Fundamental problems in rehabilitation robots based on neuro-machine interaction

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Abstract: Study results in the last decades show that amount and quality of physical exercises, then the active participation, and now the cognitive involvement of patient in rehabilitation training are crucial to enhance recovery outcome of motor dysfunction patients after stroke. Rehabilitation robots mainly have been developed along this direction to satisfy requirements of recovery therapy, or focused on one or more of the above three points. Therefore, rehabilitation robot based on neuro-machine interaction has been proposed for the paralyzed limb training of post-stroke patient, which utilizes motor related EEG, UCSDI (Ultrasound Current Source Density Imaging), EMG for the robot control and feeds back the multi-sensory interaction information such as visual, auditory, force, haptic sensation to the patient simultaneously. This neuro-controlled and perceptual rehabilitation robot will bring great benefits to post-stroke patients. In order to develop such a kind of rehabilitation robot, some key technologies, such as non-invasive precise measurement and decoding of neural signals, realistic sensation feedback, coordinated control for both the rehabilitation robot and the patient, need to be solved. In this paper, some fundamental problems in developing and optimizing such a kind of rehabilitation robot based on neuro-machine interaction are proposed and discussed.

Key words: Rehabilitation robot; neuro-machine interaction; active rehabilitation therapy; multi-sensation feedback

1 Introduction

Stroke is a leading cause of serious, long-term disability. For instance, in China every year there are about 2,000,000 people suffering from a stroke, of which approximately 66 percent survives the stroke, commonly involving deficits of motor function. Although the optimal therapy for patients who suffer from stroke or cerebrovascular accidents is still a point of discussion, one theory is that patients will recover better and faster if having intensive physiotherapy directly after the accident. Undamaged brain tissue will then take over the functionality of the damaged tissue and the lost functionality caused by those severe physical traumas will be regained [1]. In order to assist the stroke patients during rehabilitation therapy, some researchers have developed several robot-assisted rehabilitation therapy systems, such as MIME [2], ARM Guide [3], MIT-MANUS [4], UECM [5]. Robotic aids can provide programmable levels of assistance, and automatically modify their output based on sensor data using control frame works [6-7]. Rehabilitation robot usually works on two modes, one is passive recovery training mode another is active recovery training mode. Owing to the patients exhibit a wide range of arm dysfunction levels, it is important to provide optimal assistance in robot-assisted rehabilitation therapy, which has been demonstrated by Kahn et al. [8]. Passive recovery training as the initial stage of rehabilitation therapy, its aim is to reduce the muscle tone and spasticity of the impaired limb, and increase its movable region [9]. The main objective in this stage is to control the robot stably and smoothly to stretch the patient paralyzed limb moving along a predefined trajectory with the position controller. Thus, in passive recovery training mode, providing a desired movement trajectory with appropriate velocity to the patient is a key issue for rehabilitation robot control. Lots of studies focused on how to control robot to move along the desired trajectory in passive rehabilitation mode [10-12]. During recent years the field of robot-assisted rehabilitation has been inspired by new available technologies. One example is Neuro-Machine Interface (NMI) including Brain-Computer Interface (BCI), EEG and EMG based Human-Robot Interface (HRI) [13-15], another example is Virtual Reality (VR), which gives the patients multi-sensation information such as audiovisual display and haptic feedback during physical therapy [16]. Xu et al. [17] developed a novel robot-assisted rehabilitation system based on motor imagery EEG for paralyzed arm training of post-stroke patients, and the experimental results demonstrate the feasibility of the system. A clinically proven MANUS robot is integrated with the BCI to complement the robot control mechanism by the motor imagery of the patient [18]. Mauro et al. [19] developed an integrated hybrid neuro-rehabilitation systems combined with virtual reality, brain neuro-machine interface, and exoskeleton robots in order to overcome the major limitations regarding the current available robot-based rehabilitation therapies.

In this paper, we will review the development of the rehabilitation robot systems based on Neuron-Machine Interaction (NMI) and discuss the key technologies of the NMI based rehabilitation robot. At last, the fundamental problems in NMI based rehabilitation robot systems will be illustrated.

2 Rehabilitation robot systems based on neuro-machine interaction

In recent years, there is a rapid growth in Neuro-Machine Interface technologies such as BCI which assist paralyzed or locked-in patients communicate with the outside world, control devices such as television and motorized wheelchair. In particular, some studies have shown the potential ability of using BCI to control Functional Electric Stimulation (FES) system for assistive hand movements. Tan et al. [20] proposes a BCI-FES system for stroke patients' arm flexion and extension exercises. Both systems employ the motor imagery technologies. Wang et al. [18] explores the possibilities of using noninvasive BCI and mechanical robotic-aided rehabilitation for paralyzed upper limb rehabilitation of post-stroke patients. The BCI based rehabilitation robot guides the post-stroke patients to perform rehabilitation exercises effectively, which motivates the post-stroke patients towards faster recovery.

