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A Blockchain-Based Non-Invasive Cyber-Physical Occupational Therapy Framework: BCI Perspective

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ABSTRACT Although ElectroEncephaloGram (EEG) signals allow subjects suffering from neuromuscular disorders to interface their brains with the cyber-physical world, occupational therapy can be enhanced with the introduction of further modalities better assist the disabled person. In this paper, we propose an in-home occupational therapy environment, which leverages a rich set of occupational therapy-related activity recognition modalities, namely, EEG signals to understand brain activity, ElectroMyoGram (EMG) signals for muscle activity, gesture-tracking sensors for forward and inverse kinematics activities, and smart home appliance control sensors. To support a wide variety of disabled people's in-home occupational therapy, we have incorporated both selective attention and motor imagery processes for mapping a mental command with that of an occupational therapy-related command within a serious game environment. To attain higher accuracy and to avoid a higher number of false positives, a subject is first recommended to use a selective attention-based serious game in which a digital avatar of the subject acting as a model therapist will guide the therapy session. Once familiar with the generation of proper motor imagery, an advanced user can use self-paced motor imagery signals to perform occupational therapy activities within the serious game environment. The occupational therapy consists of a serious game environment in which smart home appliances are mapped with therapeutic activities through forward and inverse kinematics. The therapy data has been secured through blockchain and off-chain-based distributed repositories. The test results show the viability of using the framework in a clinical environment.

INDEX TERMS Brain computer interface, blockchain, off-chain, serious games, digital virtual avatar.

I. INTRODUCTION

Occupational therapy (OT) is intended to allow daily life activities independently [1]. The purpose of OT is to allow an individual to live as close as possible to their normal day-to-day living. For effectiveness, OT governs therapeutic features such as type, length, and frequency of motor imagery and therapeutic exercises, and change in difficulty level or course of activities to support quality of improvement [2]. Although much work has been done in the area of OT, understanding the Brain Computer Interface (BCI) and how it can help in certain types of disabilities remains an open challenge [3]. BCI leverages collaboration between the brain and any external hardware and software-based computing system [4]. BCI is used for mind state reading by probing brain activity, which is reflected in the electrical signals generated within the brain neurons. The signals portray a disabled person's mental desires to do an action [5]. A BCI intercepts these brain electrophysiological signals through an invasive or non-invasive computing hardware and software and finally maps

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each distinct brain signal with a certain action [6]. In the case of OT, the BCI is designed to understand mapping between the brain signals identified by the BCI and the corresponding occupational therapy commands [7]. The hardware interfaces with the brain, collects electrical signals, and relays them to a software component, which analyzes signals, maps the signals with a certain occupational therapy command, and actuates an external device or system that can be part of the OT environment. BCI-based research has gained attraction due to its support of neurofeedback, external IoT device interactions with brain signals, and the possibility of brain enhancement [7].

The brain generates rhythmical potentials in response to certain sensory-motor stimulus [8], which can be interpreted by EEG. The motor imagery is very popular in augmenting the rehabilitation process of disabled people [9]. In particular, the brain state signature of a disabled person, which is decoded by the interpretation of EEG signals can help during the physical rehabilitation process. Although several methods of capturing neuro signals exist, such as EEG, MagnetoEncephaloGraphy (MEG), Functional Magnetic Resonance Imaging (fMRI), and Near Infrared Spectroscopy (NIRS), EEG data is widely used as neurofeedback for mapping the brain with a set of activities being performed [10]. This is because of its non-invasive usage, ease of use, support of portability, and cost-effectiveness [11]. Being able to map brain activity with certain motor functions has the potential to support disabled people [12].

When a person's mental state of "wanting to do certain action" change, corresponding oscillatory components of EEG signals also change [13]. Event-Related Synchronization (ERS) is a notion which is characterized by an increase of EEG signal power in a certain band of brain signal frequency [14] and Event-Related Desynchronization (ERD) happens when the signal power decreases [15]. For example, during and after the imagination of a left hand movement related to an OT exercise exhibits an ERD and ERS respectively in the beta and gamma frequency bands [16], [17].

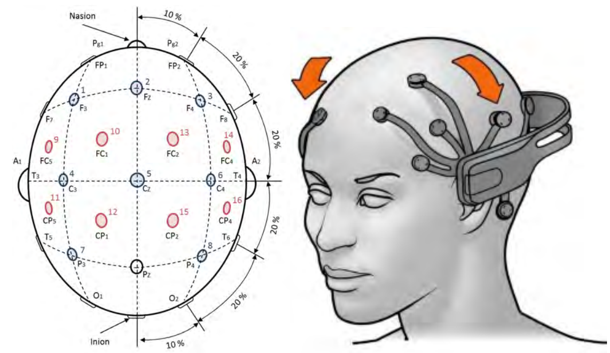
ElectroEncephaloGram (EEG) and ElectroMyoGram (EMG) are used primarily to probe the nervous system [18]. EEG data represent the electrical waves of the brain whereas EMG data evaluate nerve and muscle function in the arms or legs [10]. For example, EEG data available from the motor cortex area of the brain, which controls the muscles of the body that help in moving the arms, fingers, legs, and torso, can indicate initiation of the kinematic actions [19]. In other words, knowing which part of the brain controls which parts of muscles allows the right therapy to be given to the muscles of interest [13]. For example, Broca's area in the motor cortex controls the muscles in the mouth so that a person can express him/herself in an intelligent and coordinated way [3]. On the other hand, EMG data provides an indication of the electrical activities in the muscle, which is being stimulated by the nervous system [20]. EMG measures the electrical activity of a muscle when a person does kinematic gestures [21]. Once a person contracts any muscle, for example, by making a wrist flexion and extension, the muscle around the wrist joint responds to nerve stimulation [11].

