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RESEARCH ARTICLE

A Post-Stroke Rehabilitation System With Compensatory Movement Detection Using Virtual Reality and Electroencephalogram Technologies

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ABSTRACT Stroke is a leading cause of global population mortality and disability, imposing burdens on patients and caregivers, and significantly affecting the quality of life of patients. Therefore, in this study, we aimed to explore the application of virtual reality technology in physical therapy by using immersive interactive training and designing rehabilitation modes for individual and group settings. We also aimed to provide patients with stroke with a comprehensive home-based rehabilitation and treatment plan, ultimately enhancing training effectiveness. Patients can engage in home-based rehabilitation through this system and undergo functional, mirror, and constraint-induced therapies tailored to different task contents. Simultaneously, using brain-computer interface technology, an emotion analysis mechanism was designed to map the patients' brainwave signal data onto a two-dimensional space of positive-negative valence arousal; this approach can enable remote physical therapists to discern the patients' emotional states during the rehabilitation process through virtual spaces, facilitating timely adjustments to rehabilitation tasks. Moreover, to prevent compromised effectiveness owing to improper training postures leading to compensation, the system offers real-time identification and recording, promptly issuing alerts when compensation occurs. The system provides a multiuser virtual rehabilitation space, enabling timely corrections and data observations, offering patients with stroke a home-based rehabilitation program, thereby realizing a localized aging care model.

INDEX TERMS Compensation, electroencephalography (EEG), healthcare, post-stroke, rehabilitation, virtual reality.

I. INTRODUCTION

In recent years, prominent global technology giants like Facebook (now Meta), Microsoft, and Apple have

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significantly ventured into the metaverse domain, developing VR/MR wearable devices. TrendForce estimates that the global market for virtual reality (VR) applications will reach \$8.31 billion by 2025, with a compounded annual growth rate of 40%. The applications of VR are extensive, with many healthcare institutions already using it to create immersive environments for treating anxiety, post-traumatic stress disorder (PTSD) [1], pain management, and neural recovery. VR is capable of blocking brain pain receptors and transferring pain sensations away from injury sites, similar to the effects of prescription opioids. Existing literatures [2], [3] explores how VR virtual imagery can reshape the relationship between patients' brains and their motor nervous systems. Stroke is the second leading cause of global mortality and disability, with a lifetime incidence of one in six cases. Moreover, post-stroke disabilities are a major contributor to limb disabilities, burdening both patients and caregivers, and significantly impacting the quality of life of patients. Owing to technological advances in the digital era, VR has gained widespread use in the medical industry. Societies with progressive aging have seen an increasing demand for rehabilitation therapists. In rural areas, the accessibility of medical resources for stroke patients is challenging. Numerous studies [4], [5], [6] have demonstrated the ability of VR to stimulate visual perception and enhance brain functions.

Based on these previous works, in this study, we introduced a VR rehabilitation system that offers an efficient, safe, and engaging approach to help patients with stroke regain their health. A main contribution of this study is that we merged VR with physical therapy, blending medical expertise with technology to create interactive virtual environments for individuals and groups. Patients can engage in upper limb rehabilitation through VR by incorporating diverse treatment regimens through game tasks that enhance interaction. The rehabilitation system in this work focuses on training upper limb function to restore normal daily activities. It is because the shoulder joint, one of the body's most mobile joints, requires patients undergoing rehabilitation to develop the skill of using their hands effectively in a variety of activities. Without proper intervention, complications can easily occur when shoulder joint problems arise, leading to irreversible damage. However, according to our research, very few rehabilitation systems consider automatically detecting compensatory and showing warnings messages to help patients adjust to incorrect posture. Our system allows patients to undergo rehabilitation at home and detect and discern potential compensatory errors in real time, thereby strengthening the efficacy of rehabilitation and reducing the risk of injury from incorrect posture.

We also investigated BCI technology to enable real-time psychological monitoring during VR rehabilitation, significantly improving the patient's overall experience. The analysis of brainwave data enhances remote therapy and facilitates a better understanding of emotional states. By utilizing VR and EEG, we can accurately measure a patient's positivity, allowing for customized treatment approaches. Our VR rehabilitation system seamlessly integrates medical expertise with advanced technology to provide interactive upper limb training. Distinguishing itself from most systems, ours can identify and alerting users to improper compensatory movements, thereby reducing the risk of injuries during home-based rehabilitation.

The paper is structured as follows. Section II provides an extensive review of related works. Section III explores VR systems, focusing on multiplayer interactions, compensation detection and analysis, mirror therapy angle detection, electroencephalography signal analysis, and the Valence-Arousal (V-A) Emotional Model based on EEG. Section IV discusses therapeutic methodologies in our VR system, including occupational and mirror therapy, constraint-induced movement therapy, cognitive training, and VR rehabilitation with EEG. Section V transitions to the presentation of experimental results and engages in a detailed discussion of these findings. Finally, Section VI concludes the paper, summarizing the research findings, contributions, and future works.

II. RELATED WORKS

Subsection II-A reviews VR-Assisted Rehabilitation, exploring its application in limb and cognitive rehabilitation, whereas Subsection II-B examines Brain-Computer Interface (BCI) Technology, focusing on EEG applications in VR for monitoring psychological states and enhancing remote rehabilitation.

A. VR-ASSISTED REHABILITATION

The development of smart healthcare has diversified, and VR technology has gradually expanded into the field of medical care. It can simulate real surgeries, reducing the risks associated with complex surgical procedures. Common interdisciplinary applications include surgery, rehabilitation, minimally invasive surgery, and simulation. VR is used for treating phobias, in dentistry, and in post-traumatic stress disorder treatment, among other uses. Currently, this technology is widely used in various healthcare sectors due to its recognition by health organizations, doctors, and governments, leading to active deployment of VR applications in healthcare. Relevant literature [7], [8], [9], [10], [11], [12] also discusses the use of VR in medical care for pain distraction therapy, aiming to alleviate patients' suffering. A previous study [7] analyzed the conditions of brain neurons and observed their gradual recovery after 6 weeks, ultimately enabling the subjects to slowly control leg movements, indicating that long-term VR stimulation benefits limb rehabilitation and training. Another study [8] combined VR with neurophysiology to stimulate the participants' brains through localized induction to facilitate hand movements. The research has shown that VR-assisted rehabilitation improves neural conduction speed in the arms faster than traditional methods, leading to enhanced upper limb recovery.

Moreover, some literatures [13], [14], [15], [16] use VR training aids individuals with cognitive decline such as dementia, stroke, Alzheimer's disease, and Parkinson's disease, by improving their daily activities. VR training enhances proactive memory and slows brain degeneration, gradually restoring patient independence. Other previous studies [17], [18], [19] demonstrate integrating training for daily life activities into VR not only enhances rehabilitation engagement but also leverages visual and auditory stimuli to focus users on relevant tasks, thereby enhancing rehabilitation outcomes. These studies also show that, through controlled feedback, VR can induce users to perform specified tasks faster than traditional medical rehabilitation, making it more effective in medical contexts.