Most of the recent researches on rehabilitation robot systems based on Neuro-Machine Interface utilize movement related EEG or EMG signal acquisition and processing methods for robot control. Fig.1 illustrates the architecture of motor imagery EEG based rehabilitation robot system. This system is composed of three core modules, EEG signal acquisition and processing module, rehabilitation robot with controller module, visual display module. The system translates the mental imagination of movements acquired by analyzing EEG signal from a post-stroke patient into commands to control a robotic arm to manipulate the patient impaired arm during a physical therapy exercise.

2.1 Structure of the rehabilitation robot system based on neuro-machine interaction

According to the current neuro-plasticity research results, existing findings suggest that extrinsic visual, auditory and haptic feedback may improve motor and functional performance, and the perception feedback stimulation is vital for effective rehabilitation of post-stroke patients [21-23]. The structure of the rehabilitation robot system based on Neuro-Machine Interaction (NMI) with perception feedback is shown in Fig. 2.

The rehabilitation robot system based on NMI consists of four core modules: non-invasion neural signal acquisition and processing module, rehabilitation robot with controller, interactive virtual reality/virtual game module, and multisensory stimulation module. As comparison to the structure of existing rehabilitation robots based on BCI shown in Fig.1, the rehabilitation robot system based on NMI emphasizes the precise neural signal measurement, decoding as well as multi-sensation feedback.

The noninvasive neural signal acquisition and processing module, including EEG, EMG and UCS-

DI (Ultrasound Current Source Density Imaging, which detects neuro-signal of functional part) and some new tools for neural signal detection, measures the electrophysiological activities of the neuron systems and extracts features from raw signal data. In rehabilitation robot module, the controller unit converts the neural signal processing results into control commands for robot control. The interactive virtual reality/virtual game module such as virtual walk, virtual daily tasks, virtual car racing, haptic space exploring, etc., provides interesting interactive environments to patient. The multisensory stimulation module provides audiovisual display as well as force stimulation and haptic display, etc., to the post-stroke patient. The rehabilitation robot system based on NMI will bring great benefits to rehabilitation therapy and motor function recovery.