Each brain signal acquired against a thought can be divided into various frequency bands [22], namely, delta δ (1 – 3Hz), theta θ (4 – 7Hz), alpha α (8 – 12Hz), beta β (12 – 30Hz) and gamma γ (30 – 100Hz). Each frequency band represents a specific feature. Each frequency range contains information related to a different aspect of human thinking. For example, the β and γ rhythms ranging from 12Hz to 100Hz are related to motor activities, more specifically the visualization of motion [23]. The higher the frequency in brainwaves, the larger the number of neurons that fire up synchronously at the same time [24]. When there is increased availability of β and γ waves, a person becomes alert with complete focus and an engaged mind and can have an active conversation, play sports, or drive a car [25]. Although all the types of frequency signals are generated at any given time, a particular type of signal becomes dominant which allows the body to determine what type of activity is to take place. For example, during the day time when one needs to do some hard work, the beta or gamma wave is assumed to have higher dominance over other signals [26]. Hence, researchers have found a correlation between EEG signal's β (12 – 30Hz) and γ (30 – 100Hz) waves and the EMG signal available at the muscles during a typical working time [7]. Hence, wanting to do a motor task to perform a therapy can be correlated to a particular therapy performed by a subset of muscles around a subset of joints [22]. Understanding the EEG and EMG signal gives more latitude of information during an occupational therapy [2].

Li *et al.* [24] target spastic cerebral palsy (CP) children to evaluate their sensory-motor response and beta waves in the frontal lobe area of the brain, as it is responsible for human motor and sensory functions: the left part of the frontal lobe is the primary motor area, while the right part is the primary somatosensory area. During analysis, two parameters were studied: one is sensory-motor response (SMR) amplitude, which is higher when the corresponding sensorimotor area is immobile or in an idle state and lower during activation of motor areas, i.e., at the time of motion or motor imagery. The second parameter is Beta amplitude, that increases at the motor cortex region as muscles contract or when the movement is resisted. The study results demonstrate the effectiveness of the system on the basis of improved SMR and beta values in CP children.

Scherer *et al.* [27] used the motor imagery technique for allowing a user to navigate in a virtual environment using three commands, rotate-left, rotate-right and move forward. They used the mental commands of the right/left hand and foot movement. The same technique has been used to allow a tetraplegic patient to control his wheelchair in a Virtual Environment [28]. After an excessive amount of training lasting approximately 4 months, he was able to move his avatar in a VR environment by movement imagination of his paralyzed feet. The results of the study showed that the subject was able to execute some predefined tasks in a virtual environment with a success rate of 90%-100% and that the methods could be easily transferred from the laboratory to a real-world application.

Brain computer interfaces (BCI) have been applied to motor rehabilitation in stroke patients with promising results [29]. In order to interact with different disabled patients, different modalities can be used such as manual interaction, using voice commands, gestures, eye movement, and thoughts [30]. Combining thought, gesture, eye movement, and voice as modalities for therapy allows various factors to be optimized, such as in different situations: when a disabled person is at home alone, is surrounded by people, or desires to do something him/herself [31]. Forward kinematics data provides the therapeutic gesture data, which shows the wellbeing or improvement of target body joints. Inverse kinematics allow a subject to achieve a target goal in terms of forward kinematics [32]. For example, if a person has a disability in moving the left hand, an IoT-based door lock can be interfaced such that during occupational therapy, the door will open through the elbow flexion-extension movement of a certain range of motion. It is assumed that cortical areas control the movements of the contralateral limbs as well as playing a role in ipsilateral movements [18].



(a) (b)

FIGURE 1. **(a) 10-20 system of placing EEG signal collection electrodes, and (b) an EEG headband with electrodes touching the desired location of the brain [6].**

In order to interface the brain signals with the BCI, the international 10-20 system is widely used an industry standard [33] (see Figure 1). The 10-20 system maps a certain portion of the brain with that of the spatial location of the interfaced electrodes. Researchers use the 10-20 notations to represent certain EEG signals originating from certain portion of the brain in terms of 10-20 electrode IDs. For example, researchers have found that imagination about movement of left and right-hand can be detected by placing electrodes in C3 and C4 or F7 and F8 locations [14], [34]. On the other hand, researchers have found that eyeball movement influences brain waves' F7 and F8 electrodes [35]. The suggested placement of the corresponding electrodes is shown in Figure 1. One important aspect of knowing such distinct patterns, researchers can identify high level motor actions related to OT that is created within the brain and place the electrodes accordingly. For example, if an OT exercise requires both hand and eye movement motor actions to be monitored, the BCI can be configured to acquire signals from C3, C4, F7, and F8 [24], [35]. Existing occupational therapy research shows that motor imagery can help stroke patients who have problems moving their arms and hands, and legs after a stroke [14], [36]–[38]. Stroke sufferers have shown increased neural awareness due to motor imagery exercise during their regular occupational therapy, instead of just regular therapy alone [39].