B. BRAIN-COMPUTER INTERFACE (BCI) TECHNOLOGY

In rehabilitation training conducted by therapists, constant attention is required to the patients' conditions, encompassing both physiological and psychological states. Remote rehabilitation sessions introduce relative complexities in observing psychological status and physical pain [20]. Electroencephalography (EEG) assists physical therapists in analyzing and observing patients' operational states in VR scenarios. Adeev et al. [21], [22] employed common phobia-inducing scenarios, such as height, roller coasters, and outer space, to create stress factors. By monitoring the average heartbeat and alpha wave levels, it found that challenging VR content led to sympathetic nervous system activation, which was inversely correlated with alpha waves; this relationship helps to determine a user's stress level. In addition to the influence of VR content, in [23], it shows real-life environmental factors, including temperature, sound, and air quality, also affect users' psychological states. EEG provides insight into whether a user's current environmental conditions negatively affect their psychological well-being. Additionally, the user's level of focus during training can be detected through EEG by extracting brainwave data after accounting for blinking effects, allowing the determination of the patient's concentration level [24].

To facilitate remote rehabilitation, our study incorporates BCI technology [25] for the real-time monitoring of patients' psychological states during VR rehabilitation sessions, enabling the analysis of their emotional index status. This benefits physical therapists by promptly adjusting the training intensity during online virtual interactions with patients, enhancing patients' confidence in performing VR rehabilitation tasks, and improving their training experience. Additionally, our VR with BCI technology can provide a virtual space for physical therapists with the ability to remotely analyze patients' frontal lobe brainwaves and assist in adjusting training intensity and scope. The system also includes an emotion analysis mechanism that processes VR operators' brainwave data, which are then algorithmically analyzed and transformed to provide real-time markers in a two-dimensional space of positive-negative valence and arousal [26]. As mentioned in previous studies [26], [27], [28], this Valence-Arousal emotional two-dimensional space includes regions of fear, joy, disappointment, pleasure, sadness, and satisfaction that are usually used in psychology. We integrate this into our VR rehabilitation system. A patient's emotions can be identified based on the position of the mapped point, aiding the therapist in understanding the patient's current psychological state. Simultaneously, through a combination of EEG technology and VR, our VR rehabilitation system can quantify a patient's current level of positivity and can assist therapists in tailoring treatment according to the patient's positivity level.

III. SYSTEM PRINCIPLE AND TECHNOLOGY

The research framework provides a multi-player connected virtual space using virtual reality inverse kinematics (VRIK) technology to observe limb interactions between participants and facilitate rehabilitation activities within the VR environment [29]. Software development was conducted within the Unity engine, which is compatible with VR devices such as HTC VIVE and Oculus Rift and offers both single-player and multi-player connection modes. The single-player mode was developed using VRTK, a Unity-supported VR game development resource, which can create various interactive functionalities in VR, including patient visual movement, object manipulation, and usage interactions. The multi-player connection mode combines photon unity networking (PUN) and Final IK technologies. The PUN provides server connection services for developing multi-player online games and expands the networking capabilities of the Unity game engine to assist in creating different types of multi-player online applications. Within the Final IK technology, VRIK is a positioning script for VR controllers and virtual character modules. The following section describes the various design aspects of the system.

A. MULTIPLAYER INTERACTION IN VIRTUAL SPACES

The system uses a PUN to design VR rehabilitation as a multiplayer, interactive virtual environment. Photon Cloud is a cloud service operated by existing games worldwide, providing real time multiplayer network connectivity functionality that is compatible with Unity Networking. Through the multiuser virtual space designed by this system, physical therapists and users can interact in the same virtual environment. The system integrates a brain-computer interface and real time data, allowing physical therapists to adjust task content and interaction methods in a timely manner to meet the needs of patients. The photon-view feature is used to distinguish between different user objects during connection, with each connected object having a unique View ID number. Through object synchronization, position, rotation, and scale can be synchronized. Upon entering the connection, the system creates three synchronized objects for the user: the head, left hand, and right hand. These synchronized objects can be manipulated using a head-mounted device and controllers, driving the character module to achieve interactions between the module and scene, such as sitting down, opening doors, picking up objects, and stepping. Upper-body movements are driven by the head-mounted device and hand controllers, whereas lower-body movements are synchronized with the operator's full-body skeleton using VR motion trackers, enhancing the fluidity of interactive control.

B. COMPENSATION DETECTION AND ANALYSIS

To detect compensation occurrences, HTC VIVE motion trackers (VIVE Trackers) and SteamVR drivers were employed to capture the patients' compensatory movements and upper limb displacement values. The trackers were placed on the upper arms of both hands and the waist to detect arm movement and elbow angle, whereas the waist tracker detected user displacement and VR headset displacement and measured the angle of the upper limb forward lean. During training, if displacement or angle deviation exceeded a certain threshold in non-training areas, the system identified the compensation, recorded it, and alerted accordingly.

Compensation includes abnormal hand movements, arm displacement, and upper limb forward leaning [30]. Abnormal hand movements refer to the use of unaffected measurements during operational training. Abnormal arm displacement occurs when the arm is inappropriately moved to drive the palm area, whereas abnormal upper limb forward leaning occurs when the user excessively relies on the forward-leaning strength of the entire upper limb to complete training. Two methods of recording data are used during training; the first is real time recording in which the tracker returns values when it detects movements beyond the normal range, and the second method involves detecting every second and presenting an integrated display of five data records. Before training begins, the transform.pos() function from the SteamVR_Controller is used to obtain the current position of the tracker. This function generates 3D coordinates, and data recording begins after the return. The displacements of the elbow or waist tracker for both hands were calculated by computing the tracker's 3D spatial coordinates of the tracker in Unity. The system records the position of the tracker every second and then calculates the Euclidean distance between the previous and current positions. For example, if the previous 3D spatial coordinates are point P (0,0,0) in the previous second and the current coordinates are point Q (1,1,1), yields arm movements of three units.

During rehabilitation training, if the extent of compensation exceeds a predefined threshold, it triggers an alert and records the relevant tests, areas, exceeded values, and normal values. Angle calculation primarily involves computing the distance between the hand controller and elbow tracker positions. The system acquires the position of the controller and uses an elbow tracker as a pivot point. The horizontal movement of the hand corresponds to the x-axis in 3D space, whereas the vertical movement corresponds to the y-axis. Therefore, it is necessary to calculate the distance between the controller and tracker along the X/Y axes to determine the angle.

C. MIRROR THERAPY ANGLE DETECTION

Higher adherence to standard movements during training led to higher scores on the task game. In the sagittal plane movement test, the standard angle was set to 90°. If the angle fell between 85°and 95°, five points were awarded; if the angle fell between 80–84° or between 96–100°, three points were awarded. If the angle was $< 79°$ or $> 101°$, 1 point was awarded. Mirror therapy utilizes a mirror for training, allowing users to perform training objectives using the unaffected side with the movement reflected in the mirror. Owing to the effects of the mirror illusion, the affected side behind the mirror moved along. Therefore, the goal of mirror therapy is to allow users to simultaneously use both the affected and unaffected sides to complete the same movement. In mirror therapy, training is conducted using hand controllers, and the angle difference between the two hand controllers is calculated to determine the synchronization rate.

During mirror therapy rehabilitation training, the synchronized positions of both hands were measured in terms of the distance on the Y- and Z-axis, the rotation angle on the Y-axis. The Y-axis detects the height difference between the hands, the Z-axis detects the front-back distance between the hands, and the Y-axis rotation angle detects the direction of the hands. As the values of these three metrics approaches zero (0.01), this indicates higher synchronization when the orientation, height, and front-back positions of the hand controllers are the same, resulting in a higher synchronization rate. The values ranged between approximately 1 and 0.01, and the synchronization rate was calculated as a percentage after converting these values. The system interface provides a real time display of these values, with a normal synchronization range between 70 and 100, represented by green. Synchronization rates less than 70 and more than 50 fall within the warning range, indicating the need for corrective action and are represented in yellow. A synchronization rate less than 50 indicates poor synchronization and is indicated in red.