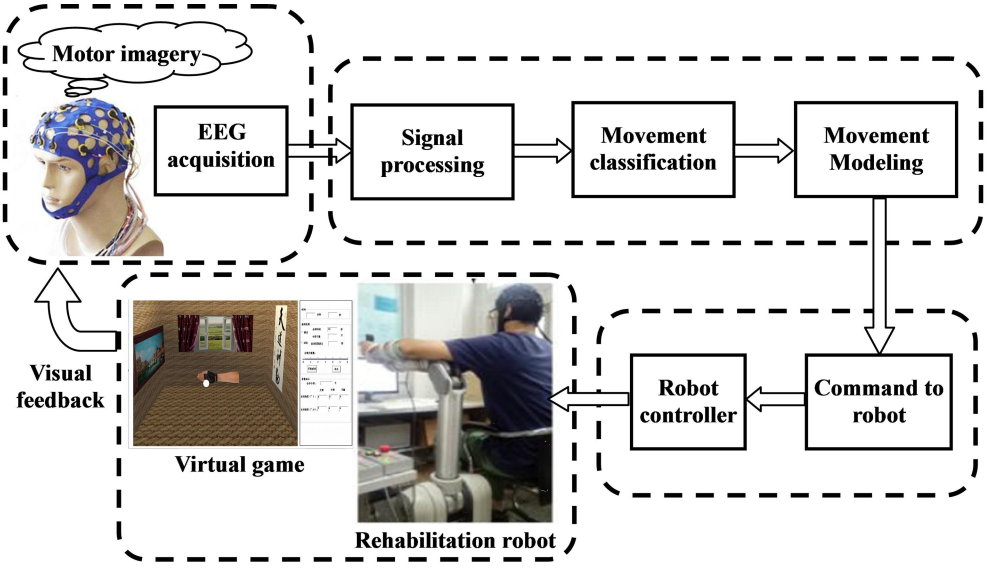

Fig. 1 Motor imagery EEG based rehabilitation robot system

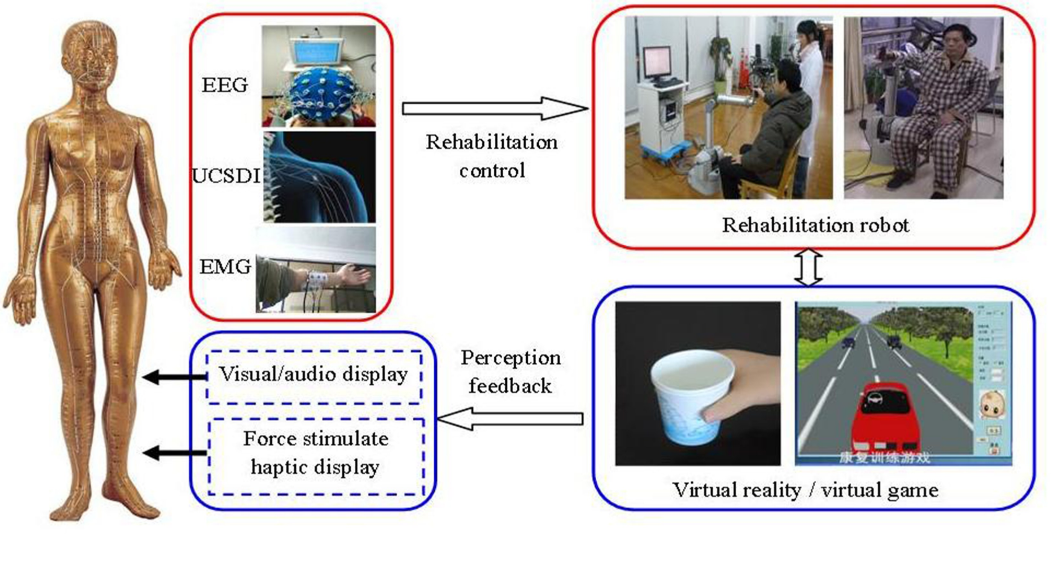

Fig. 2 The rehabilitation robot system based on Neuro-Machine Interaction

2.2 Bilateral interaction in rehabilitation robot system based on neuro-machine interaction

The bilateral interaction rehabilitation exercises are intended to simultaneously activate the efferent (motor control) and afferent (sensory perception) pathways, by providing the necessary assistance as needed and causes-effects based inspiration feelings during the execution of the therapy training. Such a kind of bilateral interaction has been proven to favor cortical reorganization and neural path recovery [19]. The rehabilitation therapy studies in the last decade show that the outcome of the rehabilitation therapy mainly depends on three aspects: 1) the active participation of the patient; 2) the quality and amount of physical activity; 3) the cognitive involvement of the patient. Therefore, advanced technologies supported bilateral interactions between human neural systems and machine (environment) are designed to optimize rehabilitation therapy, as illustrated in Fig. 2. In the proposed rehabilitation therapy system based on NMI, EEG/UCSDI/EMG based active rehabilitation robot is used for inspiring the active participation of the patients. Virtual Reality based game with visual/auditory /force/haptic feedback is used to enhance cognitive involvement, motivation and immersion of post-stroke patients during the process of rehabilitation exercise.

1) For the output (motor control) pathway: The electrophysiological signal generated by motor imagery of human brain is detected as EEG signal for reading patient's "motor-mind". The "motor-mind" is then recognized by analyzing and decoding the motor related EEG signals. Finally, the motor command is sent to control the rehabilitation robot and virtual environment for impaired limb rehabilitation training of the patient. Unfortunately, due to the partly shielding effect of the skull and low spatial resolution of EEG, it becomes a grand challenge to precisely measure and decode the movement-related EEG signals caused by motor imagery [24-25]. One possible solution is utilizing USCDI technology [25-27], which can detect neuro-signals of functional part on lesion, and EMG together with EEG to recognize complex motor commands of human brain. For the post-stroke patients with limb seriously paralyzed, i.e. can hardly move autonomously, the motor and neural function will degenerate if do nothing in a long time according to the theory of neurological rehabilitation. In this case, rehabilitation exercises based on EEG/USCDI/EMG is especially suitable for activating the muscles and nerves of the paralyzed limbs and reconstructing the motor control function in cortex. For the paralyzed limb can partly autonomously move case, the interaction with robot based on EEG/USCDI/EMG can inspire the active participation, motivation and immersion of the patient, which are crucial for recovery outcome. So the post-stroke patient can input motor commands to the robot for assisting desired exercises such as flexion-extension of elbow, stepping, performing haptic manipulations, i.e. space exploring, grabbing an egg, holding a cup of water, etc.

