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Design of a Hybrid Brain-Computer Interface and Virtual Reality System for Post-Stroke Rehabilitation

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Abstract: As one of common diseases among elderly, stroke often leads to motor impairment and even serious disability. Post-stroke rehabilitation is of great importance to restore the motor function and improve the life quality of stroke survivors. This study therefore sets out to propose a hybrid system based on brain-computer interface and virtual reality, which can provide various training programs including action observation, motor imagery and physical therapy for post-stroke patients with different motor control levels and training demands. The present work offers new insights into the way in which the conventional rehabilitation programs can be turned into innovative and interactive training experiences with advanced technologies to make optimal rehabilitation outcomes for stroke survivors.

Keywords: Rehabilitation engineering, Stroke, Virtual reality, Brain-computer interface, Motor imagery.

1. INTRODUCTION

Stroke is a leading cause of serious disability for adults worldwide. The global number of new stroke occurrence each year is around 16 million, and will keep increasing in future decades as the global population aging (Di Carlo, 2009). Stroke survivors who suffer from hemiparesis or partial paralysis due to the neurological injury, show decreasing independence and require assistance or even fully depend on caregivers in performing dressing, washing, eating and other self-care tasks in daily life (Veerbeek, 2011). Therefore, post-stroke rehabilitation is of great significance in order to improve the life quality of stroke survivors.

Post-stroke rehabilitation generally focuses on maximizing the restoration of the lost motor and cognitive function, and helps stroke survivors relearn skills which are lost due to the brain injury (Johansson et al., 2011). It is usually considered effective if the patient is capable of transferring the motor and cognitive function to the daily life (Trombly, 2002). Although the rehabilitation cannot reverse the neurological injury, it can help survivors become as independent as possible and achieve the best possible quality of life. As one common rehabilitation type, physical therapy includes a variety of muscle maneuvers and exercises, and is widely adopted around the world for stroke recovery (Langhorne, 2009). The conventional physical therapy for upper limb motor impairment which is a very common problem following stroke, involves exercises performed with the impaired arm such as pushing, circle, punching and other movements according to different levels of motor impairment, in order to stimulate injured brain areas and strengthen the motor function with the guidance and help of the therapist. Current evidence suggests that intensive training is able to help patients regain movement in affected arms (Langhorne, 2009). However, repeating the same movement for a long time in the conventional program is rigid and boring, which may result in the decrease of patients' motivation in getting involved and eventually restrict the effectiveness of post-stroke rehabilitation program (Desrosiers, 2003).

Besides the conventional physical therapy, some innovative training approaches have been established for post-stroke rehabilitation. Action observation (AO) is defined to be the training through the observation of movements performed by others and is able to activate the same brain areas used for performing actual movements, especially when the observed movements are familiar and belong to the motor repertoire of the observer (Abbruzzese et al., 2015). Motor imagery (MI) refers to the training of cognitive process in which the patient imagines performing a movement without actually doing it. This training strategy has been initially developed for athletes to improve performance (Guillot & Collet, 2008). It has been demonstrated that during MI training the activation sequences in the motor cortex are similar to those occurring during the actual movement (Carrasco & Cantalapiedra, 2016). MI can be classified as two types: external, with the visual imagery of scenes from an external observer, and internal, with the imagery content from the patient's own body. MI and AO are considered effective when used independently, and furthermore, the combined approach of AO+MI has been found more effective in motor learning for post-stroke rehabilitation and worthy of scholarly attention (Eaves et al., 2016). In fact when compared with the conventional physical therapy, AO+MI allows patients to observe other's movements and mentally practice movements which they cannot perform due to the motor impairment, and shows the special advantage in the early stage of stroke recovery when the rehabilitation is especially crucial but patients have no or very little muscle control of the affected arm.

