years)	60.31 ±7.021	20.13 ±0.797	<0.001*
Height (cm)	164.56 ±5.738	172.13 ±6.980	0.001*
Weight (kg)	63.44 ±8.107	63.21 ±10.871	0.943
MoCA score	24.56 ±3.425	27.75 ±1.225	0.002*

* indicates significant correlation at the 0.05 level.

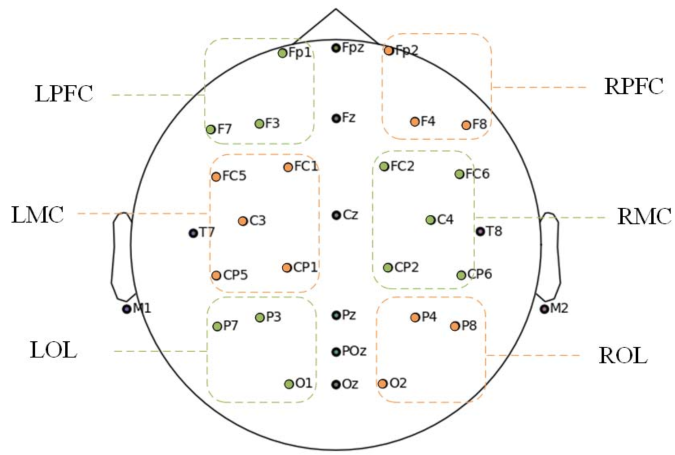

Fig. 1. The channel position of EEG.

can provide guidance for rehabilitation intervention strategies. Through timely and accurate evaluation, we can make suggestions for disease prevention, complement medical interventions with technology during the disease phase, manage the condition promptly, continuously monitor patients' recovery and assist with rehabilitation. At the same time, it allows for a new way of designing rehabilitation products for the elderly.

II. MATERIALS AND METHODS

A. Participants

Forty volunteers were recruited from Shandong University in two age groups, 16 of whom were elderly (age: 60.31±7.021 years) and 24 of whom were young (age: 20.13±0.797 years). The subjects' basic personal information such as age, height and weight were recorded before the test, and their cognitive abilities were quickly assessed using the MoCA scale. Table I shows the subjects' personal information. The inclusion criteria included the following: (1) no traumatic brain injury, (2) not suffering from any neurological disease, (3) no recent medications related to neurological effects, (4) no visual impairment, (5) adequate sleep during the week before the experiment, and (6) no motor impairment. The results of the MoCA scale ranged from 16 to 30 points. A total of 32 subjects were judged to be cognitively normal (scores of 26 points and above), and 8 were abnormal (scores below 26 points), with the abnormalities occurring in the elderly group. All experiments were conducted after receiving the informed consent of the subjects. The experimental procedures were authorised by the Human Ethics Committee of Shandong University and met the ethical standards set out in the Helsinki Declaration of 1975 (revised in 1983).

B. Experimental Equipment

EEG, VR and motion capture equipment were used in the experiment.

ANT Neuro's next-generation EEG/ERP recording and analysis system, eego™ mylab, was used to acquire the EEG data. The three products included in the system, namely waveguard™ original cap, the eego™ amplifier and the eego™ software, were all utilised. The waveguard™ original EEG cap based on the five percent electrode system was used. This electrode placement scheme is an extension of the 10/20 and 10/10 systems. Figure 1 shows the channel position of EEG. After 32 channels of electrode caps were selected, data acquisition was performed using the eego™ software, and the sampling frequency was 1000 Hz. The eego™ amplifier uses active shielding technology to ensure signal quality during the acquisition process. In previous studies, the ANT Neuro range of products was applied to assess the correlation between levels of vigilance [24] and to evaluate the correlation between the effects of continuous theta-burst stimulation on motor evoked potentials [25].