2) For the input (sensory perception) pathway of human nervous system: Re-learning of the nervous system is one of basic mechanisms for motor function recover after stroke, by that undamaged neurons will then take over the functionality of the damaged neurons [1]. The effect feedback of the interaction with environment is very important for the re-learning of the nervous system to regain coordinated motor control function just like the error back propagation for adjusting the weights of the artificial neural networks (ANN). The motor function recover is not only attributed to the physical intervention in training process but also to the stimulation of mental activity of the patient [19]. Patient's motivation and immersion in the rehabilitation training can be achieved by means of multi-sensation information feedback such as visual/auditory/force/haptic/vibrant stimulation, which are crucial for optimizing recovery outcome. Visual/auditory/force/haptic/vibrant sensations generated during the process of interaction with virtual environment of post-stroke patient through rehabilitation robot are presented to the patient. The force/hap-

tic sensations of interaction with VR can be reconstructed by back-drivable robot and force/haptic devices such as force feedback data glove. Vibrant feeling in playing virtual game can be presented by a vibratile motor array device. The patient's motivation is fundamental and can be improved by assigning a video feedback game to the therapy that will make the rehabilitation training become more attractive and interesting [28-29]. It is important to note that efferent process (motor control) and afferent process (sensory perception) are not independent. On the one hand, an efferent action (motor control) in the human neuron system can be triggered by an afferent event (sensory perception) during process of interaction with the robot (environment). On the other hand, the afferent activity (sensory perception) can be used to modify the efferent action (motor control) to interact with the robot (environment), i.e. to alter the velocity of limb motor.

Implementing such a kind of rehabilitation robot system depends on the advancements of three fundamental technologies, the first one is the noninvasive precise control information extraction technology from neural signals, as conventional noninvasive neural signal decoding methods are compromised with limited spatial resolution of EEG/EMG; the second one is the realistic sensation feedback technology, how the perception feedback inputs into the brain and how it promotes neuromuscular function recovery remains an open question; the last one is the coordinated control technology for both the rehabilitation robot and the patient, it is still not clear how to develop effective control methods that simultaneously exercise the paralyzed limb by the robot and the central nervous system of patients. In summary, there are following several fundamental problems in developing such a kind of rehabilitation robot system.

3 Fundamental problems in rehabilitation robots based on neuro-machine interaction

3.1 Extract control information from neural signals

In the rehabilitation robot based on neuro-machine interface, the commands for the rehabilitation robot control should be extracted from the neural signals firstly. Recent researches on such a task mainly focus on the following three progressive directions:

1) Pattern recognition based approaches:

EEG and EMG are widely used non-invasive NMI due to their low expense and high temporal resolution. The EEG/EMG data acquisition is followed by a pre-processing stage which attenuates the artifacts and noises present in the recorded signal, to enhance the relevant information. The subsequent feature extraction stage is responsible for forming discriminative set of features in the form of frequency patterns [30], temporal patterns [31], time-frequency patterns [32], autoregressive models [33], or spatial patterns [34-35] for predefined imagined or normal muscle-based motion performed. The features extracted are used to train a classifier to decode the users´ intent and subsequently translate the features into a set of output commands for operating the rehabilitation robot. Decades of research in EEG/EMG pattern recognition have provided frameworks that achieve high classification accuracies (>95%) on a few predefined motions (>4 classes for EEG, and >10 classes for EMG) [15, 17, 36-38].

However, there are several drawbacks for the pattern recognition based approaches applied to the rehabilitation robot system based on NMI [39]. First, such a kind of approaches can only provide limited number of control commands with the predefined discrete motion classes. For example, Most of the BCIs that studied movement-related features use brain signals during movement of different body parts such as right hand, left hand, foot, and tongue [40]. Second, the control, exact as it might be, is still sequential, with the possibility of controlling only one motion at a time, apart from few exceptions of systems that were recently shown in laboratory settings to be able to activate two classes concurrently. Therefore, the pattern recognition systems may not be able to provide a natural way for manipulating the rehabilitation robots [41].

In addition to the above limitations of pattern recognition based control, there are several problems in translating the promising results obtained with these systems in laboratory settings to practical rehabilitation robot systems. One factor is the inherent non-stationarity in a single recording session of EEG/EMG signals, which tends to deteriorate classification performance with the conventional pattern recognition approaches [42]. For example, during a session when the BCI user performing motor imagery for training and testing, they are also subject to variations from many sources, for instance changes in attention and motivation, changes in impedance when electrodes get loose, eye blinking and movement, swallowing, teeth crunching and etc. Such changes may introduce strong non-task related activities into user's background activity, e.g., the electro-oculogram (EOG) artifacts due to the eye movement affecting the recordings from the frontal lobe, and the α-activity due to changes in the vigilance affecting the recordings from the occipital lobe. Other factor is the between-session non-stationarity [42], where the training trials and testing trials may be recorded in different sessions such as on different days, employing different neurofeedbacks, experimental protocols and so on. The combined action of these factors leads to the practical inapplicability of the pattern recognition control systems developed so far [39]. In this respect, there is an increasing the attention in reducing the impact of the above factors of influence [43-44].