Recently, advanced technologies such as brain-computer interface (BCI) and virtual reality (VR) have attracted lots of attention as promising tools to improve the rehabilitation outcome. BCI is based on the real-time analysis of acquired brain signals, and is a perfect tool to determine whether the patient is correctly performing MI training (Alonso-Valerdi et al., 2015). As a direct communication pathway between the brain and external devices, BCI is generally composed of six main steps: brain signal acquisition, pre-processing, feature extraction, signal classification, command translation and real-time feedback. It is considered as a new input approach that can change patients' way to interact with the virtual environment, by interpreting brain signals into machine codes or commands (Silvoni et al., 2011). VR technology, which is characterized by the capability of the creation of customized virtual environment and generation of highly immersive user experience, can enable new opportunities for a variety of rehabilitation applications. It has already been used nowadays for treating neurological symptoms and disorders, including but not limited to stroke, Parkinson's disease, dementia, balance and gait disorders (Kellmeyer, 2018). Especially for illnesses requiring upper limb rehabilitation, patients are able to interact with a virtual arm in the virtual environment to perform active exercises. It has been suggested that the implementation of VR technology can improve the rehabilitation effectiveness by increasing patients' interest and engagement in the form of VR game (Fluet & Deutsch, 2013; Lohse et al., 2014). To date, several VR based systems have been developed to provide more options for post-stroke rehabilitation in addition to conventional programs (Laver et al., 2017). There is also emerging evidence that the implementation of VR for rehabilitation can bring benefits to the recovery following stroke (i Badia et al., 2016).

The aim of this study was to propose a hybrid system for post-stroke rehabilitation by combining BCI and VR to enable innovative and interactive training programs including AO, MI and physical therapy. It is hoped that this proposed system can serve as a novel platform for post-stroke patients, in order to make optimal rehabilitation gains based on advanced technologies.

2. METHOD

2.1 Overall system architecture

The hybrid system based on promising technologies of both BCI and VR was proposed for post-stroke patients with different motor control levels and training demands, with the overall architecture shown in Fig. 1. The VR training is divided into two parts: AO+MI which is especially suitable for patients with low levels of motor control, and innovative physical therapy which involves upper limb movements for patients with some volitional motor control of the affected arm. Thus, patients in any stage of stroke recovery can benefit from the current system, which allows patients to control a wide range of training experiences in the virtual environment through their brain activities or upper limb movements by merging BCI and VR technologies.

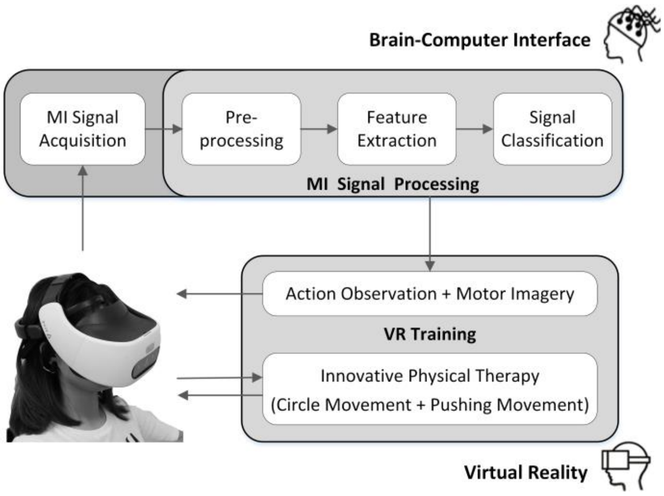

Fig. 1. Architecture of the proposed system

BCI technology in the current system helps to establish a bridge between the patient's brain and the VR training by identifying the patient's internal motor intentions. MI signals from the patient's brain activity which indicate the attempt of body movement is first acquired and pre-processed before analysis due to the influence of noise. Then, features of MI signals can be utilized from feature extraction for signal classification. The identified MI signals after processing is finally used to drive the movement of upper limb of the virtual avatar for MI in VR training. The entire process of MI training is displayed in real-time in the virtual environment, therefore allowing the visual feedback delivered to the patient functioning as AO training through VR technology.

