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Challenges in neuro-machine interaction based active robotic rehabilitation of stroke patients

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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 known of crux to enhance recovery outcome of motor dysfunction patients after stroke. Rehabilitation robots mainly have been developing along this direction to satisfy requirements of recovery therapy, or focusing on one or more of the above three points. Therefore, neuro-machine interaction based active rehabilitation robot has been proposed for assisting paralyzed limb performing designed tasks, which utilizes motor related EEG, UCSDI (Ultrasound Current Source Density Imaging), EMG for rehabilitation 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 kind of robot, some key technologies such as noninvasive precise detection of neural signal and realistic sensation feedback need to be solved. There are still some grand challenges in solving the fundamental questions to develop and optimize such kind of neuro-machine interaction based active rehabilitation robot.

Keywords: rehabilitation robot; neuro-machine interaction; active rehabilitation therapy; multi-sensation feedback

1. Introduction

Cerebrovascular accidents severely impair motor functions. Although the optimal therapy for patients who suffer from 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 (Michel *et al*. 2005). In order to assist the stroke patients during rehabilitation therapy, some researchers have developed several robot-assisted rehabilitation therapy systems, such as MIME (Burgar *et al.* 2000), ARM Guide (Reinkensmeyer *et al.* 2000), MIT-MANUS (Krebs *et al.* 2000), UECM (Zhang *et al.* 2005). Robotic aids can provide programmable levels of assistance, and automatically modify their output based on sensor data using control frame works (Krebs *et al.* 1998, Lum *et al.* 1997). Rehabilitation robot usually works on two modes, one is passive recovery training mode another is

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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.* (2004). 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 (Lindberg *et al.* 2004). 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 (Duygun *et al.* 2005, Xu *et al.* 2011a, 2011b). 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) (Huang *et al.* 2011, Lenzi *et al.* 2012, Yang *et al.* 2010), another example is Virtual Reality (VR), which gives the patients multi-sensation information such as audiovisual display and haptic feedback during physical therapy (Saposnik and Levin 2011). Xu *et al.* (2011) 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 (Wang *et al.* 2009). Mauro *et al.* (2012) 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 review the development of the Neuron-Machine Interaction (NMI) based active rehabilitation robot systems and discuss the key technologies of the NMI based rehabilitation robot. At last, the grand challenges in NMI based rehabilitation robot systems are addressed.

2. Neuro-machine interaction based active rehabilitation robot systems

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.* (2008) proposes a BCI-FES system for stroke patients’ arm flexion and extension exercises. Both systems employ the motor imagery technologies. Wang *et al.* (2009) 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 Neuro-Machine Interface based active rehabilitation robot systems 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

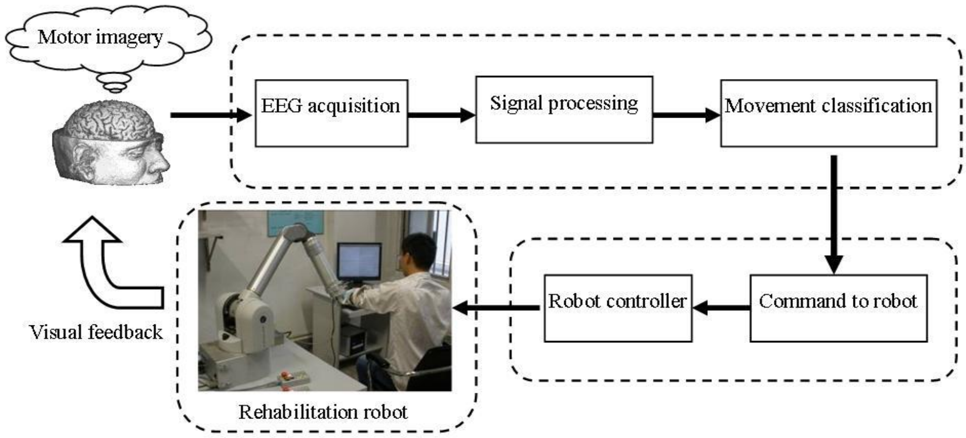

Fig. 1 Motor imagery EEG based rehabilitation robot system

into commands to control a robotic arm to manipulate the patient impaired arm during a physical therapy exercise. 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 (Ferilli *et al.* 2012, Johansson *et al.* 2012, Parker *et al.* 2011). The Neuro-Machine Interaction (NMI) based rehabilitation robot system with perception feedback is shown in Fig. 2.