Unity offers two methods for representing the angles: Euler angles and quaternions. The Euler angles represent rotations around the X-, Y-, and Z-axes and are typically expressed using the Vector3 class. However, Euler angles suffer from gimbal lock issues, making them unsuitable for continuous rotation. In contrast, quaternions provide a four-dimensional rotational representation in space, using quaternion values to express rotation angles. Quaternions help to avoid gimbal lock issues and offer advantages in rotational composition and interpolation calculations, resulting in them being commonly used for controlling object rotation in VR [31]. Moreover, when calculating the synchronization rate of the dual-hand controllers, the algorithm directly employs the quaternion, which is used to calculate the dot product of

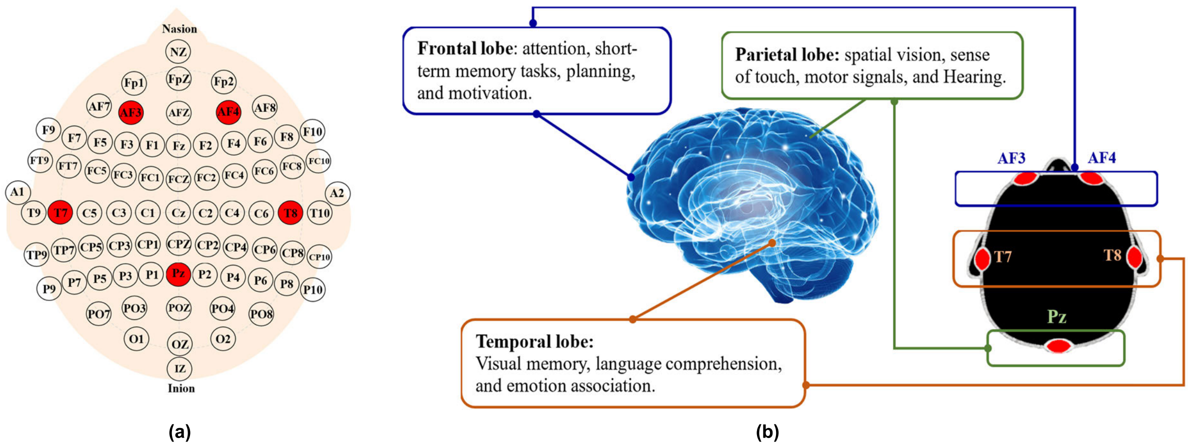


FIGURE 1. **(a) Electrode locations for the 10–20 system. (b) Five channels of the Emotiv Insight 2.0.**

the two quaternion types. The quaternion, which performs an inner product operation on the rotation angles of the two quaternion types, measures the similarity between the two rotation angles. The synchronization rate between them can be determined by computing the dot product of the quaternions of the two hand controllers; this was used to assess whether the user had completed mirror therapy training.

D. ANALYSIS OF ELECTROENCEPHALOGRAPHY SIGNALS

The Emotiv Insight 2 EEG headset was employed as the brainwave detection device. The electrode configuration of the device is shown in Fig. 1(a), which follows the international 10–20 EEG system, with five red dots indicating the positions AF3, AF4, T7, T8, and Pz, corresponding to different brain regions; these positions cover critical areas of the cerebral cortex, and can be used to detect user emotions and expressions. Fig. 1(b) illustrates the sensor locations in the EEG headset. AF3 and AF4 are situated in the frontal lobe and are responsible for planning, organization, problem solving, selective attention, personality, and higher cognitive functions related to behavior and emotion [32]. Therefore, when users contemplate upper-limb movements during rehabilitation, stronger brainwave signals in this area lead to better outcomes. The T7 and T8 electrodes were positioned near the ear, corresponding to the temporal lobe; these regions play a role in auditory and olfactory discrimination and processing of new information. The right hemisphere is primarily responsible for visual memories, such as recognizing shapes and faces, whereas the left hemisphere is involved in language-related memories, such as words, names, and phrases. T7 and T8 were further assessed using musical elements to evaluate brainwave activity and detect relevant responses to the music provided by the system. The Pz electrode was placed in the midline parietal area, and the position of the parietal lobe was detected. It is responsible for spatial perception, and damage to this area may lead to difficulties in recognizing spatial positions. In cases of damage to the left parietal lobe, language abilities in speech and writing may be impaired, leading to communication obstacles [33].

Brain signal data detection is primarily used to assist with assessing patients' mental and physical conditions, enhancing their rehabilitation willingness and motivation through real time adjustments. The Emotiv Insight 2 is oversampled at 2048Hz/channel and this is filtered heavily to remove all traces of environmental electromagnetic interference and then down sampled to 128 samples per second per channel, providing EEG data collection capabilities. It employs Fast Fourier Transform (FFT) technology to convert time-domain signals into the frequency-domain spectrum and calculates the amplitude of various brainwave bands corresponding to specific frequency intervals. Through this system, physical therapists can gain a clearer understanding of patients' mental and physical states, thereby enabling the design of personalized rehabilitation plans based on individual circumstances. After data collection, the system proceeds to data processing, which involves a spectral analysis of the collected raw brainwave signals. Using FFT, the time-domain signals were transformed into the frequency-domain spectrum, and the amplitude values of various brainwave bands within specific frequency intervals were computed. The system categorizes these data using machine-learning algorithms and classifies them into different states, such as focused attention or relaxation. Finally, the data were formatted and presented at the system. During system usage, the Emotiv Insight brainwave sensor detects connection status by sensing the current at electrode points, as depicted in Fig. 2. When all connection statuses are green, the system begins to detect data every 5 seconds. The brainwave data during eye blinks and baseline brainwave data were recorded before recording formal brainwave data. These data points were subsequently used for synchronization and calibration during the later stages of data processing.

Before processing the EEG data, it is essential to nullify the DC offset of the brainwaves by calculating the average

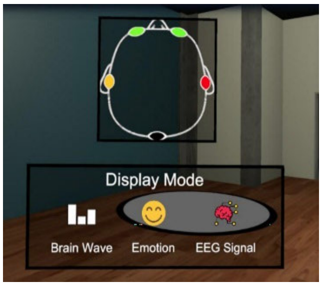


FIGURE 2. **EEG signal connection status.**

for each sample and subsequently subtracting the median to eliminate adverse effects; this step ensures that the signal remains balanced between high and low frequencies. Additionally, when converting raw EEG data into waveforms (e.g., raw data), it is necessary to limit the time required to reach the maximum peak and minimum trough to reduce the slew rate. An excessive slew rate can result in drastic waveform changes that may exceed the measurement range of the device, thereby leading to signal distortion. Therefore, during EEG signal processing, controlling the slew rate is crucial to achieve smooth and stable transitions, thereby obtaining more reliable outcomes.

The discrete brainwave data were processed using FFT to create a waveform graph, which is represented with decibels per hertz (dB/Hz) on the axis, as illustrated in Fig. 3. Following conversion, a high-pass filter (HPF) was applied to remove low-frequency signals from the brainwave data (EEG_data) to prevent signal drift and maintain spectrum stability. Subsequently, an infinite impulse response (IIR) filter was used with two coefficients to constrain noise from other frequencies, thereby enhancing precision. Simultaneously, a Hanning window function was set up for waveform correction to eliminate interference, thereby reducing the spectrum leakage generated during the truncation of periodic signals. This process is iterated using an IIR filter to further enhance accuracy [34].