In the proposed system, VR serves as a base platform by providing rich and motivating virtual environments and feedbacks for post-stroke rehabilitation. In VR training of AO+MI shown in Fig. 2, the patient can observe the upper limb movement of the virtual avatar and imagine performing the movement without actual doing it. This training approach can be used in all stages of stroke recovery to restore the motor function, and is especially suitable for patients in the early stage of recovery with very limited motor control of upper limb movements. In this study, the innovative physical therapy in VR training focuses on the circle and pushing movements of upper limb. The circle movement of upper limb shown in Fig. 3 is a beneficial exercise for post-stroke rehabilitation, when the patient has enough strength to move arms but is not able to keep balance in sitting. The pushing movement of upper limb shown in Fig. 3 is also a commonly adopted exercise for stroke recovery with the normal arm helping the affected arm.

Fig. 2. AO+MI training without actual movement

Fig. 3. Circle movement (left) and pushing movement (right)

2.2 MI signal processing

To apply BCI properly and accurately in the current system, it is necessary to design a MI signal classifier. However, this is very challenging due to the low signal-to-noise ratio of brain signals (Wolpaw et al., 2002) and the non-stationary property over time (Grosse-Wentrup, 2011). Therefore, the classification of MI signal generally consists of two processes: an offline model training process based on available dataset of MI signals generated from subjects and measured via corresponding sensors, and an online identification process for pattern recognition (Lotte, 2014). The offline training process can also help with the calibration of classification model for reliable results as MI signals are highly dependent on subjects.

Similar as many other types of signals, MI signals have both temporal and spatial features which can be utilized for feature extraction and classification. The conventional procedure for analysing such kind of signals is to extract features using feature selection algorithms and apply classifier based on these features. However, this process is very domain-specific and hand engineered. Moreover, as the representations of the MI signal are not fully understood by researchers, it is very difficult to design algorithms to select features manually.

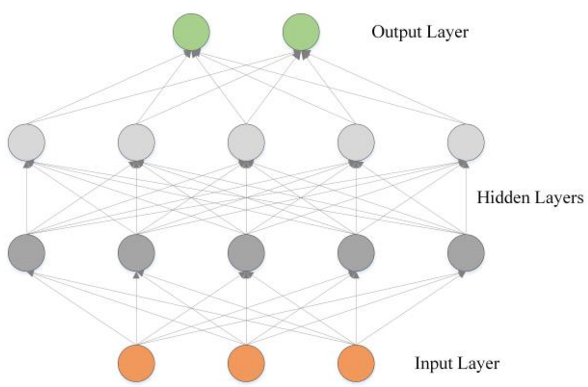

Fig. 4. Neural network structure

With the advantages in approximation and classification, artificial neural networks are widely used in signal processing and pattern recognition. Due to the strong representational power which can learn any function with arbitrary accuracy, multi-layer perceptron (MLP) with hierarchical structure of several perceptrons is one of the most popular neural network types. Besides the above mentioned benefits, hidden and hierarchical features which are very difficult to extract using conventional methods can be learned from data directly to achieve end-to-end learning due to the hierarchical multi-layer structure, which is more suitable for classification problem in complex systems. In this study, MLP was utilized to analyse MI signal patterns for classification purpose, with its structure shown in Fig. 4.

To evaluate the proposed classification model and the effectiveness of the method with relatively low risk at the testing stage, a public dataset with MI recording from the 3rd BCI competition (Lal et al., 2005) was utilized in this study. In the dataset, the time series of the brain activity of a subject performing imagined movements of left small finger or the tongue were recorded using 8x8 platinum electrode grid which was placed on the contralateral (right) motor cortex. The sampling rate is 1000 Hz and the record duration of each experiment trial (i.e.: imagined tongue or finger movement) is 3 seconds. In total there are 278 trials of raw data with labels. The raw signal is shown in Fig. 5. To smoothen the signal for better signal-noise-ratio and improve the analysis efficiency, down sampling technique was applied in the pre-processing stage of the signal from 3000 samples to 100 samples of each electrode for each trial. The signal after down-sampling is shown in Fig. 6.