2) Movement kinematics decoding based approaches:

The pattern recognition based control is usually sequential and requires on/off mode of operation (a class is either active or non-active). Natural movements are very different from these approaches since they are based on the simultaneous and proportional control of multiple DoFs [41]. In order to provide continuous control with multiple DoFs for the robot, it is desired to directly decode the movement kinematics such as the velocity, direction, trajectory and so on from the neural signals. Recent findings show the neural activity using invasive intracortical local field potentials over Electrocorticography (ECoG) to decode movement directions and continuous movement trajectories [45]. ECoG is an invasive technique where grids of electrodes are implanted and summed currents over a volume of tissue are recorded as signals. However, it is impossible and unsuitable for patients only having motor disorder to accept this kind of invasive techniques [24]. The noninvasive electrophysiological detecting modalities such as EEG and EMG are much safer and cost lower. Nevertheless, it is not clear whether the motor kinematics information is present in the non-invasive EEG/EMG. In fact, EEG signals were believed to lack sufficient signal-to-noise ratio and bandwidth to encode detailed movement kinematics [46]. This assumption has been challenged in recent years generating a vivid discussion in the field [45-47]. Using low frequency EEG, reconstruction of hand movement profiles have been reported (e.g., position and velocity profiles in 2D [48-49] and 3D workspaces [50-52]). These results indicate that detailed limb kinematic information could be present in the low frequency components of EEG, indicating the possibility of continuous decoding in a noninvasive manner.

However, the performance of existing such a type of approaches is still far from an acceptable one. Besides, there are three main basic problems in non-invasive NMI for movement kinematics decoding. First, it is difficult to understand the underlying neurophysiology, due to lack of generic and consistent information regarding correlates of movement parameter in EEG/EMG. Second, it should perform proper NMI experimental design since tracking MI parameters is difficult, and restrict artifacts, such as imposing eye movement and muscle activation restrictions and so on. Third, it is necessary to investigate the impact of decoding error on the rehabilitation robot system based on NMI, attributing to the inter-relation between direction, speed and force.

3) Two-way communication based approaches:

Many simple tasks still prove difficult even with today's very advanced rehabilitation robots because no sensory signals travel from the rehabilitation robot back to the brain. Amputees have to consciously direct every discrete movement of the robot, relying on what their eyes see for feedback rather than on their natural sense of proprioception [53-55]. This level of effort results in clumsy and slow movements that leave people exhausted by the concentration and time needed to accomplish such tasks as reaching a target. A critical goal, then, is to engineer an interface between the nervous system and the robot that allows two-way communication of both motor and sensory information [53-55]. Such a two-way communication technique would permit the development of rehabilitation robots that can be controlled by intuitive thought and that can feel the presence of limb.

More and more researchers are now pursuing this objective. Cullen and Smith have developed a kind of "adapter cord" that translates nerve impulses into electrical signals, using laboratory-grown nerve fibers and electricity-conducting polymers [53-55]. Such a kind of adapter plug have been built in rats, if all goes well, they will eventually use such biohybrid bridges to link up the severed peripheral nerves in a human being in such a way that a prosthetic device can directly receive motor control instruction from the brain, and can inversely transmit the force/haptic sensory information back to the brain so that the prosthetic device feels like a natural hand [53-55]. However, such an invasive direct two-way communication interface has to undergo a surgery to setup it in the paralyzed limb. In addition, this technique is still in its infancy and very expensive, which may not be acceptable for patients only having motor disorder. Therefore, it is a great challenge to develop a noninvasive interface that can provide the two-way communication. To create such a NMI, the noninvasive technology that can detect neurophysiological signals in the two-way communication should be developed first.

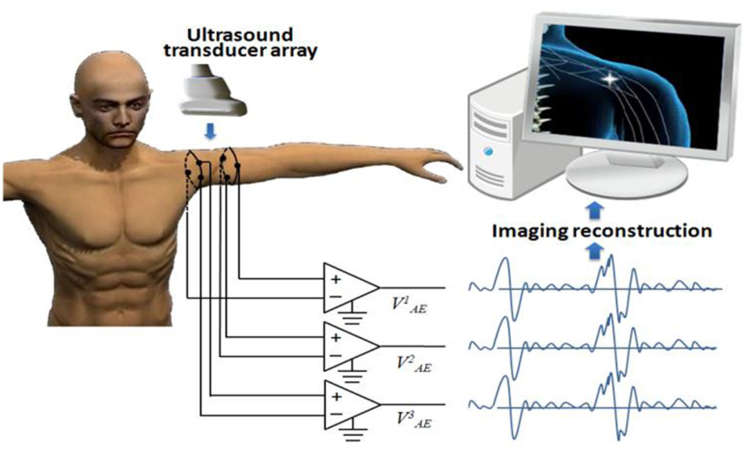

Fig. 3 Measure electroneurographic signal in high spatial and temporal resolution by ultrasound current source density imaging (UCSDI)