The Oculus Quest 2 was chosen as the VR device. The Oculus Quest 2 is a wireless all-in-one VR device, weighing 503 g, with a built-in Android core, powered by the Qualcomm Snapdragon XR2 platform and an integrated engine for visual analytics. It has a monocular resolution of 1832 $\times$ 1920, supports 60, 72 and 90 Hz refresh rates and enables controller-free gesture tracking. The device supports a large number of games and contains different categories. After testing, we chose for our experimental task the game Beat Saber, where the gamepad is used to cut through two coloured squares with music and which requires large continuous movements of the upper limbs. This game takes full advantage of the multi-sensory engagement of VR to better assess and train subjects' cognitive levels. On the visual side, subjects can see different-coloured squares in the immersive environment, and by judging the colours, their cognitive skills can be trained. On the auditory side, subjects can hear music, and the speed of the game varies with the speed of the music. This stimulates the brain, enhancing their attention and reflecting the differences in cognitive levels more fully. In terms of movement, both speed and the left and right hands corresponding to different colours affected the subjects' behaviour, helping to make a better assessment and showing the effect of cognitive level and age on behavioural ability.

Microsoft's Kinect V2 that uses infrared light to track multiple parts of the body in real-time was chosen as the motion capture device. Kinect V2 supports up to 25 skeleton nodes, and nodes numbered 1–11 and 20–24 were selected for the analysis of upper-limb data. The data object type was provided in the form of skeleton frames. Each frame can hold up to the maximum number of supported bone points.

C. Experimental Procedure

Before the experiment, each subject was shown a video of the game to make sure they understood the rules and were ready for the test. The subject was equipped with an EEG acquisition device, and a conductive paste was injected into the electrode cap to reduce impedance until all channels were shown in green on the software page. After the subject had relaxed in a chair and the researchers had ensured that the subject's upper limb movements were recognised by the motion capture device, the experiment was begun.

The experiment was divided into two parts: the resting state and the task state, with each lasting for 15 minutes.

The first 15 minutes were spent in the resting state, where the subject was asked to remain still in the chair in a natural, relaxed, non-sleeping state while EEG data were collected through electrode caps. The surrounding environment was kept quiet during the experiment. External disturbances were kept to a minimum to minimise abnormal fluctuations in the subject's brain waves.

After 15 minutes, the subject was put in the task state, where a VR device was added to the electrode cap and the Kinect device was switched on to capture upper limb–movement data. The subject was asked to play Beat Saber, a continuous VR game, for 15 minutes. To ensure that the data collected was not affected by other factors, the game was set to the same music, at the highest difficulty level, with an automatic restart mode in the event of failure. Figure 2 shows the experimental procedure.