Data originated during OT requires privacy, confidentiality, and integrity while in storage, or transmission or processing. Also, a large volume of multimedia data is being generated during each OT session. In order to provide occupational data security, recent advancement in blockchain and off-chain-based decentralized digital repository shows promising options [40]. The new generation of blockchain and off-chain solutions even guarantees availability and scalability of OT data [41], proper end-to-end encryption, digital wallet with secure cryptographic public/private keys, and high speed transaction overlays such as Lightning Network (LN).

In this paper, we propose a novel in-home occupational therapy environment, which incorporates off-the-shelf EEG, EMG, eye tracking sensors, smart home IoT sensors [42], and kinematic gesture tracking non-invasive sensors to support forward and inverse kinematic actions. We have developed a 3D game environment in which the sensory data from the brain, muscles, joint range of motion and eye positions are fed to a digital avatar. The occupational therapy environment has been created with a subset of therapies that incorporate the brain commands, the hand muscle movement, and different hand and eye gestures to interact with the serious game environment in which different smart home IoT devices can be controlled with gestures. The game environment consists of two phases: during the first phase, a digital model occupational therapist guides a subject with model occupational therapy movements. During this time, the subject develops motor imagery in his/her brain. During the actual therapy time, the subject performs the action, which is recorded by the multimodal sensors. At the end of the therapy session, a summary of the kinematic data and quality of improvement is saved in the secure therapy blockchain while the raw EEG, EMG, and other kinematic data are saved in an off-chain repository for immutable storage. The therapeutic data can be shared with a remote therapist, which consists of an improvement in terms of motor movement, muscle power gain, and the ability to do certain motor tasks, as defined within the therapy.

The remainder of this paper is organized as follows. Section II outlines some preliminary background. Section III describes the proposed research framework, while Section IV presents the implementation, results, and discussion. Finally, Section V concludes the paper.

II. BACKGROUND

1) MOTOR IMAGERY FOR OCCUPATIONAL THERAPY APPLICATIONS

Motor imagery is a form of neurophysiological therapy that allows a disabled person to mentally rehearse the movement of the affected body parts, without actually needing to perform the movement. In other words, a subject imagines doing the movement as shown or guided by a computer system, e.g. a virtual or augmented reality game. A subject may imagine opening a door using their right hand or moving an object from left to right using his/her left hand [34], [36], [37]. Motor imagery can be integrated within the OT lifecycle in many ways, for example:

- Model therapy – serious games containing a virtual therapist showing the steps required to complete an occupational therapy task (e.g. switching on/off a light using wrist flexion/extension). The serious game incorporates those actions and tasks the patient has difficulty with performing on a daily basis.
- Imagining the therapeutic actions – the subject is instructed to recall the mistakes made.
- Following the model therapist – the subject practices the prescribed tasks through imagination and subsequently performs that OT in self-paced mode.

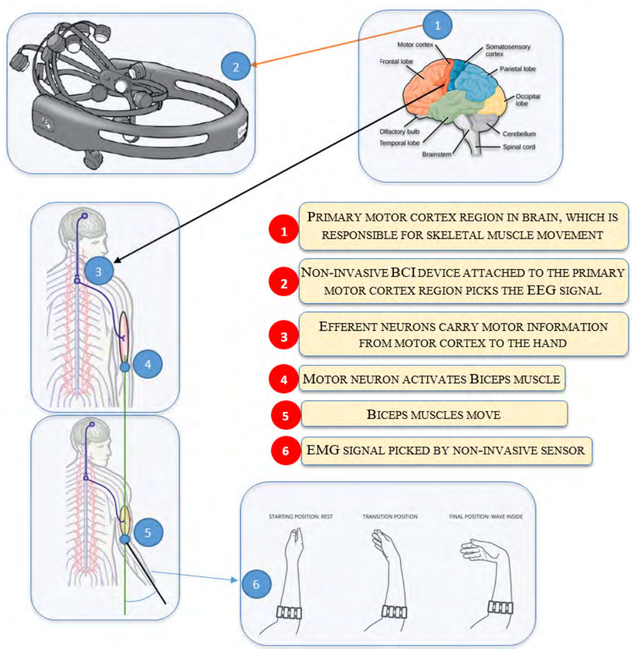


FIGURE 2. Motor imagery can help in actual occupational therapy activities [14].

Figure 2 shows a sample scenario in which a person is intending to perform an elbow flexion operation. Appropriate motor signals are sensed by the EEG headset from the motor cortex area and the corresponding EMG signal is sensed by the EMG armband.

2) MULTIMODAL OCCUPATIONAL THERAPY SENSORS

Adding multiple dimensions to occupational therapy brings richer immersiveness and greater insights. For example, during a motor imagery session, the coordination of eye and motor signals together make the intercepted signal higher in power for recognition of the movement intention.