Recently hybrid imaging modalities combing ultrasound scanning and electrical current density imaging through the acousto-electric (AE) effect to achieve high resolution in both space and time domains, namely acoustoelectric tomography (AET) and ultrasound current source density imaging (UCSDI), have attracted considerable attentions [25, 26, 56-62]. Those noninvasive imaging modalities have the potential to provide electrophysiological functional maps with ultrasonic resolution. Initial experiments under controlled conditions indicate that UCSDI has potential of achieving sub-millimeter spatial resolution and decent sensitivity of measuring current densities ($2 \sim 4$ mA/cm^2) [56, 58-59]. Such a kind of hybrid imaging modalities can be use to image current flowing in lobster nerve cord with physiologically realistic current densities [59], electrocardio-pulse propagation process, cardiac activation of a rabbit heart [57], the local potential field and weak current flowing in volume conductor [63]. This kind of noninvasive nature imaging measures the neurophysiological signal directly and has high resolution in both space and time domains (millimeter-microsecond scale even better) [27] so it is desirable for detecting the electrophysiological signals for rehabilitation robot control, and is suitable for imaging the neurophysiological processes how the neuron system control musculoskeletal motor performing a action as well as how the multi-sensorial signals are back-propagated through neural paths to the brain. As illustrated in Fig. 2 and Fig. 3, the limb motor related electrophysiological signals in the peripheral nerve is detected using this UCSDI and then sent to a signal processing unit which convert motor related neural signals into commands of robot to control the robot performing rehabilitation therapy. With UCSDI, it is now able to record the signals of the nerves going in one direction (down the limb) and to stimulate the nerves going in the other direction (toward the brain).

One major challenge for using UCSDI to imaging electrophysiological activity of the brain and detect the neurophysiological signal in the motor cortex is that the skull which envelops the encephalon fully will block the ultrasound conducting into the cortex, so the AE signal in UCSDI can't gain for detecting motor cortex electrophysiological signal. Fortunately, the motor related electrophysiological signal in peripheral nerve can be detected by using UCSDI. Similar to the skull, the bone will block the propagation of ultrasound, generating echo in the interface between muscle and bone that will also be a challenge for detecting the electrophysiological signal in peripheral nerve. Possible solution is that scan from one side and then from the opposite side or arrange two phased ultrasound arrays in the two opposite sides to improve frame speed. The influence of echo can be comparatively easily eliminated because the echo generates after the AE signal so they can be separated in time domain [62]. Further researches will be needed for fitting UCSDI to detect motor related electrophysiological signal for rehabilitation robot control and image the neurophysiological process how the neuron system control musculoskeletal motor.

Although the same as imaging outputted neural signal in technology, imaging/detecting how the sensorial electrophysiological signals of limb are activated, back-propagated and then perceived by the brain is more important for robot-assisted active rehabilitation due to activation of neural pathway and re-learning of neuron system by sensorial feedback are essential for regaining coordinated motor control function of patient. This will be discussed in the following section.

3.2 How the perception feedback affects the neuromuscular rehabilitation

Although robot-assisted rehabilitation training has established itself an important rehabilitation therapy method for patients suffering motor dysfunction following stroke [64-65], how the mechanical and multi-sensation feedback affect the neuromuscular recovery is still an important and interesting question need to be solved in neuroengineering. A variety of therapeutic approaches are used in rehabilitation of post-stroke patients, however, the evidence basis of these interventions is weak and a physiological model of their effect is often lacking. The recent advancements show that rehabilitation training mainly take effect in three aspects:

1) Stimulates and exercises the neuromuscular, for keeping the function, preventing a complication of the neuromuscular characterized by tremor. Repetitive, passive-active movement training can improve limb motor function by preventing neuromuscular atrophy, spasm, quivering [66-67]. Positive effects in the post-acute phase have been reported with func-

tional exercises for the arm [66] and training of movement components [67]. Thus, there exists a rationale for the use of passive movements, not only to prevent local tissue complications but also to improve motor function after stroke for those patients who cannot actively achieve functional movements of the paretic limb. This problem seems straightforward due to "exercise makes body stronger" has propagandized deep into people. However, by what neurobiological mechanism the mechanical stimulation promotes the neuromuscular recovery, how the training changes the anisotropic muscle motor into regular motor are remain open questions. Optimizing the training according to neurobiological mechanism to promote recovery of neuromuscular system is still a challenge in rehabilitation engineering.