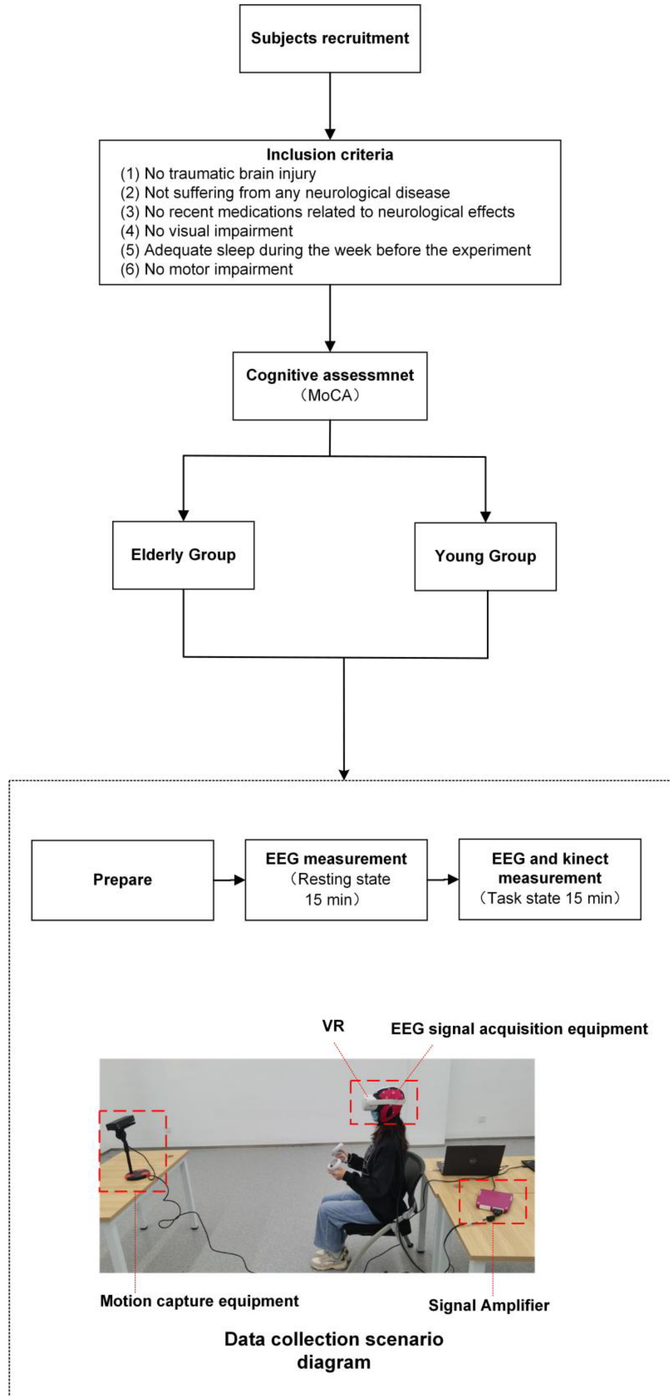

Fig. 2. The experimental procedure.

D. EEG Data Pre-Processing

The EEG signal is a random signal that varies over time and has a small amplitude. It is highly susceptible to interference from other signals unrelated to brain activity, known as artefacts. These mainly include oculogram artefacts, blink artefacts, eye-movement artefacts, myoelectric artefacts, cardiac artefacts, DC offsets and industrial frequency interference. To remove these artefacts, a triple filtering and independent component analysis (ICA) method was used. Before filtering, channel localisation and a re-reference were carried out. The re-referencing method considered the average reference, which takes the average of all electrode potentials after the acquisition as the reference signal and is equivalent to artificially constructing a zero potential point as the reference electrode. A high-pass filter with a cut-off frequency of 1 Hz was first chosen to eliminate baseline drift. To stop interference from high-frequency signals such as myoelectric artefacts and ensure that the fast waves in the EEG signal were not affected, a low-pass filter with a cut-off frequency of 40 Hz was selected for the second filtering. For the third filtering, a notch filter at 49–51 Hz was used to remove industrial frequency interference. ICA was then performed to eliminate artefacts embedded in the data without removing the affected part of the data. ICA separates the linear mixed signals generated by multiple source signals into independent signals that are uncorrelated and non-Gaussian, thus separating the n source components from the EEG signal channels. As shown in (1), ICA finds a component 'unmixing' matrix (W) that, when multiplied by the original data (X), yields the matrix (U) of IC time courses. In (2), the whole data (X) is the sum of the ICs (Xi) [26]. Finally, the artefacts were identified and removed with the help of the ADJUST algorithm, which is a completely automatic method for the detection of artefacted ICs from EEG data. For each feature contained in the detectors, the threshold value was calculated using a fully automated image processing thresholding algorithm based on the expectation-maximisation (EM) technique [27]. Equation (3) captures how the algorithm recognises eye movements. The above-mentioned pre-processing operations were performed using

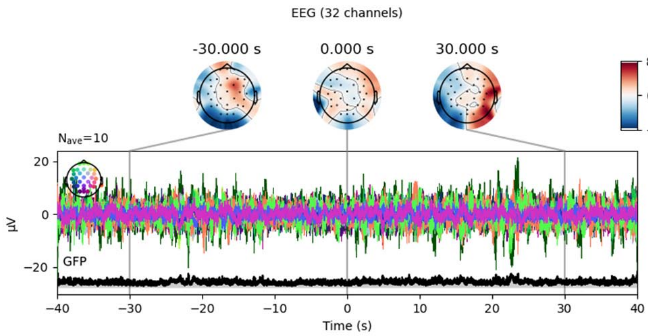

Fig. 3. All 32 channels of voltage activity.

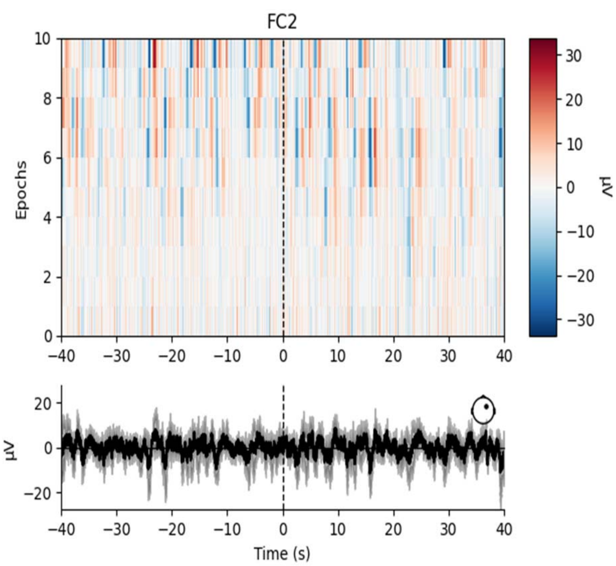

Fig. 4. One of the channel voltage activities.