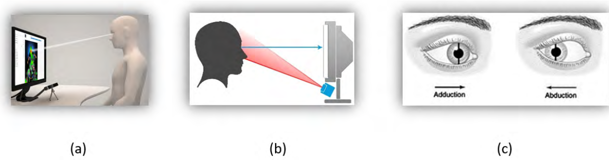


FIGURE 3. Eye tracking used for occupational therapy: (a) an eye tracking device has been setup, (b) the proper field of view for the gaze tracker is maintained, and (c) sample left and right eye movement can be tracked by the device.

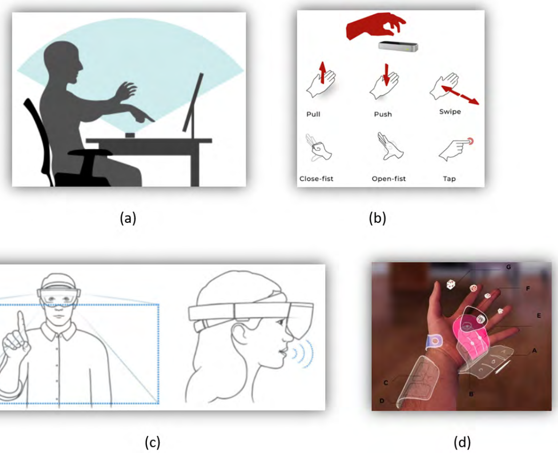


FIGURE 4. Hand kinematic data recognition for OT: (a) 50 Hz Hand Kinematic Data available from the Leap Motion Kinematic Sensor, (b) samples of different gestures recognized by Leap Motion, (c) Microsoft Hololens for hand gesture tracking, and (d) an augmented reality view of gesture based sensors.

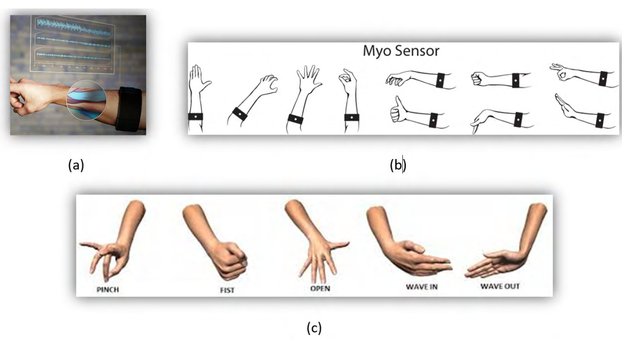


FIGURE 5. (a) 200 Hz, 8-channel EMG Sensors, 9-axis IMU with haptic feedback MYO Armband, (b) Position of placing at the hand, and (c) ability to recognize different hand gestures from the analysis of EMG signals.

Further, the intention imagery can be recognized and verified by actual eye movement data available from eye tracking sensor, the EMG data, and the subsequent gesture tracking data available from gesture tracking sensors. Figure 3 shows a sample eye tracking environment. Figures 4, 5, and 6 show gesture tracking sensors, different joints and body parts each sensor can track and their coverage. A mashup of these sensors provides a rich set of human joint movements for our research. Figure 7 shows how these gesture tracking sensors play a role within the framework. Figure 7(a) shows sample

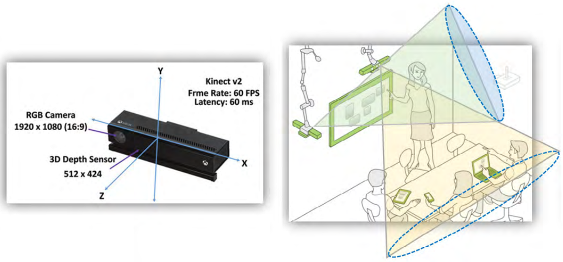


FIGURE 6. Microsoft Kinect V2 sensor, which can detect the motions around 25 joints of a human body within its field of view.

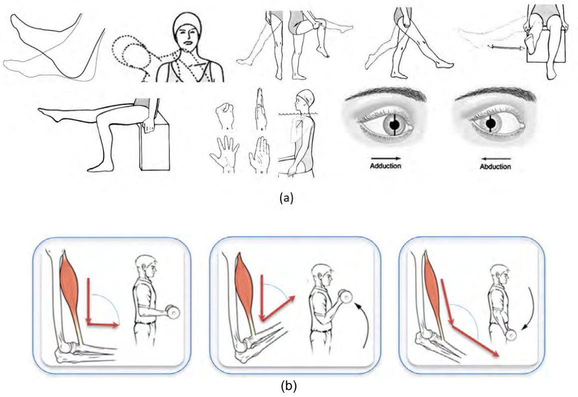


FIGURE 7. (a) Different gestures from various parts of the body that are used for occupational therapy, (b) human body joint anatomy and muscles around joints of interest help in making the required gestures [courtesy 44].

motions around different joints of the body, Figure 7(b) shows the motions around each joint, and how the muscles around each joint respond to each motion type. All of these different sensors together provide real-time maps of joints, motions and muscle tones around the hand [43].

3) FORWARD AND INVERSE KINEMATICS-BASED SERIOUS GAMES

Forward kinematics data, after classification, are fed into a serious game to be able to follow the model therapist avatar. The objective of the controller is to move the suggested joints to the desired set point and return the kinematic data of the attempted action. The therapy engine controller [32] measures the difference between the desired position of the model therapist in the cyber world and the actual position, and help drive the BCI interface with a signal proportional to this. Figure 8 (a) shows the collection of kinematic data from different joints while the occupational therapy exercise takes place. Figure 8(b) shows a scenario a user is shown for target hand position in augmented reality view. The user follows the suggested skeletal position and adjusts his hand position, as shown in Figure 8(c).