E. VALENCE-AROUSAL EMOTIONAL MODEL BASED ON EEG

Brainwave signals were categorized into different frequency bands. Theta waves (4–7.5 Hz) are typically associated with relaxation and meditation; alpha waves (8–11.5 Hz) are related to states of attention and relaxation; beta waves (12–24.5 Hz) are related to states of thinking and learning; and gamma waves (25-45 Hz) are associated with high focus and cognitive states [35]. The system primarily references the activity of alpha and beta waves to infer user attention, relaxation, or tension. The transformation of brainwave signals employs a wavelet transform, converting transient and long-term slowly changing signals into high-resolution forms. Prior to brainwave analysis, preprocessing was necessary to filter out interference noise caused by external factors using the Pywavelets module for discrete wavelet transform (DWT) [36].

Algorithm 1: EEG IIR High-Pass Filtering Algorithm

```
BEGIN
    Import EEG_data
    Use high-pass filter with cutoff frequency fc to preprocess EEG_data
    Let back = first row of preprocessed EEG_data
    Set IIR_TC = 256;                          // 2 second time constant
    for each row r of preprocessed EEG_data
        back = (back * (IIR_TC - 1) + pre_EEG_data(r,:)) / IIR_TC;
        eeg.iirfilt(r,:) = pre_EEG_data(r,:) - back;
    endfor

    // Set FFT length to 1024 and apply Hanning Window Function
    Set FFT length to 1024
    Apply Hanning Window Function to each row of eeg.iirfilt

    // Compute Amplitude Spectrum of Channels
    Set SampleLength as number of rows in eeg.iirfilt
    Set Amplitude Spectrum of Channels using FFT of each row of eeg.iirfilt

    // Set plot labels
    Set label_x to Frequency in Hz
    Set label_y to Amplitude in dB
END
```

FIGURE 3. **EEG infinite impulse response high-pass filtering algorithm.**

In the analysis of brainwave signals, valence arousal is a significant emotional dimension used to describe the degree of positive or negative emotions and the level of arousal [37]. As referenced previously [38], the extraction of Arousal and Valence from EEG data is conducted through a detailed analysis of specific EEG parameters. The EEG raw data with a sampling rate of 128 samples per second (128 Hz) enable the capture of detailed brainwave data. To translate the EEG data into meaningful VA values, each second's worth of samples are processed through specific equations ((1) and (2)). These equations are designed to convert the raw EEG signals into quantifiable measures of Valence and Arousal. Thus, we utilized the positive-negative affect algorithm to convert brainwave signals into a Valence-Arousal (V-A) coordinate map, as shown in Fig. 4. This approach enables us to instantaneously capture the emotional states of remote patients. The positive-negative affect algorithm, grounded in emotional computing theory, calculates emotions such as positive low arousal, negative low arousal, positive high arousal, and negative high arousal from brainwave signals. These emotions are displayed on a two-dimensional V-A coordinate map. This visual representation provides an intuitive understanding of the patient's emotional state and acts as a reference for monitoring emotions during VR rehabilitation sessions.

The parameters within the Valence-Arousal Emotional Model are represented on a two-dimensional plane that depicts arousal (ranging from low to high) and valence (ranging from negative to positive). Emotions with high arousal and positive valence, such as excitement, delight, and happiness, indicate a state of stimulation and pleasure. High arousal combined with negative valence emotions, including tension, anger, and frustration, reflect a state of high energy but distress. Low arousal coupled with negative valence emotions, including depression, boredom, and fatigue, are

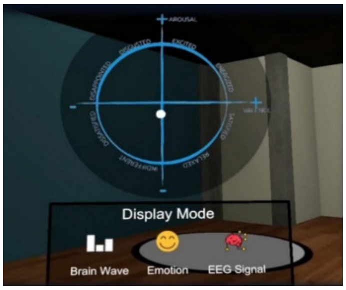


FIGURE 4. VR valence-arousal emotion model.

characterized by a lack of energy and a negative mood. On the other hand, low arousal along with positive valence emotions, such as calmness, relaxation, and serenity, signify a peaceful state. These parameters are quantified using EEG signals to objectively measure and respond to emotional states during VR rehabilitation.

Arousal and valence values are calculated by acquiring βH (high range) and βL (low range) brainwave signals from scalp electrodes. The β wave in brainwaves encompasses two primary frequency ranges, namely βL (12-16Hz) and βH (16-24.5Hz). Generally, during attention-intensive tasks, βH tends to increase. βL is associated with relaxed and alert states, while βH is linked to a more focused and concentrated attentional state. An increase in βH reflects enhanced attentiveness, indicating a focus on rehabilitation tasks. Conversely, βL is associated with relaxed and lower alertness states, and its energy may be relatively higher during relaxation activities or periods of low attention demand. Therefore, both βL and βH brainwave data are observed in this study to evaluate the attention of patients during rehabilitation processes, aiming to understand the users' attentional states and guide subsequent recovery plans. In brainwave analysis, we utilize Differential Entropy (DE) to quantify of the electroencephalogram signals. Assuming there are two probability density functions, $p_{\mathrm{L}}(x)$ and $p_{\mathrm{H}}(x)$, representing the total number of records x concentrated in the βL and βH datasets, with the calculation formula as in (1) and (2):

$$DE_{\beta\mathrm{L}} = -\int p_{\mathrm{L}}(x) \cdot \log\left(p_{\mathrm{L}}(x)\right) dx \tag{1}$$

$$DE_{\beta\mathrm{H}} = -\int p_{H}(x) \cdot \log\left(p_{\mathrm{H}}(x)\right) dx \tag{2}$$

From the perspective of differential entropy, we can express the differential entropy of βF4 as the weighted average of the differential entropy of βL and βH as in (3). Taking the electrode F4 of brainwave as an example, the differential entropy of βL is denoted as $DE_{\beta\mathrm{L}}$, and the differential entropy of βH is denoted as $DE_{\beta\mathrm{H}}$. The distribution of βL at time t is denoted as $P_{\beta\mathrm{L}}(t)$, and the distribution of βH at time t is denoted as $P_{\beta\mathrm{H}}(t)$. Then, the differential entropy of βF4 is represented as below:

$$DE_{\beta\mathrm{F4}} = P_{\beta\mathrm{L}}(t) \cdot DE_{\beta\mathrm{L}} + P_{\beta\mathrm{H}}(t) \cdot DE_{\beta\mathrm{H}} \tag{3}$$

In which, $P_{\beta L}(t) + P_{\beta\mathrm{H}}(t) = 1$. Next, further calculations are made to compute Arousal and Valence. The βF4 values in Equations (4) and (5) are the results obtained from the calculation of $DE_{\beta\mathrm{F4}}$ in Equation (3). Similarly, the βF3, βAF3, and βAF4 values are also derived from the analysis of βL and βH brainwave signals in F3, AF3, and AF4 by differential entropy. However, it's important to clarify that the EEG device captures both low and high beta activity from electrode locations. Therefore, while our terminology may have implied separate high and low beta signals, in practice, our equations account for the collective beta activity encompassing frequency ranges.