the open-source toolkit EEGLAB based on MATLAB (The MathWorks, Inc, Natick, Massachusetts, USA) [28].

$$\mathrm{U} = \mathrm{WX} \tag{1}$$

$$\mathrm{X} = \sum \mathrm{X_i} \quad \text{where } i = 1, 2, \ldots \mathrm{n} \tag{2}$$

$$\mathrm{Max}imum\ Epoch\ Variance = \frac{trim\_and\_\max(< s_i(t)^2 >_{ep} - < s_i(t) >_{ep}^2)_i}{trim\_and\_mean(< s_i(t)^2 >_{ep} - < s_i(t) >_{ep}^2)_i} \tag{3}$$

where $\mathrm{trim\_and\_max}(\ldots)_{\mathrm{i}}$ indicates the maximum of the trimmed vector of variance values over the epochs, and $\mathrm{trim\_and\_mean}(\ldots)_{\mathrm{i}}$ denotes the average across epochs computed after the top 1% of the values have been removed [27].

An item of data was selected, and multiple events were inserted into it, with 80 seconds between events. The period from the first 40 seconds to the last 40 seconds of each event was taken as an epoch. These epochs were superimposed and averaged. Nave indicates the number of epochs, and Nave = 10 means that 10 epochs were involved in the superimposing and averaging. The global field power is the standard deviation of the electrical activity on all electrodes. Figures 3, 4, and 5 visualise the electrical activity of the brain.

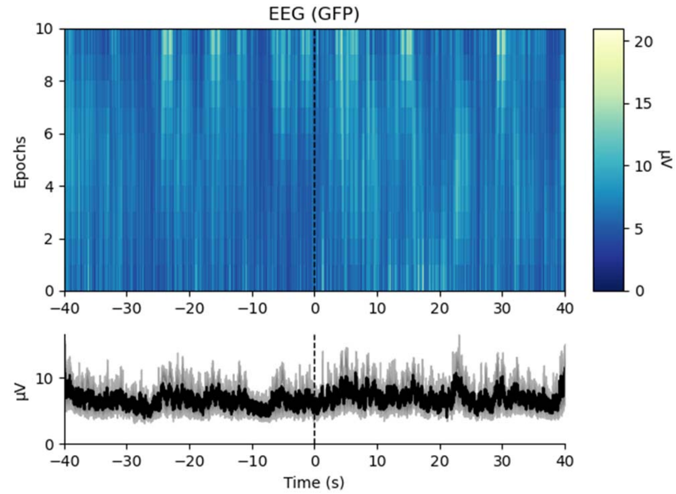

Fig. 5. Global field power for all channels.

E. Functional Connectivity

Based on the pre-processing of eighty pieces of EEG data, the functional connectivity (FC) between six brain regions, namely the left prefrontal cortex (LPFC), right prefrontal cortex (RPFC), left motor cortex (LMC), right motor cortex (RMC), left occipital lobe (LOL) and right occipital lobe (ROL), was calculated using the MNE-Connectivity library in Python [29].

The signal connectivity between channels was calculated using the spectral_connectivity_epochs method. As shown in (4), the phase locking value (PLV) was chosen as a measure of connectivity. This method uses responses to a repeated stimulus and looks for latencies at which the phase difference between the signals varies little across trials (phase locking) [30]. Fourier was chosen as the method for spectral estimation. The sampling frequency was fixed at 1000 Hz. The frequency bands of interest were alpha waves at 8–12 Hz frequency range and beta waves at 12–40 Hz frequency range. All 22 channels in the six brain regions were selected, and by varying the indices parameter, inter-signal connectivity was obtained for all channels between each of the six brain regions. The final FC metric was obtained by averaging the data between each of the six brain regions to get 15 values in each frequency band, for a total of 30 values in the three frequency bands.

$$\mathrm{PLV} = |\mathrm{E}[\frac{Sxy}{|Sxy|}]| \tag{4}$$

E[ ] denotes the average over epochs. The connectivity method is based on estimates of the cross- and power-spectral densities (CSD/PSD) Sxy and Sxx, Syy [29].