In order to evaluate the system performance, some datasets were reserved as the testing set for evaluation purpose, and the classification accuracy based on testing set was used as the performance measure. In this study, 228 groups of data were randomly selected as the training set and the rest 50 groups were the testing set. In the training process, a neural network with two hidden layers with 50 and 10 neurons respectively was designed. 80% of the training set was used for training and the rest 20% was used for validation.

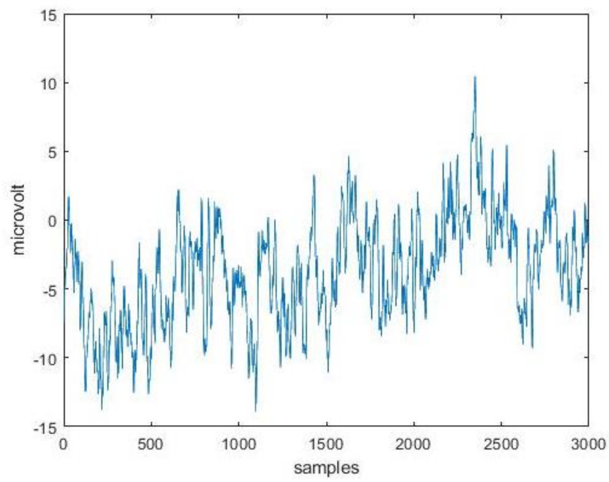

Fig. 5. Raw MI signal of one electrode for one trial sampled at 1000 Hz

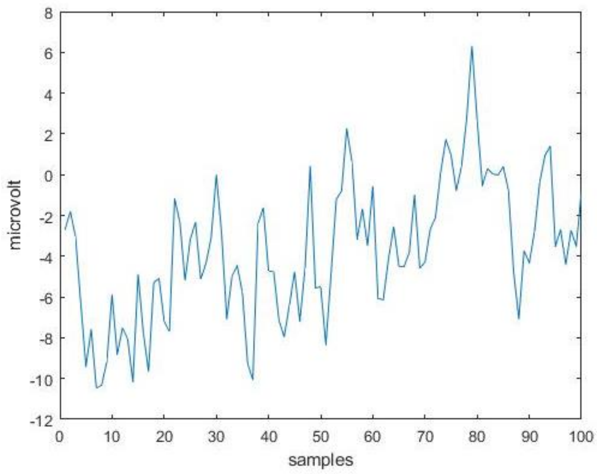

Fig. 6. MI signal after down-sampling

2.3 *Virtual environment design*

The immersive virtual environment in this hybrid BCI-VR system is presented to the patient via the VR device-HTC VIVE Focus Plus shown in Fig. 7, including one head-mounted display (HMD) and one wireless controller. The HMD that supports 6-DOF tracking is powered by a Qualcomm Snapdragon 835 and equipped with two 3.5-inch AMOLED displays. The controller has two main function buttons: teleport and trigger. In order to simplify the operation process for the patient in virtual environments, only the trigger button of the controller is used during the training of upper limb movements in the proposed system.