$$\text{Arousal} = \frac{\alpha\mathrm{AF3}+\alpha\mathrm{AF4}+\alpha\mathrm{F3}+\alpha\mathrm{F4}}{\beta\mathrm{AF3}+\beta\mathrm{AF4}+\beta\mathrm{F3}+\beta\mathrm{F4}} \tag{4}$$

$$\text{Valence} = \frac{\alpha\mathrm{F4}}{\beta\mathrm{F4}} - \frac{\alpha\mathrm{F3}}{\beta\mathrm{F3}} \tag{5}$$

The integration of the Valence-Arousal emotion model into the VR system was achieved by applying angle transformation using an inverse trigonometric function. Each 45-degree sector within the positive-negative arousal two-dimensional map was designated as an emotional segment, enabling the identification of transitions in the patient's emotional state. Subsequently, Pearson's product-moment correlation coefficient and standard deviation are employed to confine the boundaries of the two-dimensional map within the range of -1. After acquiring the patient's brainwave data position on the two-dimensional map and computing the arousal values, the quadrant X-axis corresponding to the arousal value was divided into four levels. The system expresses the patient's emotions using coordinates from the quadrant chart. Subsequently, a comparison is made between the disparities in brainwave data before and after rehabilitation, facilitating an analysis of the differences in the extent of brainwave transformations and emotional responses during the pre-training, rehabilitation, and rest periods.

IV. SYSTEM IMPLEMENTATION: METHOD AND FUNCTION

The system offers both single-player and multiplayer rehabilitation modes to enhance interaction between patients and rehabilitation therapists, thus improving training effectiveness. In the single-player mode, three types of occupational therapy (OT) [39], two variations of mirror therapy (MT), and three types of constraint-induced movement therapy (CIMT) training programs are available. OT covers various aspects of daily life activities and hand and upper limb functionality, helping patients regain self-care and social capabilities. MT uses mirrors to reflect movements, enhancing sensory and visual feedback of the affected limb and improving motor control. CIMT restricts healthy limb movement to strengthen the motor abilities of the affected side, aiding in the restoration of limb functions. In multiplayer connection training mode, the system offers exercises focused on reaction, memory, and balance training. These programs aim to improve patients' reaction time, memory, and balance, enhancing their overall movement abilities in daily life. Patients can interact with rehabilitation therapists through multiplayer connections, receiving remote exercise guidance for more precise and personalized treatment plans. Finally, the system automatically records the training results in the cloud, enabling medical professionals to access them at any time to further adjust rehabilitation solutions.

The architecture of the VR Rehabilitation System clearly outlines the patient's journey through various stages of physical therapy, as depicted in Fig. 5. It begins with 'Rehab. Program Selection,' where the system guides patients toward tailored rehabilitation experiences. Patients can choose between 'Multiplayer Interaction Training Mode' for group interactions or 'Single-player Training Mode' for individualized therapy sessions. In VR Rehabilitation System's multiplayer setting, physical therapists utilize 'Real-time Electroencephalography analysis' to observe and analyze the cerebral activity. This feature helps them assess patient engagement levels and detect any neurological changes that occur in response to the therapy. Simultaneously, the 'Valence-Arousal Emotion Model' evaluates patients' emotional responses, providing therapists with critical psychological insights that shape personalized therapeutic strategies. The system also offers 'Cognitive and Interactive Training' to enhance memory and reaction speed. An integral component of the system is the 'Compensation detection and warning' feature, which utilizes biomechanical analysis to identify and rectify improper movement patterns, ensuring that patients maintain correct posture and movement techniques to optimize their recovery. For individualized therapy sessions, the VR Rehabilitation System offers custom-tailored physical therapy modalities. OT is focused on enhancing daily living activities through targeted upper extremity rehabilitation. MT aids in improving motor function and proprioception through movement mirroring, and CIMT is utilized to amplify the use of affected limbs, encouraging neuroplasticity and motor recovery. Patients have the autonomy to select tasks aligned with their specific upper limb rehabilitation needs, ensuring a personalized and effective rehab experience. Each session's data is meticulously tracked in the 'Rehab. Recording and Analysis' phase for continuous therapeutic improvement.

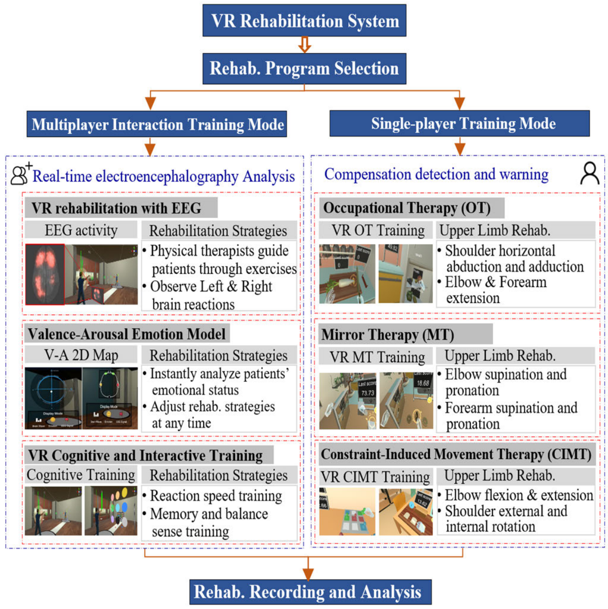


FIGURE 5. VR rehabilitation system architecture.

A. OCCUPATIONAL THERAPY (OT)

During occupational therapy, the system automatically records the time taken for each test, the accuracy of movements, and any compensatory actions; it guides patients through effective rehabilitation movements and records the precision and average time spent. Maintaining balance in the seated or standing position is essential for performing daily activities. Therefore, the system designs functional tasks with varying difficulty levels that involve different degrees of weight-shifting and posture control abilities; this enables patients to apply these skills in their daily lives. The common limb postures used in daily life include elbow flexion and extension, as shown in Fig. 6(a). For instance, the motion of raising and lowering a knife involves elbow/forearm flexion and extension in the sagittal plane. As shown in Fig. 6(b), this exercise involves grasping a specific object, moving it horizontally, and placing it back, designed to train shoulder muscles in horizontal abduction and adduction. The training focuses on performing repetitive back-and-forth movements with the designated target object. During this process, it was necessary to raise and bend the shoulder, rotate the forearm, and maintain the gripping motion while completing the objective. This is one of the most challenging tasks of rehabilitation.

(a) (b)

FIGURE 6. (a) Elbow/Forearm extension (b) Shoulder horizontal abduction and adduction.

In OT, the action of rotating and placing items afterward is difficult. In addition to horizontal shoulder abduction and adduction, forearm rotation is required to place the object in the target position. Incorporating multiple body parts into an exercise program increases the level of difficulty. Training should gradually progress based on the individual's capabilities and range of motion.

B. MIRROR THERAPY (MT)

Mirror therapy entails engaging in upper limb activities whereas viewing the reflected image of the unaffected upper limb in a VR mirror and mentally visualizing the affected upper limb mimicking the same movements. This method facilitates the brain's relearning of the affected limb's movements, fostering neural plasticity and contributing to the restoration of motor function. Essentially, it assists the brain in regaining control over the impaired limb by creating a reflective illusion, which activates both the motor and sensory regions of the affected limb as if it were in motion [40].