F. Extraction of Kinect Data Metrics

Using Python to read the json file generated by the Kinect device and obtain the corresponding points of the upper limb, we calculated eight behavioural metrics: overall upper-limb velocity, the standard deviation of upper-limb velocity, median upper-limb velocity, overall upper-limb acceleration,

TABLE II
MEANING OF BEHAVIOURAL INDICATORS

Number	Indicator	Meaning
1	Overall upper-limb velocity	Overall upper-limb velocity kinematic posture
2	The standard deviation of upper-limb velocity	Degree of upper-limb velocity deviation
3	Median upper-limb velocity	Upper-limb motion level representation
4	Overall upper-limb acceleration	Overall upper-limb acceleration
5	The standard deviation of overall upper-limb acceleration	Upper-limb acceleration deviation
6	The left-arm mean angle of motion	Left-arm motion flexibility
7	Discrete stability ratio	Overall upper-limb motion stability
8	Continuous stability ratio	Continuous stability of upper-limb movements

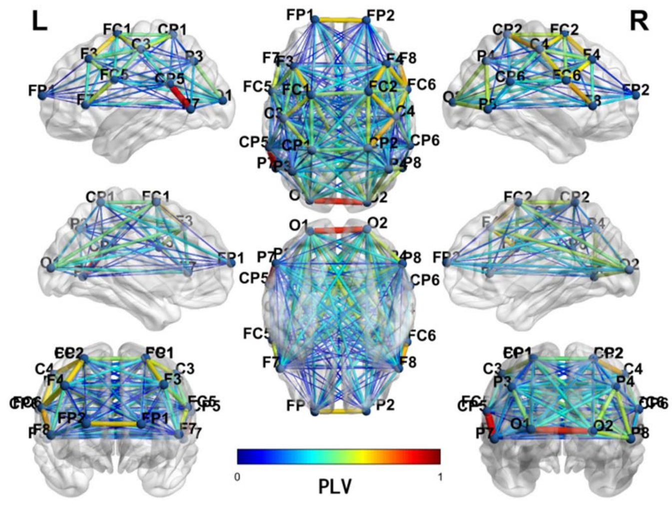

Fig. 6. FC demonstration of 22 channels of one item of task state data.

the standard deviation of overall upper-limb acceleration, the left-arm mean angle of motion, discrete stability ratio and continuous stability ratio. Table II explains the meaning of behavioral indicators.

G. Statistical Analyses

For the FC, a one-way ANOVA test was performed on the data from the task and resting states within the group, using age as the basis for grouping, to explore the effect of state on the FC of brain areas. An independent samples t-test was performed on the younger and older groups within the group, using the state as the basis for grouping, to investigate the effect of age on the FC of brain regions. For the Kinect data metrics, a one-way ANOVA test was used on the overall data to analyse whether age has a significant effect on behaviour, using eight behavioural indicators as dependent variables and age group as a factor. Pearson correlation analyses were conducted on behaviour, cognitive level, age and FC. The statistical significance level (P) was set to 0.05 for all analyses.

III. RESULTS

A. Functional Connectivity Results

Independent samples t-tests were used to compare the task states pertaining to the younger and older groups. In the alpha band, the PLV values of brain regions LPFC–LMC ($F = 1.530$, $P = 0.040$), LPFC–LOL ($F = 0.031$, $P = 0.040$), RPFC–RMC ($F = 0.949$, $P = 0.037$), LMC–RMC ($F = 0.934$, $P = 0.042$), LMC–LOL ($F = 6.698$, $P = 0.027$) and RMC–LOL ($F = 1.091$, $P = 0.043$) were significantly higher in the elderly than those in the young. In the beta band, the PLV values of brain regions LPFC–LMC ($F = 1.043$, $P = 0.028$), LPFC–RMC ($F = 1.153$, $P = 0.035$), RPFC–RMC ($F = 1.445$, $P = 0.034$) and RMC–ROL ($F = 1.272$, $P = 0.041$) were significantly higher in the elderly than those in the young.