III. SYSTEM DESIGN

A. BCI SYSTEM OVERVIEW

Figure 9 shows high level BCI data processing framework. Frequency and spatial filtering is performed prior to feature extraction process. The Common Spatial Pattern (CSP) algorithm is employed to optimally discriminate oscillatory band powers [8], [45]. Classifiers are used to classify between EEG of two different motor actions due to imaginary motor function. Classifiers must be chosen according to the set of the features. Linear discriminant analysis (LDA) is used for a two-class problem [46] while Quadratic Discriminant Analysis (QDA) is used when the hyperplane shows a quadratic signature instead of linear [46]. A Support Vector Machine (SVM) classifier [47] is used as a discriminant hyperplane to further identify classes with maximized margins.

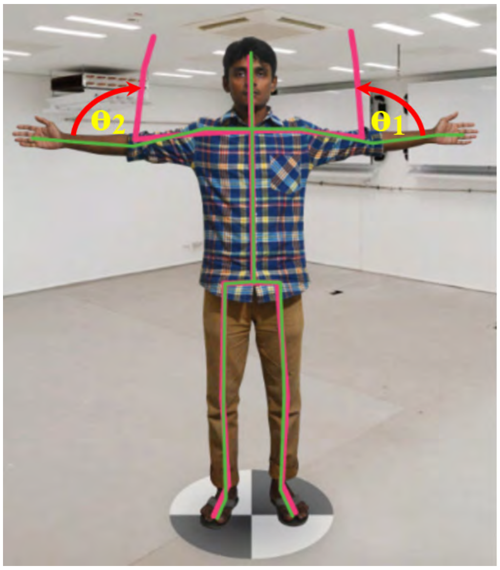


FIGURE 8. Forward kinematic data obtained from gesture tracking sensor shown in Figure 7 is applied to deduce inverse kinematic principles in order to follow the virtual occupational therapist in an augmented reality view.

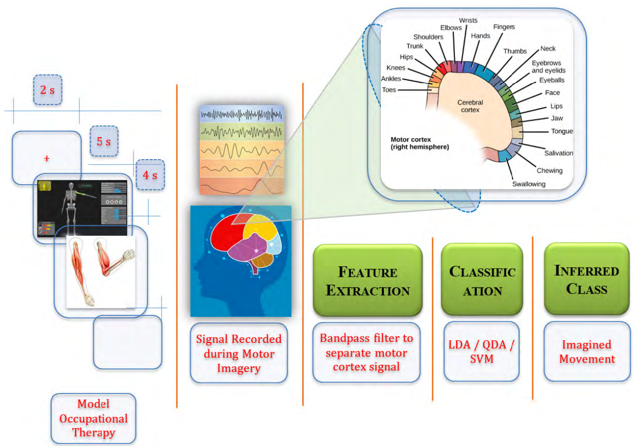


FIGURE 9. BCI data processing (image courtesy [48]).

B. HIGH-LEVEL SYSTEM AND SOFTWARE COMPONENTS

Figure 10 (a) shows the high-level architecture of the proposed system. A subject is assumed to be interfaced and