During mirror therapy, the impaired limb is placed behind the mirror, whereas the healthy limb is positioned in front of the mirror to correspond to the relative position of the affected limb. Visual feedback is used to make the patient perceive movement in the affected limb, even when it remains stationary. The patients positioned their healthy limbs on one side of the mirror and their affected limbs on the other side. They observed the mirror from the perspective of a healthy limb and performed symmetrical mirror movements. This visual feedback creates an illusion of movement in the affected limb, making movement possible and providing relief from the potential pain associated with the phantom limb positions. This treatment leverages the brain's preference for visual feedback over proprioceptive or tactile feedback in determining the limb position.

MT has the potential to alleviate pain, particularly phantom limb pain resulting from limb amputation. This therapy consists of two primary components. Fig. 7(a) primarily focuses on training hand grasping and forearm pronation and supination, while Fig. 7(b) involves training elbow pronation and supination. Engaging in rotational movements can be challenging for stroke patients, and this task specifically targets rotational object manipulation training.

FIGURE 7. (a) Forearm supination and pronation (b) Elbow supination and pronation.

C. CONSTRAINT-INDUCED MOVEMENT THERAPY (CIMT)

When stroke patients engage in rehabilitation exercises using the affected limb, they often face difficulties and pain, leading to psychological resistance towards using the affected limb; this can lead to a vicious cycle in which patients increasingly rely on the unaffected limb for daily activities, gradually avoiding the use of the affected limb, resulting in learned disuse and subsequent decline in limb function [41]. CIMT focuses on restricting the use of the unaffected limb and forcing the use of the affected limb during training.

Traditional CIMT involves restricting the unaffected limb for 90% of the waking hours each day and is suitable for chronic stroke patients, but is often challenging. The modified CIMT restricts the unaffected limb to 30 min to 6 h per day and is more suitable for patients with early or subacute stroke. A 2-week CIMT intervention enhanced activation in the primary sensory cortex of the affected hemisphere, which was positively correlated with improvements in movement performance. Daily repetitions and practice over 2 weeks or more can strengthen patients' limb motor function [42], [43]. If the system detected that the specified task was not being performed with the affected limb, a warning was displayed during the rehabilitation process, prompting the patient to return to the restricted state with the unaffected limb.

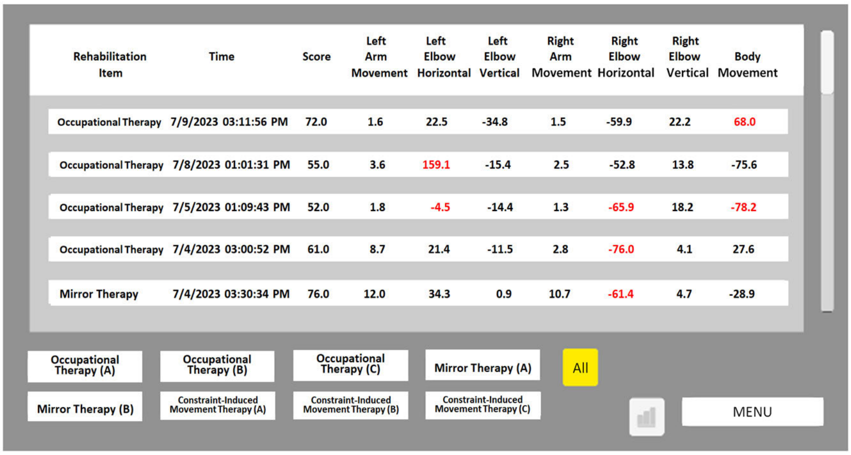
As illustrated in Fig. 8, the CIMT task involves the patient grasping chess pieces with the affected limb and correctly positioning them in squares of the same color. In the event that a patient assumes an improper posture during rehabilitation, such as leaning the upper body forward whereas arranging the chess pieces, the system detects the compensation and issues an immediate warning. This alert prompts the patient to rectify their posture and maintain the correct training angle for either the elbow or shoulder flexion and extension.

FIGURE 8. Elbow flexion and extension, Shoulder external and internal rotation.

D. VR REHABILITATION WITH EEG

Throughout the rehabilitation process, the system records the performance scores of the operators in task execution. These scores, along with other crucial metrics, are thoroughly presented in Fig. 9. The comprehensive rehabilitation dataset encompasses various metrics, including training name, duration, score, and detailed measurements of arm and elbow movements in both the left and right limbs, along with the overall upper limb movement angle. This assessment encompasses a total of ten parameters. Compensatory movements during rehabilitation are highlighted in red to facilitate the identification of segments that often require compensation.

To further analyze the brain state during rehabilitation exercises, the integration of EEG equipment with the VR rehabilitation system allows us to understand the users' real-time status in the VR environment, including spatial orientation, balance, and rehabilitation task performance, while observing changes in EEG signals; this was used to analyze the brainwave responses of the patients during



Rehabilitation Item	Time	Score	Left Arm Movement	Left Elbow Horizontal	Left Elbow Vertical	Right Arm Movement	Right Elbow Horizontal	Right Elbow Vertical	Body Movement
Occupational Therapy	7/9/2023 03:11:56 PM	72.0	1.6	22.5	-34.8	1.5	-59.9	22.2	68.0
Occupational Therapy	7/8/2023 01:01:31 PM	55.0	3.6	159.1	-15.4	2.5	-52.8	13.8	-75.6
Occupational Therapy	7/5/2023 01:09:43 PM	52.0	1.8	-4.5	-14.4	1.3	-65.9	18.2	-78.2
Occupational Therapy	7/4/2023 03:00:52 PM	61.0	8.7	21.4	-11.5	2.8	-76.0	4.1	27.6
Mirror Therapy	7/4/2023 03:30:34 PM	76.0	12.0	34.3	0.9	10.7	-61.4	4.7	-28.9

FIGURE 9. Training record for VR rehabilitation.

rehabilitation. For the detection task, considering individual differences in EEG signals, baseline values for the five electrode points of the EEG headset were established before conducting the detection analysis. These baseline values were used to determine the activity state data, which illustrates the forearm pronation and supination movements during mirror therapy. Remote multiplayer VR rehabilitation enables physical therapists to interact with multiple patients in the same virtual space. Through a VR brain-computer interface and real-time data, therapists can adjust and interact with the patients' task content. The system identifies the identities of both the therapist and patient through their accounts. Each connected object was assigned a unique View ID number, allowing object synchronization during the connection process, including position, rotation, and scale synchronization. Once connected, participants could observe each other's movements.

Fig. 10 depicts a multiuser virtual space integrated with EEG. A Canvas object was positioned on the screen with the Render Mode set to overlay, enabling real-time overlay of the EEG signal overview on the screen. As therapists guide the rehabilitation exercises, they can observe patients' limb movements and simultaneously monitor the intensity and status of left and right brain reactions. This dual monitoring approach during rehabilitation sessions provides therapists with a comprehensive understanding of the patient's engagement and the effectiveness of their participation in the rehabilitation process.

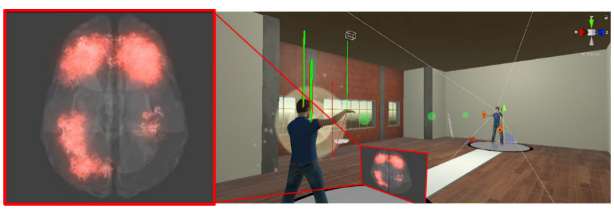
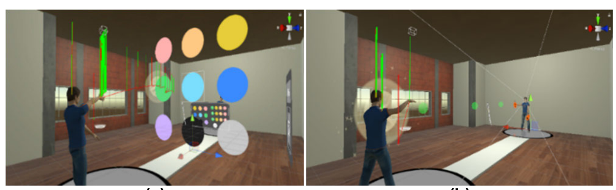


FIGURE 10. VR rehabilitation with EEG for multiplayer.