In a one-way ANOVA test for resting and task states in the younger group, the PLV values of brain regions LPFC–RPFC ($F = 4.705$, $P = 0.035$), LPFC–RMC ($F = 4.724$, $P = 0.035$), RPFC–LMC ($F = 5.439$, $P = 0.024$), RPFC–LOL ($F = 4.447$, $P = 0.040$), RPFC–ROL ($F = 5.991$, $P = 0.018$), LMC–LOL ($F = 4.087$, $P = 0.049$), LMC–ROL ($F = 5.214$, $P = 0.027$) and RMC–ROL ($F = 4.611$, $P = 0.037$) were significantly higher in the resting state than those in the task state in the alpha band.

As shown in Figure 6, when the FC indicator, PLV, is between 0 and 1, the closer the PLV is to 1, the closer the two signals are to synchronisation and stronger the connectivity is. Figure 7 shows the correlation of brain regions in three conditions, (a) in the alpha band, comparison of task states in the younger and older groups, (b) in the beta band, comparison of task states in the younger and older groups, and (c) in the alpha band, comparison of resting and task states in the younger group.

B. Kinect Results

In terms of overall upper-limb velocity ($F = 1.028$, $P < 0.001$), median upper-limb velocity ($F = 0.415$, $P < 0.001$) and overall upper-limb acceleration ($F = 2.731$, $P < 0.001$), the younger group was significantly higher than the older group. Figure 8 shows the results of the analysis of the behavioral indicators.

C. Correlation Results

Overall upper-limb velocity ($r = 0.353$, $P = 0.026$), median upper-limb velocity ($r = 0.365$, $P = 0.021$), and overall upper-limb acceleration ($r = 0.338$, $P = 0.033$) were significantly correlated with cognitive level. In the alpha band, the FC in brain regions LPFC–LOL ($r = 0.225$, $P = 0.045$) and LMC–LOL ($r = 0.239$, $P = 0.033$) were significantly correlated with age. A significant correlation was also observed between functional connectivity and behavioural indicators. In the alpha band, the FC of LPFC–LMC was significantly correlated with continuous stability ratio ($r = 0.326$, $P = 0.040$), and the FC of RPFC–RMC was significantly correlated with the standard deviation of overall-upper limb acceleration ($r = 0.318$, $P = 0.046$).

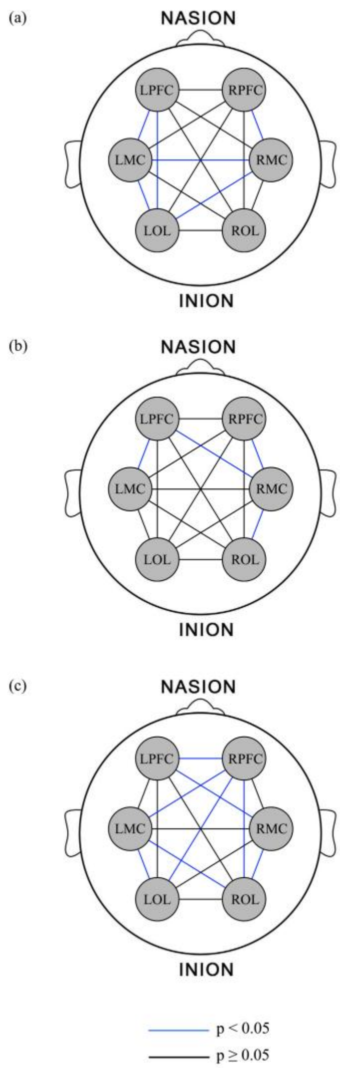

Fig. 7. Correlation between brain regions reflected by PLV indicators.