Fig. 7. HTC VIVE Focus Plus

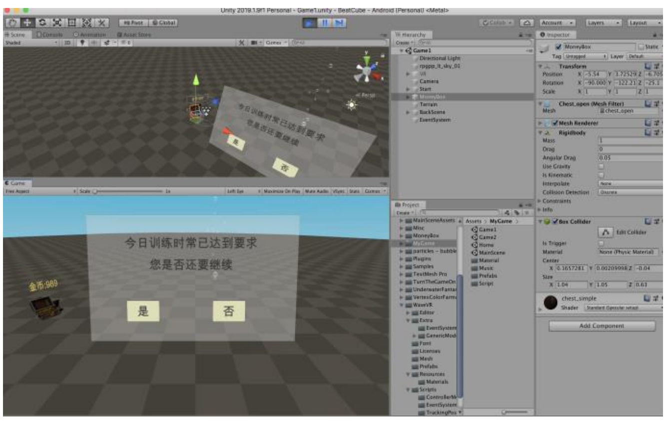

Fig. 8. Unity interface

The virtual reality game scene and game code were developed by Unity and Visual Studio Code software respectively. Unity is a multi-platform game engine for creating interactive 3D contents for virtual reality applications, as shown in Fig. 8. The virtual environment in the current system consists of a game lobby, a game store and various training programs, with 3D models in the virtual environment by both self-building and downloading from the Unity official store. The training programs are presented with various visual stimuli and based on the first perspective of the patient in the virtual environment in order to enable an immersive and engaging user experience.

While wearing the VR HMD in the proposed system, the patient or the therapist can enter the game lobby shown in Fig. 9 to choose the training program. During the training, virtual gold coins can be earned and exchanged for rewards in the game store shown in Fig. 9 to enable a motivating training experience for the patient. Three training programs including AO+MI, circle movement and pushing movement, are available in the current system.

Fig. 9. VR game lobby (left) and game store (right)

In the AO scenario shown in Fig. 10, the patient observes the virtual adult avatar representing the therapist performing the swinging movement of upper limb to activate the same brain areas used for performing the actual swinging movement. The MI scenario shown in Fig. 10 involves two virtual avatars: an adult avatar representing the therapist which is the same as that in AO training, and a teenager avatar representing the patient who is conducting the MI training.

Fig. 10. VR training of AO (left) and MI (right)

The scenario of circle movement is shown in Fig. 11 and was defined that the patient moves the knife representing the controller in the virtual environment, to cut off the string of balloons by performing the circle movement. The pushing movement scenario was designed that a virtual hand representing the controller pokes a bubble after the pushing movement, as shown in Fig. 12.

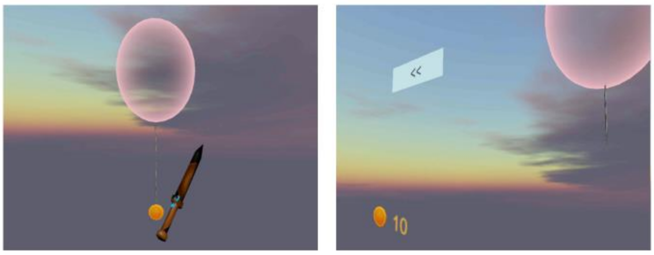

Fig. 11. VR training of the circle movement

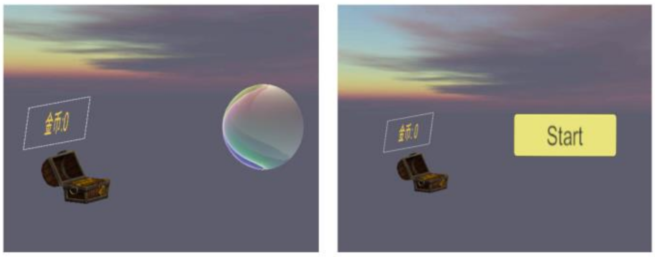

Fig. 12. VR training of the pushing movement

3. RESULTS

3.1 MI signal classification

The network performance for MI signal classification in the training process is shown in Fig. 13 with good validation performance. In the testing process with the 50 groups of data as the testing set, the accuracy of the network was found to be 92%. This implies only 4 groups of data are misclassified, which is acceptable considering the low signal-to-noise nature of MI signals.