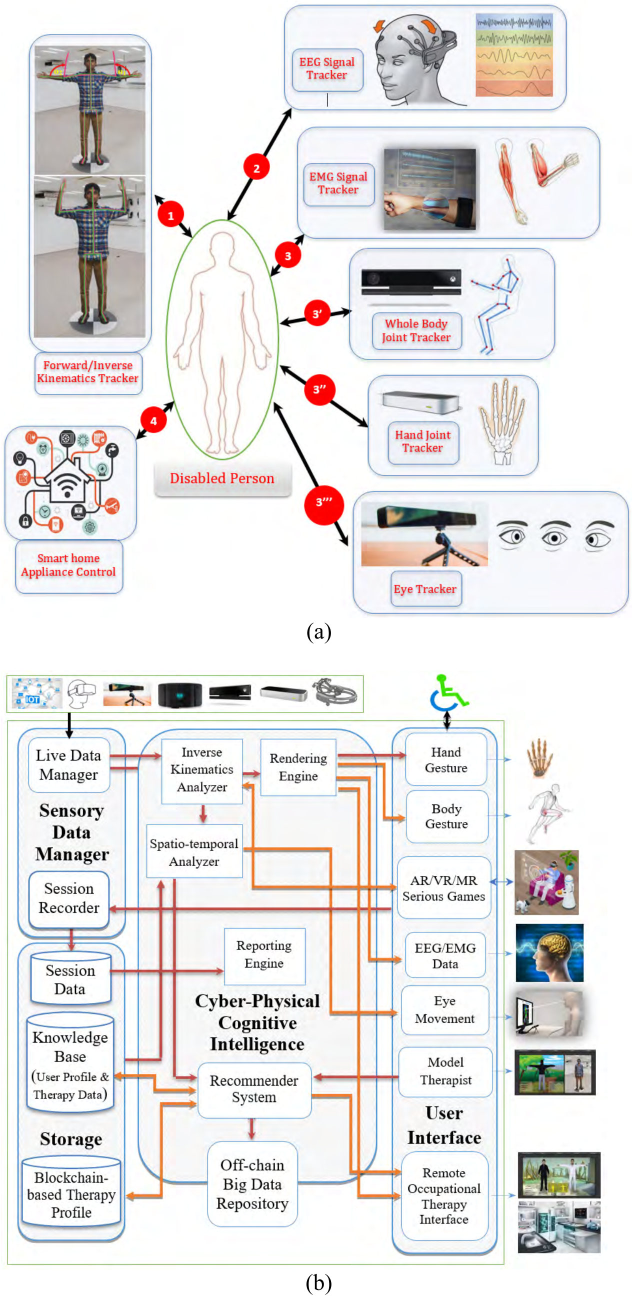


FIGURE 10. **(a) High-level multisensory occupational therapy environment, and (b) high-level system components.**

within the sensory coverage of the EEG, EMG, eye tracker, smart home IoT, and the gesture tracking sensors. The subject is presented with an occupational therapy serious game, which is designed, customized and personalized for the subject, i.e., the gameplay actions and objects are presented such that the person can either use it in observation mode, motor imagery mode or actual therapy mode. The serious games can be in different visual metaphors, such as virtual reality, augmented reality or mixed reality. The subject first creates an image map from the game environment, in which a model digital therapist shows how to perform the therapy. This creates an impression in the motor cortex area, which is intercepted by the EEG sensor. When the user actually intends to start the action, the motor actions are recorded by the other sensors.

Figure 10 (b) shows the software system for supporting the therapy exercise. The **Sensory Data Manager** houses the *Live Data Manager* component which receives the raw sensory data from different sensory media. It also hosts the *Session Recorder*, which provides a recorder suitable for capturing different types of raw data from different **User Interface** components. The **Storage** component is responsible for storing each occupational therapy *Session Data*, *Knowledge Base* and *Blockchain-based Therapy Profile*. The **Cyber-Physical Cognitive Intelligence** engine incorporates several key components. The Inverse Kinematics Analyzer helps in achieving the goal of a therapy session by working with other components such as the *Rendering Engine* and *Spatio-Temporal Analyzer*. The *Rendering Engine* updates the sensory data to the appropriate **User Interface** components. The *Reporting Engine* provides live and historical reports, which can be shared with one's community of interest. The *Recommender System* is an AI-based system, which leverages the knowledge and data available in the *Blockchain*, *Off-chain*, *Knowledge Base* and suggestions available from the *Model Therapist* interface to assist in performing the occupational therapy at home.

C. BCI-BASED SERIOUS GAMES DESIGN

The system is designed based on a research concept of making the brain simulate [49] the action of "want to move" by incorporating the following notions:

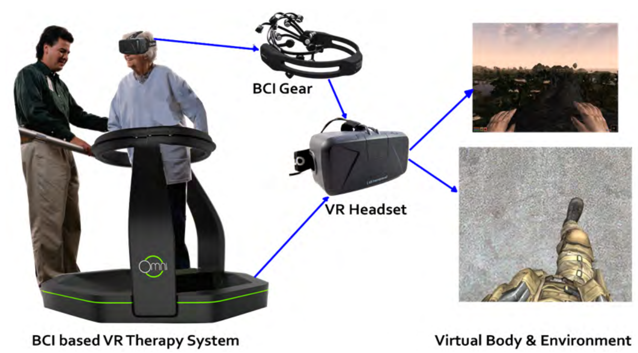


FIGURE 11. **BCI-based occupational therapy scenario.**

- The BCI based Virtual Reality (VR) therapy [49] will provide rich photorealistic virtual environments, along with matching 3D body sensor networks that will be controlled via sensory data generated from the brain and the physical movement of the body in an Omni treadmill that is connected with the head mounted display (see Figure 11).
- A VR environment will be provided to the patient to stimulate his brain into generating a "desiring to make an action" signal. A patient fitted with the setup shown

in Figure 11 can move and interact within a virtual environment just by thinking.

- This thought of "wanting to move" is detected by the BCI wearable device, such as the Emotiv EPOC EEG.
- This will strongly motivate the patient, as it will provide a fully immersive environment with fun activities to perform. If a goal is achieved, the patient will be rewarded in the virtual environment and become motivated to try harder goals.
- Through regular sessions using this system, patients will have higher rates of recovery.

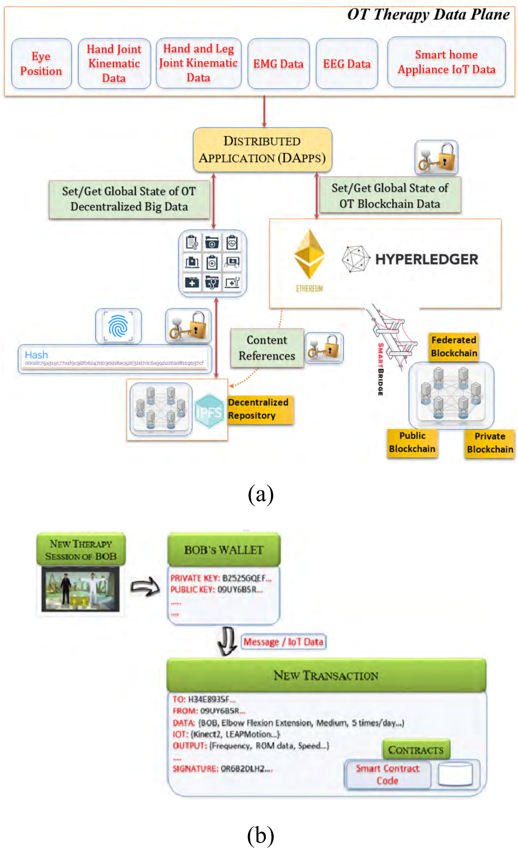


FIGURE 12. **Blockchain and off-chain solution for BCI-based occupational therapy data security.**