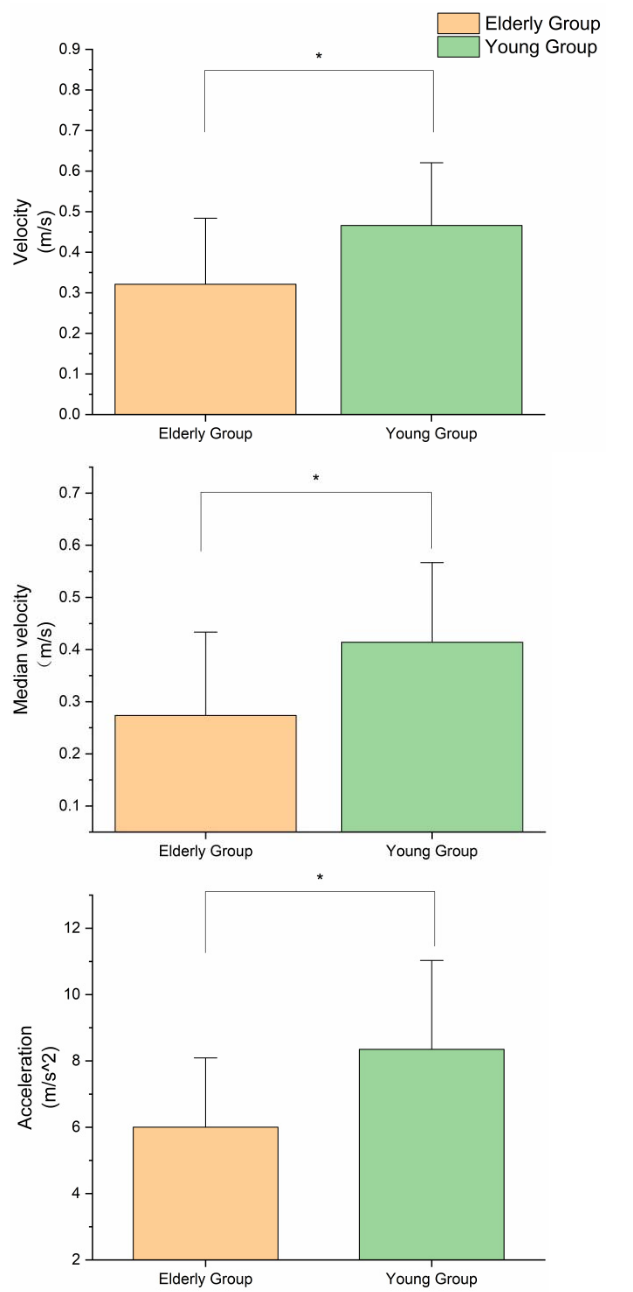

Fig. 8. Comparison of data on behavioural indicators between the elderly and the young groups.

IV. Discussion

This study assessed the effects of age on brain function in terms of brain FC, cognitive level and behavioural performance. The prefrontal cortex is closely associated with higher cognitive functions in humans [31]. In concert with other brain structures, the prefrontal cortex plays an important role in attention, perception, motivation, planning, sustained behaviour, working memory, language, control of interference and executive functions [32]. The area of the cerebral cortex associated with the emergence of movement is known as the motor area, and the stimulation of this area causes muscle movement in various parts of the body. The occipital lobe is the most dominant visual cortex, and damage to the occipital lobe results in not only visual impairment but also symptoms such as memory deficit and motor perception impairment. FC measures reveal statistical dependencies between the activity patterns of anatomically separated brain regions and are often used to assess the functional relationships between brain regions [33]. In this study, PLV was chosen as an indicator of FC [34], with the former reflecting the overall convergence of the phase difference between two real signals.

The results of the brain FC between the young and elderly groups for the task state showed that in the alpha band, the PLV values between the six brain regions were significantly higher in the elderly group than those in the young group. In the beta band, four groups of inter-brain interval PLV values were significantly higher in the older group than those in the younger group. We suggest that this change in FC may be due to ageing and also correlates with cognitive level. When a person engages in a conscious visual activity or intense thinking exercise, the alpha rhythm decreases, and there is a corresponding increase in high-frequency, low-amplitude beta waves. Ageing affects many aspects of brain structure and function and is associated with cognitive decline [35]. The brain age gap is a better predictor of cognitive decline in subjects than their actual age [36]. Previous studies have shown that cognitive decline with age is evidenced by a significant increase in theta and alpha1 bandwidths, an increase in the theta-beta differential [37], and an increase in relative theta power in the posterior quadrant [38]. Neurological measures of quantitative electroencephalogram (QEEG) have been found to be a sensitive indicator of the degree of cognitive impairment, with previous research showing that cognitive decline is reflected in increased absolute and relative power in the theta band and increased power in the delta band during the later stages of deterioration [39]. Claus *et al.* found that higher theta values in the frontocentral and parieto-occipital regions were significantly associated with a decline in the overall cognitive function [40]. Koyama *et al.* observed significantly higher relative beta power in older subjects [41]. Many of the brain's higher cognitive functions rely on the synergy between different brain regions rather than being reliant on just a specific brain region. FC is commonly used as a measure of brain function. Previous research has shown that subjects with age-related frailty exhibit reduced FC between posterior regions of the parietal cortex [34]. Zhao *et al.* found differences in the strength of dynamic FC in the left anterior wedge, default mode network and dorsal attentional network between normal controls, amnestic mild cognitive impairment (aMCI) patients and Alzheimer's disease (AD) patients [42]. Chen *et al.* identified that dynamic FC in individuals with subjective cognitive decline showed a significant correlation with cognitive performance [43]. The EEG signal is a highly stochastic physiological signal with a wide variety of rhythms, and a variety of different emotions and states of mind can affect the changes in brain waves. As with others, our results reflect the influence of age and cognitive level on brain function, but the subtle differences in the significance of the various frequency bands and brain regions demonstrated may be influenced by the experiment, the imaging technique and the FC metrics selected.