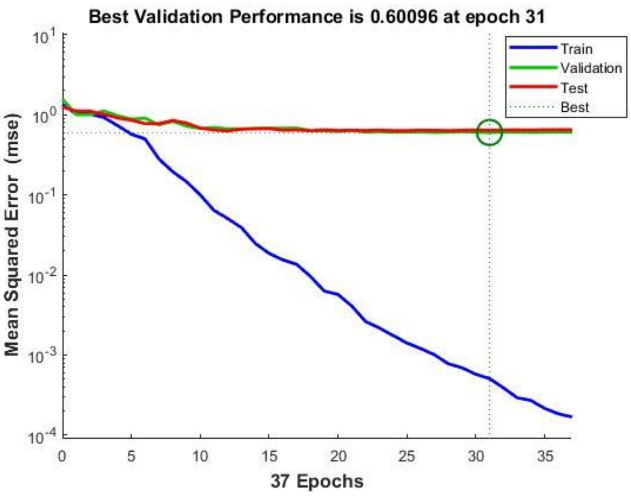

Fig. 13. Network performance in the training process

The good classification result in MI signal classification of the public dataset demonstrates the effectiveness of the neural network method, and also provides the confidence in working with practical experiment data towards the solid performance of the proposed system.

3.2 VR training programs

As an innovative training program with no need for patients performing any actual movement, AO+MI in the VR training of the proposed system requires the patient to observe other's movements and mentally practice movements. After observing the therapist performing the movement, the patient is encouraged to imagine performing the same task, thereby moving the avatar's arm with visual scenes from an external observer. The avatar's arm is essentially controlled by the patient's MI signals acquired and classified through BCI, and can only show the same movement when the patient is correctly conducting the MI training. Owning to this hybrid BCI-VR system, the patient is able to observe the immediate result of MI training through the real-time visual feedback of the avatar's arm movement in the virtual environment, which could be considered as an additional AO training conducted along with MI training.

The physical therapy in the proposed system includes two types of upper limb exercises: the circle movement and the pushing movement. Both these movements are controlled by the corresponding movement of the controller, with the patient's normal arm helping the affected arm. In the circle movement training, the patient can use the controller to move the knife to approach the string and press the trigger button to cut off the string to receive a gold coin. The balloon rises quickly after the cutting and disappears when reaching a certain height. Then a new balloon appears to start the second scene of this scenario. Enough time between two balloons is allowed for the patient to adjust the posture. In the pushing movement training, the moving distance between the virtual hand and the bubble is set according to the arm's length to enable a relatively complete pushing movement. When the virtual hand approaches the bubble through a pushing movement, the patient can press the trigger button of the controller to poke it to burst and collect a gold coin. There is no time limit for each scene, as the bubble bursts only after a complete pushing, and a new bubble appears to activate the next scene.

4. CONCLUSIONS

The aim of the current study was to propose a hybrid system for post-stroke rehabilitation by combining BCI and VR technologies to improve the rehabilitation effectiveness, which has the advantages to offer the innovative training program without actual body movement, various physical trainings on movement patterns and repetitions, immersive virtual training environments, real-time and motivating training feedbacks, etc. The results of current study indicate that the proposed system shows great potential as a rehabilitation tool by turning the conventional trainings into interesting and engaging interactive experiences in virtual environment for patients with different motor control levels and training demands.

The main limitation of this study was the absence of practical experiment data of MI signals to validate the proposed signal classification method. Although the current study was based on a public dataset with MI recording, the findings of the high classification accuracy suggest the effectiveness of the neural network method. The research on experimental MI signal classification is the focus of future work to establish a complete hybrid system for post-stroke rehabilitation.

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REFERENCES

Abbruzzese, G., Avanzino, L., Marchese, R., & Pelosin, E. (2015). Action observation and motor imagery: innovative cognitive tools in the rehabilitation of Parkinson's disease. *Parkinson's Disease*, 3, 1-9.

Alonso-Valerdi, L. M., Salido-Ruiz, R. A., & Ramirez-Mendoza, R. A. (2015). Motor imagery based brain–computer interfaces: An emerging technology to rehabilitate motor deficits. *Neuropsychologia*, 79, 354-363.

Carrasco, D. G., & Cantalapiedra, J. A. (2016). Effectiveness of motor imagery or mental practice in functional recovery after stroke: a systematic review. *Neurología*, 31(1), 43-52.