Figure 12 (a) shows the blockchain and off-chain therapeutic data repository architecture while Figure 12 (b) shows a sample architecture of a transaction. While the blockchain stores key OT transactions and other performance related metrics, the off-chain is used to store raw EEG/EMG/skeletal data, and other types of multimedia data related to the therapy. As shown in Figure 12, a certain user's OT data related to one session is stored in one of the blocks in the blockchain, which includes a link of the raw OT data as Electronic Medical Record (EMR) within the off-chain to be able to maintain a global view of a particular OT session [13], [21]. The OT transactions can be automated using smart contract, a sample of which is shown in Figure 12 (b).

IV. IMPLEMENTATION

We have tested the framework with healthy subjects via an EEG cap mounted on the participants' heads, performing a standard signal quality check for all electrodes, following by the calibration of the eye-tracking, Leap Motion, and Kinect V2 devices. One test session per subject took around 20 minutes to complete, including the mounting of the psychophysiology measurement equipment and pre-testing. Participants were seated in a comfortable condition and were asked to keep as motionless as possible during the entire procedure, to minimize possible signal interference due to movement. We have used both Emotiv and MUSE EEG headsets as suggested by Zaki *et al.* [6]. We have used a Node.js and AngularJS based framework to access data from the Emotiv EPOC brain sensor or the open dataset available from Emotiv. This supports the Emotiv EPOC EEG headset, analyzing a Raw EEG data stream of 14 electrodes with 128Hz sample rate. Using the API, we can log events such as a person smiling, looking up, down, left or right, blinking an eye, winking left or right, laughing or not, spatial coordinates from gyroscope, and cognitive actions [24], [35], [50].

To record EMG signal, we chose the MYO EMG armband, which was placed over four selected forearm muscles as suggested by Hashimoto *et al.* [19]. This helps in identifying EMG signals responsible for wrist flexion with ulnar deviation, wrist flexion, extension of four fingers and extension of the wrist, and extension and radial abduction of the wrist [51], [53], [54]. Eye-tracking data was recorded using the stationary Eye Tribe eye-tracker with a 60 Hz sampling rate [52]. The eye-tracker was calibrated using the native Eye Tribe calibration system. During the experiment, the following eye data was tracked and recorded: i) x and y coordinates for the on-screen gaze positions of the eyes, ii) pupil dilation for right and left eyes, iii) x and y coordinates for on-screen left and right eye positions. Each on-screen gaze position recorded by the eye-tracker was converted to a fixation point. For classification of a fixation point, the maximum gaze position was set to a 160 pixels distance from the previous sampled gaze position and the minimum number of samples was set to 6 Hz.

To run the aforementioned experimental design conditions, a custom-made stimulus presentation therapy environment was implemented using Unity3D. The application was implemented to handle the following functions: i) present the stimuli via immersive and game-based event, ii) present baseline experimental conditions, iii) assign unique identification triggers to each of the presented conditions, and iv) send the triggers to the EEG/EMG/IoT/Gesture tracking software components.

Through our developed smart home cyber physical game environment. A subject sees a natural daily life environment with appliances which he/she interacts or intends to interact on a daily basis. The OT environment has been interfaced such that the OT exercise comprises those brain and gesture commands that will allow interacting with the surrounding smart home IoT devices through virtual reality, augmented reality, or mixed reality serious game metaphors. This will make one engaged and immersed and allow a therapist to know how many of the daily life activities are performed by the subject. While a subject interacts with the IoT appliances, the corresponding EEG/EMG/eye position/skeletal data is recorded and analyzed by the system.

V. TEST RESULTS

In this paper, we have proposed a smart home appliance control serious game environment based on motor imagery tasks and present the preliminary experimental results. Two types of experiments are being performed: a guided and a self-paced therapeutic exercise. The self-paced BCI paradigm supports two different benefits of occupational therapy. Firstly, it increases the degrees of freedom of brain excitation area. Secondly, it improves the independence and controllability of the BCI system. Finally, it allows adding more dimensions of modality at any given motor imagery session. Hence, the EEG headset will pick up greater number of determinant spatial signals from the brain. Figure 13 shows the EEG signals received from C3, C4, F7, and F8 electrodes containing motor imagery and ERD/ERS stimulation. The results are in line with the findings of Li *et al.* [24].