2) Activates the neural pathway by motor control output and sensorial feedback input. The number of neurons and the strength of the neural networks involved in a task are directly related to intensity and frequency of the task [68]. Sensory information feedback is regarded as crucial in motor learning and recovery post-stroke and regained sensory function is considered a positive prognostic indicator of therapy outcome [69]. This neural pathway activation by "use-dependent plasticity" is an important factor to highlight in the rehabilitation therapy [70]. Conflicting results exist with regards to the effects of superficial sensory stimulation in the rehabilitation of post-stroke patients [71-72]. However, studies in healthy subjects and post-stroke patients have suggested that proprioceptive inflow can lead to improvements in limb motor control function [73-76]. However, the evidence basis of these activations is weak and a physiological process of their effect is often lacking. An invivo imaging of the electrophysiology signal propagation in neural system may shed light on unlocking the activation physiological process.

3) Inspires the re-learning of neuron system through neural plasticity by the execution of coordinated movements and effect perception feedback. The adult brain is capable of reorganizing itself after suffering a stroke because the healthy parts of the brain learn and take over the functions previously carried out by the damaged regions of the brain [18]. Increased activity in primary motor cortex imaged by fMRI has been found during recovery from stroke [77, 78]. The brain's reorganizing capability is commonly known as neuro-plasticity [79], which can be seen as the moving of the position of a given function from one location to another in the brain through repeated learning. Generally, the motor disorder following stroke mainly caused by lesions in nervous system, therefore, the essential effect of neurorehabilitation training is to inspire the re-learning of the nervous system through neural plasticity by the execution of motor tasks and effect feedback by perception. Just like training an artificial neural network (ANN), the motor control output (training data set in ANN) and perception feedback of the effect (error feedback in ANN) take key roles in re-learning of the nervous system. The re-learning of the nervous system for motor function recovery is just a training process that the nervous system according to the effect feedbacks to adjust and reorganize the neuro-networks physiologically and functionally by neuro-plasticity for correcting the motor control output to finish a desired movement, action, or manipulation. Clinical experimental studies during the last decade show that the outcome of rehabilitation training fluctuates greatly depending on subjects [9]. A fundamental question rises naturally: how and by what neurobiological mechanism the perception feedback of motor control effect (that like error back propagation algorithm for adjusting the weights of ANN) affects the re-learning of the neuron system? Conflicting opinions exist due to lack of sufficient evidences. Some researchers persist assisting strategies, conversely, some agree to challenge strategies for providing mechanical and sensorial feedback to patient for promoting motor control function recovery [80, 18]. Therefore, it is still a grand challenge to provide effective and optimized perception feedback to promote the re-learning of the neuron system for

motor control function recovery.

3.3 Coordinated control for both the rehabilitation robot and the patient

As mention above, the quality and amount of exercises are key important for motor function recovery. Although the optimal rehabilitation training is still an open question, stable and smooth control method is needed for robot assisting post-stroke patient indoing designed exercise rightly and successfully. Trajectory control, kinetics based control including impedance control, force-position hybrid control, EEG/EMG-based autonomous control, performance-based control, safety strategies, etc., have been proposed and applied in all kinds of rehabilitation robot [81-87]. However, the essential mechanism of neurorehabilitation training is to favor the re-learning of the central nervous system of patient through neural plasticity by the execution of coordinated movements and effect feedback by perception. Unfortunately, the control methods discussed above focused on exercising the paralyzed limb, rather than training the central nervous system, that limits the outcome of rehabilitation training.