Desrosiers, J., Malouin, F., Richards, C., Bourbonnais, D., Rochette, A., & Bravo, G. (2003). Comparison of changes in upper and lower extremity impairments and disabilities after stroke. *International Journal of Rehabilitation Research*, 26(2), 109-116.

Di Carlo, A. (2009). Human and economic burden of stroke. *Age Ageing*, 38, 4-5.

Eaves, D. L., Riach, M., Holmes, P. S., & Wright, D. J. (2016). Motor imagery during action observation: a brief review of evidence, theory and future research opportunities. *Frontiers in Neuroscience*, 10, 514.

Fluet, G. G., & Deutsch, J. E. (2013). Virtual reality for sensorimotor rehabilitation post-stroke: the promise and current state of the field. *Current Physical Medicine and Rehabilitation Reports*, 1(1), 9-20.

Grosse-Wentrup, M. (2011). What are the causes of performance variation in brain-computer interfacing? *International Journal of Bioelectromagnetism*, 13(3), 115-116.

Guillot, A., & Collet, C. (2008). Construction of the motor imagery integrative model in sport: a review and theoretical investigation of motor imagery use. *International Review of Sport and Exercise Psychology*, 1(1), 31-44.

i Badia, S. B., Fluet, G. G., Llorens, R., & Deutsch, J. E. (2016). Virtual reality for sensorimotor rehabilitation post stroke: Design principles and evidence. In *Neurorehabilitation Technology*, 573-603. Springer, Cham.

Johansson, B. B. (2011). Current trends in stroke rehabilitation. A review with focus on brain plasticity. *Acta Neurologica Scandinavica*, 123(3), 147-159.

Kellmeyer, P. (2018). Neurophilosophical and ethical aspects of virtual reality therapy in neurology and psychiatry. *Cambridge Quarterly of Healthcare Ethics*, 27(4), 610-627.

Lal, T., Hinterberger, T., Widman, G., Schröder, M., Hill, J., Rosenstiel, W., Elger, C., Schölkopf, B., and Birbaumer, N. (2005). Methods towards invasive human brain computer interfaces. In *Advances in Neural Information Processing Systems*, 737-744.

Langhorne, P., Coupar, F., & Pollock, A. (2009). Motor recovery after stroke: a systematic review. *The Lancet Neurology*, 8(8), 741-754.

Laver, K. E., Lange, B., George, S., Deutsch, J. E., Saposnik, G., & Crotty, M. (2017). Virtual reality for stroke rehabilitation. *Cochrane database of systematic reviews*, 11, CD008349.

Lohse, K. R., Hilderman, C. G., Cheung, K. L., Tatla, S., & Van der Loos, H. M. (2014). Virtual reality therapy for adults post-stroke: a systematic review and meta-analysis exploring virtual environments and commercial games in therapy. *PloS one*, 9(3), e93318.

Lotte, F. (2014). A tutorial on EEG signal-processing techniques for mental-state recognition in brain–computer interfaces. In *Guide to Brain-Computer Music Interfacing*, 133-161. Springer, London.

Silvoni, S., Ramos-Murguialday, A., Cavinato, M., Volpato, C., Cisotto, G., Turolla, Piccione, F. & Birbaumer, N. (2011). Brain-computer interface in stroke: a review of progress. *Clinical EEG and Neuroscience*, 42(4), 245-252.

Trombly, C. A., & Ma, H. I. (2002). A synthesis of the effects of occupational therapy for persons with stroke, Part I: Restoration of roles, tasks, and activities. *American Journal of Occupational Therapy*, 56(3), 250-259.

Veerbeek, J. M., Kwakkel, G., van Wegen, E. E., Ket, J. C., & Heymans, M. W. (2011). Early prediction of outcome of activities of daily living after stroke: a systematic review. *Stroke*, 42(5), 1482-1488.

Wolpaw, J. R., Birbaumer, N., McFarland, D. J., Pfurtscheller, G., & Vaughan, T. M. (2002). Brain–computer interfaces for communication and control. *Clinical Neurophysiology*, 113(6), 767-791.