E. VR COGNITIVE AND MULTI-PLAYER INTERACTIVE TRAINING

The VR cognitive and multiplayer interactive training module encompasses activities including speed, memory, and balance. For reaction speed, the therapist launches balls towards the patient, who must touch the balls to score points, as shown in Fig. 11(a). The therapist can launch balls from different directions, even with both hands, requiring the patient to move their body to touch the balls and earn points. The therapist can display various colors, which the patient must click on in the correct sequence. The therapist can adjust the number of colors based on a patient's success rate in each round, thereby enhancing their memory skills. The balance training segment, the third part of the program, involves patients replicating a three-dimensional shape drawn by the therapist. This task, depicted in Fig. 11(b), requires the patient to accurately mirror the therapist's design, enhancing their balance and coordination skills. The exercise also includes an aspect of drawing simultaneously with both hands, further promoting limb coordination and dexterity.



(a) (b)

FIGURE 11. (a) Reaction speed training. (b) Memory and balance sense training.

V. EXPERIMENTATION RESULT AND DISCUSSION

To validate the usability of the proposed system, we recruited 20 participants for a practical system operation and conducted a post-usage effectiveness survey through questionnaires. This experiment aimed to verify the following aspects:

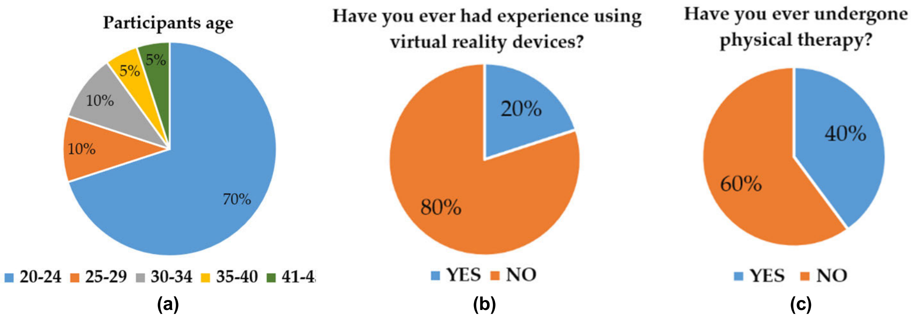


FIGURE 12. **The statistics of the participant's basic information and experience.**

(1) User Interface and Content: We assessed whether the system's user interface and content were user-friendly and comprehensible, focusing on the system's ease of use for rehabilitation activities.
(2) Compensatory Warning Messages: We examined whether the system's compensatory warning messages allowed users to adjust their rehabilitation movements correctly and promptly during VR rehabilitation activities.
(3) User Brainwave Responses: We evaluated the system's representation of participants' emotional states based on their brainwave reactions. This verification aimed to enable remote physical therapists to understand users' emotions through the system, facilitating real-time adjustments of rehabilitation task difficulty based on users' emotions. For instance, if a participant displayed anxiety during rehabilitation, simple and soothing rehabilitation tasks could be incorporated to help the user relax.

In the experiment, therapists were essential in guiding participants through the multiplayer VR rehabilitation environment, customizing the VR content on the fly to meet individual requirements. Whenever participants encountered difficulties with specific tasks, therapists adeptly fine-tuned the difficulty levels to provide suitable and individualized challenges. This experiment involved 20 participants engaging in the system test, consisting of 13 males, who represented 65% of the total, and seven females, accounting for the remaining 35%. When considering visual acuity, we observed a split where six participants had normal eyesight, whereas 14 exhibited nearsightedness, with their myopia levels ranging from approximately 150 to 300 degrees. In terms of hand dominance, a significant majority of 18 participants were right-handed, complemented by two left-handed individuals. Regarding the age distribution, 70% of the participants were aged 20-24 years, with 10% in the 25-29 age group and another 10% in the 30-34 age group. The remaining 5% each belonged to the 35-40 and 41-45 age groups, as illustrated in Fig. 12(a). Regarding education, 85% had a bachelor's degree and 15% held a master's degree. Concerning participants' prior experience with VR devices, as indicated in Fig. 12(b), 20% had previous exposure to these devices, whereas 80% had no prior VR experience. Fig. 12(c) presents the participants' experience with physical therapy, indicating that 40% had participated in limb rehabilitation, whereas the remaining 60% had no such experience.

To accommodate the 11 out of 20 participants who lacked prior experience in operating VR equipment, we organized a foundational 5-minute VR training session before the start of the experiment. This session comprehensively covered aspects of VR handling such as managing the controller, employing interactive methods, and navigating the virtual space. The objective was to endow these participants with both the necessary operational skills and the confidence required for the forthcoming VR tasks. Before the experiment commenced, participants were instructed to close their eyes and rest on a chair for 3 min without any visual or auditory interference. Following the rest period, the participants were asked to wear the devices and commence the formal system operation experience. The participant questionnaire consisted of eight questions, each measured using the Likert 5-Point Scale. Participants made selections from the following options: "Strongly Agree," "Agree," "Neutral," "Disagree," and "Strongly Disagree." Each question was rated on a scale of 5, 4, 3, 2, and 1, corresponding to the above options, where a higher score indicated a higher level of agreement with the item.

In this study, we utilized Cronbach's α coefficient to assess the reliability of our questionnaire. It demonstrated an impressive α coefficient of 0.829, surpassing the threshold of 0.8, confirming its internal consistency. To further support our methodology, we included references from Kourtesis et al. [44], Salvatore and Christina [45]. These references provided a comprehensive framework that guided our experimental design, ensuring scientific accuracy and relevance to our research objectives. The questionnaire items are detailed in Table 1.

Questions Q1 to Q6 aim to validate the user interface and content of this VR rehabilitation system, assessing its ease of use and understanding among users. Q7 aims to verify if the system can display compensation alerts during user operation. As each rehabilitation task corresponds to specific limb movements, patients might use their healthy side instead of the affected one or attempt rehabilitation with

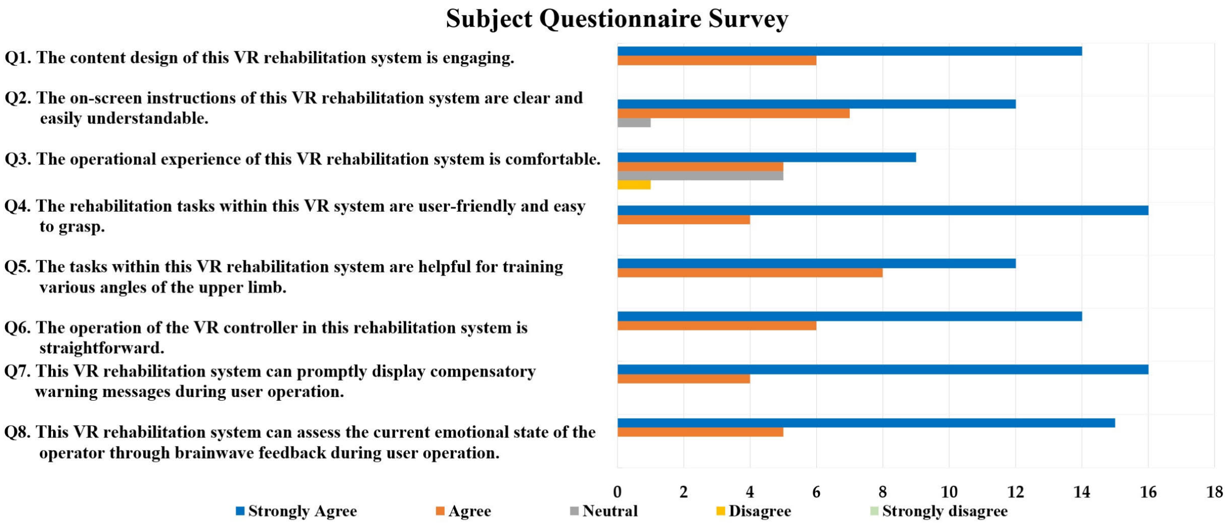


FIGURE 13. Summary of the responses obtained through the questionnaire.