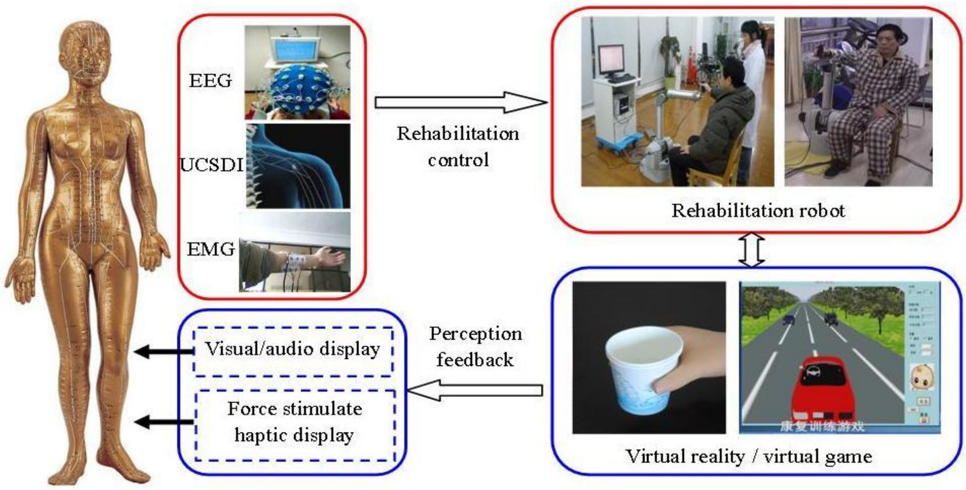

Fig. 2 Neuro-Machine Interaction based active rehabilitation robot system

The NMI based rehabilitation robot system 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 existing BCI based rehabilitation robot shown in Fig.1, the NMI based active rehabilitation robot system emphasizes the precise neural signal detection as well as multi-sensation feedback.

The noninvasive neural signal acquisition and processing module, including EEG, EMG and UCSDI (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 NMI based active rehabilitation robot system will bring great benefits to rehabilitation therapy and motor function recovery. However, such kind of rehabilitation robot system depends on the advancements of two fundamental technologies, one is noninvasive precise detection of neural signal technology another is realistic sensation feedback technology. On the one hand, conventional noninvasive electrophysiological detection methods such as EEG, EMG are compromised with limited spatial resolution; on the other hand, how the sensation feedback inputs into the brain and how it promotes neuromuscular function recovery remains an open question. Therefore, there are still some grand challenges in developing such kind of rehabilitation robot system.

3. Bilateral interaction between human neuron systems and machine

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 kind of bilateral interaction has been proven to favor cortical reorganization and neural path recovery (Mauro *et al.* 2012). 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 NMI based active rehabilitation therapy system, 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 (He *et al.* 2011, Yang *et al.* 2011). One possible solution is utilizing USCDI technology (Olafsson *et al.* 2008,

Yang *et al.* 2011, Yang *et al.* 2012a), 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 (Michel *et al.* 2005). 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 (Mauro *et al.* 2012). 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/haptic 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 (Holden 2005, Weiss *et al.* 2006). 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.

4. Grand challenging problems

4.1 Detection of bilateral electroneurographic signals for robot coordinative control

Unlocking how the “motor commands” through neural system (paths) to control limb motor, how the multi-sensation information caused by limb interacting with environment is back-propagated through the neural system and perceived by human brain, and how the perception stimulation activates the neuron system, will be of great benefit to optimizing robot-assisted rehabilitation therapy. Generally, the motor mind generates electrophysiological signal in the motor cortical neurons. This signal then propagates through the spinal cord and peripheral nerve to control musculoskeletal activity performing an action (He 2005). Although there are some anatomical and electrophysiological knowledge about the working process, imaging or detecting the electrophysiological process noninvasively still remains a grand challenge because of volume conduction effect (He 2005). Electrophysiological signals in high spatial and temporal resolution are needed to image the working process. Conventional electrophysiological recordings of neurocord activity, single or multi neuron unit activity, local field potential, and electrocorticography (ECoG) by implanted electrodes have high temporal/spatial resolution, but limited coverage, and unfortunately are invasive techniques. It is impossible and unsuitable for patients only having motor disorder to accept this kind of invasive techniques (He *et al.* 2011). The noninvasive electrophysiological detecting modalities such as EEG and EMG, which share the superior temporal resolution of the invasive recordings, have been attractive for studying brain states and assessing motor control functions. However, EEG and MEG are compromised with limited spatial resolution owing to the fact that a single electrode records a weighted average of neuron activity from a large number of neurons and thus it is difficult to directly relate the measurements to a defined anatomical neural substrate (He 2004, He *et al.* 2011). High spatial resolution images, on the other hand, can be obtained by functional magnetic resonance image (fMRI) which based on the blood-oxygen-level-dependent contrast. However, its information about functional activities of neural system is limited because fMRI does not directly measure the neural signal. It has therefore been a major challenge to enhance the spatial precision of noninvasive electrophysiological detection to achieve high spatiotemporal mapping of the electrophysiological signals of neuron system to image the working process of how the neuron system control limbs' motors. Integration of EEG/MEG with fMRI combining EEG/MEG's temporal resolution and fMRI's spatial resolution based on neurovascular coupling relationship was proposed to delineate complex neuron system activities with high resolution in both space and time domains (He *et al.* 2011). However, challenges may be further appreciated by considering the highly different temporal/spatial scales of the hemodynamic and electrophysiological responses.