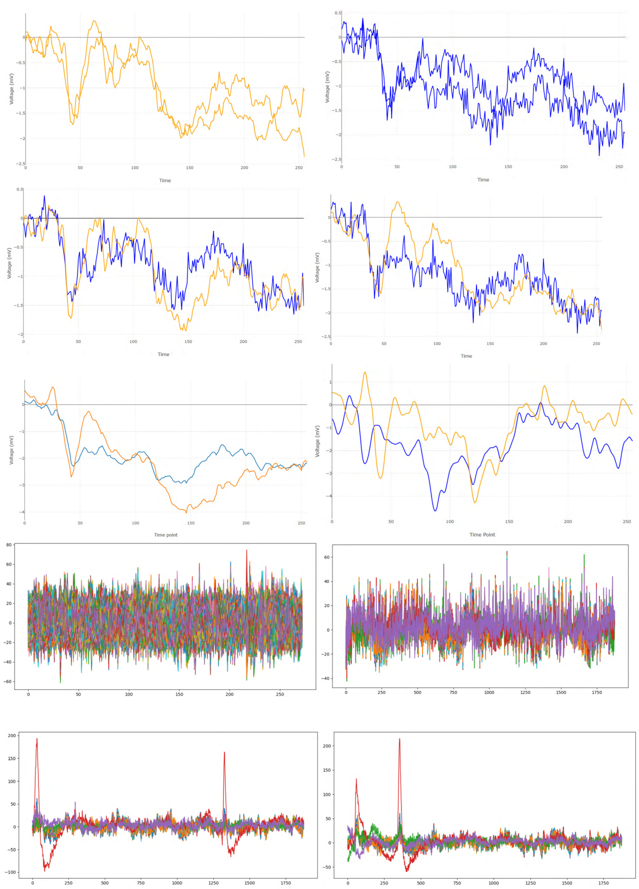


FIGURE 13. EEG signals originated during multi-class occupational therapy mental tasks.

Figure 13 shows the time varying beta and gamma frequency bands (13-100 Hz), which cover most of the frequency information in sensorimotor rhythm, and provide a comprehensive view of the current frequency band used for classification and analysis.

As shown in Figure 13, we have found correlation among different obtained signals such as EEG, EMG, Kinematic, eye tracking sensors and the corresponding occupational therapeutic exercise. For example, in our experiment, the occupation therapy named "70 degrees flexion followed by 75 degrees extension of left hand wrist joint" was broken down into "motor imagery" and "actual therapeutic movement" sessions. During the motor imagery session, a subject follows a model therapist in the VR/AR mode. During this mode, the intention along with the eye movement is tracked from the respective EEG and eye tracking sensors. Subsequently, the subject actually performs the wrist flexion-extension movement as shown to a subject during the motor imagery session. The recorded session data analysis shows that adding multi-dimensional occupational data bring more confidence into how a subject's brain, muscle and joints work as a combined unit while performing daily life activities in its normal state. Since occupational therapy is aimed at helping each patient going to his/her normal life, tracking multiple human body parts that allows a subject in performing a certain high level task through occupational therapy will bring better insight about the quality of improvement.

During the analysis of the dataset as shown in Figure 13, we have found that there is a strong correlation between the motor imagery session and the afterwards actual motor actions' data available from the additional sensory data. This follows the pattern shown in Figure 2 and Figure 11. In other words, the excitation of neuronal activities through the motor imagery session in which a particular occupational therapy session is being shown in a screen is found to be mapped with the subsequent motor neuronal actions that is available through EMG signal at the hand FCU, ED, PL, and ECR muscles, the eye movement data available from the eye tracker and the kinematic data available from hand gesture tracking sensors. This result shows that the occupational therapy can be augmented with the effective EEG, EMG monitoring systems to enhance the interaction with the brain functionality. In particular, the neuro-occupational therapy research would bring more in depth knowledge about a disabled user's quality of improvement in all the arenas such as brain activity, disabled joints, muscle tone and other types of therapeutic gains.

However, we have found several challenges while performing the tests with the dataset. The EEG data is extremely noisy as the off-the-shelf sensors such as emotive and MUSE have to carefully setup to intercept the frequency bands. For example, the beta and gamma wave's discrimination of EEG signal originated due to left and right hand movement motor imagery along with gaze movement captured from C3 and C4 electrodes and F7 and F8 electrodes exhibit different patterns. In addition, the pattern recognition algorithms and the filter designs are highly sensitive to the available dataset. Using a completely automated and tightly synched occupational therapy in which brain though is part of the therapeutic process is highly challenging given the fact that the brain signal controls certain hardware such as smart bulb, smart lock or other types of IoT devices. In our future research, we will address these challenges of improving the recognition rate and the better correlation with brain and other therapeutic movements.

VI. CONCLUSION

In this paper, we have proposed an occupational therapy environment in which a multimodal set of media is used to track the quality of improvement of a subject. The occupational therapy consists of using motor imagery stimulation for an exercise, which is followed by the actual therapeutic exercise. The motor imagery phase is assisted by an online virtual model therapist, during which the EEG signal is recorded about the intention of the user. Afterwards, during the actual exercise, the affected and utilized body joints and motions are recorded through EEG, eye tracker, gesture tracking and IoT sensors. The multisensory occupational therapy data gives a therapist rich insights and greater dimensions of the inner conditions of a subject. In the near future, we intend to stabilize the testing procedure through real-life disabled subjects.

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