As illustrated in Fig. 4, the proposed rehabilitation robot system based on Neuro-Machine Interaction utilizes motor related EEG, UCSDI, EMG to control robot assisting paralyzed limb in performing designed task, and provides visual, auditory, force, haptic information to the patient, in such way to promote the re-learning of the nervous system to regain motor control function. A coordination control method is needed for this rehabilitation robot based on Neuro-Machine Interaction providing safe, smooth, predesigned exercises such as moments, actions, and manipulations with realistic feeling feedbacks to the patient for motor control function reconstruction. To provide flexible, versatile manipulation assistance, not only sophisticated, multiple degrees of freedom robotic mechanisms are needed, but also miniature measure devices, which measure angle, velocity, force/torque, etc. of each actuator for state feedback control[85, 88]. Although the posture trackers, data glove and force/torque sensors are available, it is still a challenge to integrate the distributed measure devices to the robotic mechanisms [89-91]. Implementation of visual, auditory feedbacks are easy to complete, but high spatial resolution forcefeedback and realistic haptic sensation are still difficult to reconstruct and input into person. Patient's active force/torque can be estimated through musculoskeletal model using video information of limb movement, but it is very difficult to measure the active force/torque directly and accurately, this bring uncertainty for coordination control of the rehabilitation robot. The development of neuro-machine interface technology in the recent years make it possible to recognize 15~20 actions of up-limb and hand using EEG together with EMG, but the decoding rate is limited to 4 actions per second [92]. Assuming the idea decoding output is a continuous signal, this low frequency decoding is equivalent to low frequency sampling for the continuous signal. Commonly, human's electrophysiological signals are in the range of 3~200 Hz, so this low frequency decoding will result in serious frequency overlapping, which imposes great difficulty to the robot control. In addition, there is sill no ideal recognition algorithm at present, which is able to recognize all kinetics information for all possible interactions with a limited training set of EEG and EMG signals [93]. The nonlinearity of the kinetics of human limb especially paralyzed limb is another important problem need to be considered for rehabilitation robot control [94]. Current studies indicate that there are several large nonlinearities exist in the relationship between neural activity and joint torque. These nonlinearities include the nonlinear transformation from joint angles to muscle lengths, the transformation from forces to torques, and the nonlinearities in the generation of muscle force [95-97].

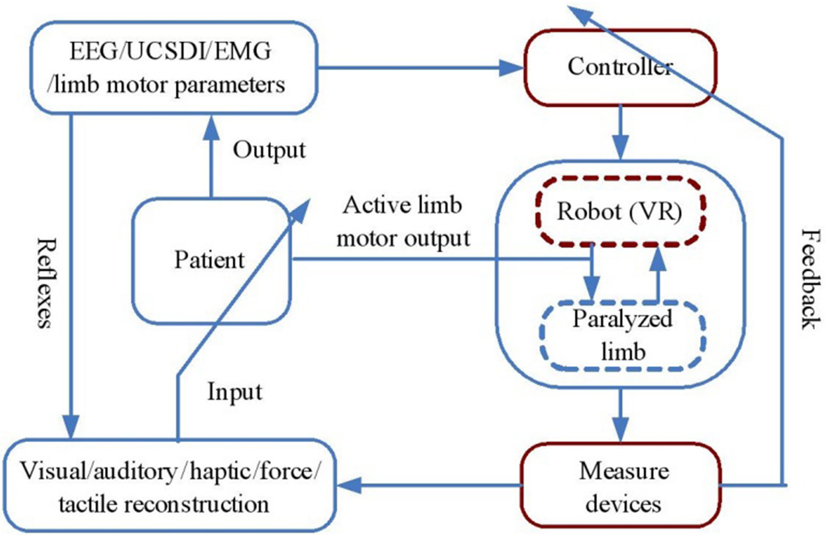

Fig. 4 Scheme of coordinated control for both the rehabilitation robot and the patient

Owing to the difficulties of kinetics state measurement, multi-sensation feedback, patient's active kinetics measurement, low decoding rate for neural control information, safety guarantee, together with the multiple DOFs, strong coupling, nonlinearity nature of limb's kinetics, it is a grand challenge to coordinately control such a kind of rehabilitation robot based on Neuro-Machine Interaction for providing safe, smooth, pre-designed exercises, which let patient actively interact with virtual environment related to walk, hand actions, daily tasks, playing games and haptic exploring. Fully overcoming this difficulty may depend on the solving of the fundamental problems in neuroengineering such as how the mind control limb motor through the neuro-musculo-skeletal system, how the perceptionis inputted as electroneurographic signals and perceived by the human brain through the neural system, and how the active rehabilitation training promote the motor function recovery of post-stroke patient in neurophysiology. On the other hand, the advancements of neuro-machine bilateral interaction technology will be able to solve some fundamental problems.

4 Concluding remarks

The study results in rehabilitation therapy of post-stroke patients show that the outcome of the rehabilitation training mainly depends on three aspects: 1) the active participation of the patient; 2) the amount and quality of physical activity; 3) the cognitive involvement of the patient. The rehabilitation robot based on Neuro-Machine Interaction has been currently proposed, which measures and decodes neural signals to control robot assisting paralyzed limb in performing designed tasks and provides realistic sensation feedback of the interaction effects to the patient simultaneously. It will greatly enhance post-stroke patient recovery from motor dysfunction. For developing such a kind of rehabilitation robot based on Neuro-Machine Interaction, there are some fundamental problems unsolved as follows: how to precisely extract limb movement imagery information from neural signals measured noninvasively for robot control, how the bilateral interaction especially perception feedback affects the neuromuscular rehabilitation, and how to optimize the coordination control of both the rehabilitation robot and the patient.

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