TABLE 1. Set of questions from questionnaire.

Q1. The content design of this VR rehabilitation system is engaging.
Q2. The on-screen instructions of this VR rehabilitation system are clear and easily understandable.
Q3. The operational experience of this VR rehabilitation system is comfortable.
Q4. The rehabilitation tasks within this VR system are user-friendly and easy to grasp.
Q5. The tasks within this VR rehabilitation system are helpful for training various angles of the upper limb.
Q6. The operation of the VR controller in this rehabilitation system is straightforward.
Q7. This VR rehabilitation system can promptly display compensatory warning messages during user operation.
Q8. This VR rehabilitation system can assess the current emotional state of the operator through brainwave feedback during user operation.

incorrect muscle groups and angles. The system detects these compensations and instantly displays alerts, reminding the operator to perform tasks with the designated limb posture. Since the emotional state of the rehabilitation participants can impact the training effectiveness, physical therapists can access Valence-Arousal coordinate charts in the VR space to understand the remote participant's emotional state, allowing real-time adjustments to rehabilitation tasks. For instance, if the participant is feeling positive emotions such as fun and happiness, therapists can assist them in completing training tasks more effectively. Conversely, if therapists observe signs of anxiety or frustration, they can promptly guide them to perform less complex rehabilitation tasks. Therefore, Q8 assesses participants' perception of whether the V-A coordinate chart displayed by the VR system accurately reflects their emotions during the operation process.

As shown in Fig. 13, the questionnaire survey results for Q1 indicate that 70% of respondents strongly found the system's content interesting, with the remaining 30% in agreement. Participants perceived the interactive process as enjoyable due to the system's use of game-like tasks with vivid and colorful content. For Q2, 60% strongly agreed that the system's instructions were clear and easy to understand, 35% agreed, and 5% were neutral. It implies that adding voice-guided instructions could enhance user guidance during operations. However, 30% of participants experienced discomfort due to wearing glasses during the system's use, which resulted in 25% being neutral and 5% disagreeing regarding the comfort of the system experience (Q3).

Concerning VR rehabilitation content, all tasks mimic daily activities such as pouring water, flipping coins, and placing plates. For Q4, 80% of participants strongly agreed that the system's operational content was easy to learn, and 20% agreed. These results demonstrate that the user interface and content of the system are user-friendly and easily understandable. The rehabilitation tasks in the system include exercises such as elbow flexion and extension, forearm pronation and supination, and shoulder abduction and adduction. For Q5, 60% of participants strongly agreed that they felt their muscles being trained during the operation, indicating the helpfulness of the rehabilitation system. Additionally, 40% agreed with this statement. Regarding the selection actions on the screen, which require the assistance of the VR controller, 70% strongly agreed, and 30% agreed that the VR controller was easy to use (Q6). This indicates that among participants with no prior experience with VR devices, most found the VR controller easy to use, without negatively impacting the usage process of the VR rehabilitation system.

Q7 and Q8 aimed to verify the accuracy of the compensation alerts and the emotional state detected by brainwaves. For Q7, 80% of participants strongly agreed that the system's designed compensation detection mechanism effectively detected compensations and provided timely alerts, preventing injuries resulting from improper rehabilitation postures. In Q8, regarding the real-time Valence-Arousal coordinate chart analyzed through brainwaves in a multiuser VR environment, 75% of participants strongly agreed, and 25% agreed that the system accurately reflected the participants' emotional states during the operation process. These results demonstrate that the system can display users' emotional states through brainwaves, allowing physical therapists to assist remote rehabilitation participants in adjusting training task complexity in real-time, thereby enhancing rehabilitation effectiveness.

The questionnaire results of this VR rehabilitation system study indicate positive evaluations from participants regarding the system's design and functionality. These feedbacks will serve as crucial references for future system improvements. Furthermore, challenges faced by participants during system operation, such as inconvenience for glasses wearers, were noted. Future efforts will focus on transferring the rehabilitation system to lighter mixed reality devices like Meta Quest Pro or Apple Vision Pro, alleviating discomfort for glasses wearers and providing a more convenient and comfortable user experience. Additionally, enhancements will be made to the brainwave detection and compensation alert mechanisms to improve system accuracy and real-time responsiveness.

VI. CONCLUSION AND FUTURE WORKS

This study underscores the broad impact of stroke on physical, behavioral, and cognitive functions, with potential links to post-stroke dementia. Our VR-based remote rehabilitation system integrated intensive training and specific learning tasks to foster neural reorganization. Utilizing BCI technology, this system allows physiotherapists to remotely guide patients. Given challenges such as limited medical access and mobility concerns, this approach provides essential home-based rehabilitation for stroke survivors and others with diverse rehabilitation needs. The key innovation of this study lies in the seamless integration of the EEG technology and real-time compensatory detection. EEG empowers remote therapists to discern users' emotions, enabling real-time adjustments in rehabilitation task difficulty based on their emotional states. Simultaneously, real-time compensatory detection ensures users can promptly and accurately correct their movements during VR rehabilitation activities. Remote therapists can expertly guide patients with stroke through a range of exercises, tailoring training movements to address specific impairment areas. The experimental results strongly affirm the usability of the VR-based remote rehabilitation system and validate the effectiveness of integrating BCI technology and real-time compensatory detection. Looking ahead, our research will incorporate extended reality (XR) technology, enhancing the immersive rehabilitation experience by integrating real-life scenarios. This integration will be designed to significantly bolster patient-therapist interactions, leading to improved rehabilitation outcomes.

In future endeavors, we aim to conduct more extensive clinical trials to validate the efficacy and feasibility of our system across different clinical scenarios. Additionally, we plan to integrate multimodal physiological parameters, such as heart rate and electromyography, to enhance the accuracy of monitoring emotional and physiological states. A key focus will be on developing personalized rehabilitation plans that adapt to individual differences and progression, thereby improving rehabilitation effectiveness. We also plan to stay updated with the latest developments in mixed reality technology, actively incorporating higher-quality immerse experiences to provide more engaging and effective rehabilitation training. Furthermore, conducting long-term follow-ups to assess the sustainability and long-term impacts of treatment effects is a critical aspect of our ongoing research. These initiatives will contribute to expanding our research outcomes, increasing the applicability of mixed reality in rehabilitation therapy and opening up more possibilities for clinical practice.

AVAILABILITY OF DATA AND MATERIALS

The supplementary videos showcasing the operation and functionality of the system are available at https://reurl.cc/549Z4R. These videos offer visual demonstrations of the system in practical use, highlighting its features and capabilities within real-world rehabilitation scenarios. This resource significantly enhances the comprehension and practical relevance of the presented research.

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