The results of FC in the resting and task states of the young group showed that the PLV values between the eight brain regions were significantly higher in the resting state than those in the task state in the alpha band. We suggest that this difference in FC between the resting and task states is due to VR incorporation and limb movements. In this study, VR was used for the experiment, and a game was chosen that could reflect the cognitive level of the subjects to a certain extent, aided by the acquisition of other data such as behavioural data. VR is widely used in the field of rehabilitation, and in addition to multi-sensory stimulation, the computer programme can be set up in such a way that the subject's condition can be acquired in time and the difficulty of the training and the training programme can be adjusted accordingly, bringing about better rehabilitation outcomes. Scenes in VR cause different stimulations of brain electrical activity in humans [8]. The study shows that the FC between the core cortex of the mirror neuron system and the sensorimotor cortex is significantly enhanced in the first-person view of VR scenes [44]. Alpha waves, with a frequency of 8–12 Hz, represent the predominant waveform in adults in the quiet, closed-eye state and are associated with human attention, emotion, cognition and awareness. Alpha waves are most pronounced in the parietal and occipital regions, and are suppressed in the presence of external stimuli. Since the resting state was followed by a short rest period of a few minutes only before the task state was initiated, the subjects may have experienced fatigue, thus affecting EEG activity.

In the analysis of the EEG data, besides the significant differences presented previously, we found that the results of FC showed very significant individual variability within the same group. Furthermore, in the beta band, the mean FC values for the region LPFC–RPFC as well as LMC–ROL were lower in the older group than those in the younger group, although this difference was not significant.

Behavioural data from the younger and elderly groups showed that the younger group scored significantly higher than the elderly group in overall upper-limb velocity, median upper-limb velocity and overall upper-limb acceleration. There is a widespread decrease in sensorimotor function with age. A weakening of cognitive abilities can also lead to a reduction in motor ability [45]. We believe that this may account for the obtaining of this result. Pearson correlation analyses showed significant correlations between FC, motor ability, cognitive level and age, validating the multimodal approach to combining data.

The current study has several limitations. The population included in this study was selected based only on age and cognitive differences and generally represented a relatively healthy group of people. Regarding EEG data pre-processing, the strong subjectivity of identifying artefacts might have had some impact on the results.

V. Conclusion

In this study, the subjects' brain signals in the resting and task states were monitored using EEG, and VR was utilised for the experimental design. Drawing on the multimodal data, brain function was assessed more fully from multiple perspectives, including subjective and objective. The results show that VR stimulation of the brain leads to changes in FC. When comparing the younger and elderly groups, it was found that a significant decline in sensorimotor ability along with ageing and declining cognitive levels leads to changes in functional brain connectivity. These findings contribute to a new and valid assessment method that could be useful in the field of rehabilitation medicine. The multimodal data–based rehabilitation assessment method proposed in this paper combines measures of VR, behavioural indicators, subjective scales and EEG activity, fully combining their strengths. The use of data from multiple sources allows for a more accurate identification of a patient's condition and facilitates timely adjustment of rehabilitation training programmes, which offer assistance in the field of rehabilitation medicine.

In future research schemes, based on the consideration of the application of this method in rehabilitation medicine, the selection of subjects could be expanded to include those with neurological disorders such as AD and stroke. Meanwhile, other signal processing methods to improve data accuracy could be used, such as canonical correlation analysis and short-time Fourier transform.

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