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 (Olafsson *et al.* 2006, Olafsson *et al.* 2008, Olafsson *et al.* 2009, Sumi 2009, Witte *et al.* 2007, Witte *et al.* 2006, Yang *et al.* 2011, Yang *et al.* 2012b, Zhang and Wang 2004). 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 (2–4 mA/cm^2) (Olafsson *et al.* 2006, Sumi 2009, Witte *et al.* 2006). Such kind of hybrid imaging modalities can be used to image current flowing in lobster nerve cord with physiologically realistic current densities (Witte *et al.* 2006), electrocardio-pulse propagation process, cardiac activation of a rabbit heart (Olafsson *et al.* 2009), the local potential field and weak current flowing in volume conductor (Wang *et al.* 2011). 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) (Yang *et al.* 2012a) 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 an action as well as how the multi-sensorial signals are back-propagated through neural paths to the

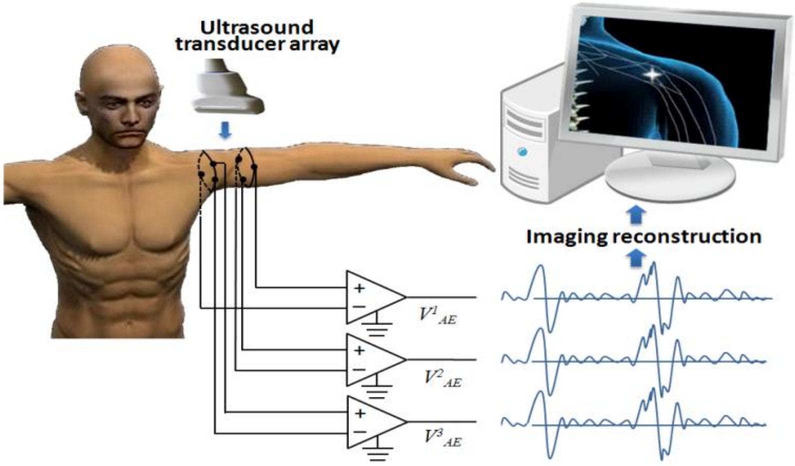

Fig. 3 Measure electroneurographic signal in high spatial and temporal resolution by ultrasound current source density imaging (UCSDI)

brain. As illustrated in Figs. 2 and 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. 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 (Zhang and Wang 2004). 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.

4.2 How the interaction affect the neuromuscular rehabilitation

Although robot-assisted rehabilitation training has established itself an important rehabilitation therapy method for patients suffering motor dysfunction following stroke (Lum *et al.* 2002, Riener *et al.* 2005), 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 (Kwakkel *et al.* 1999). 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 (Kwakkel *et al.* 1999, Platz *et al.* 2001). Positive effects in the post-acute phase have been reported with functional exercises for the arm (Kwakkel *et al.* 1999) and training of movement components (Platz *et al.* 2001). 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 (Nudo *et al.* 2001). 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 (Weiller 1998). This neural pathway activation by "use-dependent plasticity" is an important factor to highlight in the rehabilitation therapy (Taub *et al.* 2002). Conflicting results exist with regards to the effects of superficial sensory stimulation in the rehabilitation of post-stroke patients (Johansson *et al.* 2001, Sonde *et al.* 2000). However, studies in healthy subjects and post-stroke patients have suggested that proprioceptive inflow can lead to improvements in limb motor control function (Carel *et al.* 2000, Glanz *et al.* 1996, Ridding *et al.* 2000, Lang *et al.* 2002). 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 (Wang *et al.* 2009). Increased activity in primary motor cortex imaged by fMRI has been found during recovery from stroke (Carey *et al.* 2002, Marshall *et al.* 2000). The brain's reorganizing capability is commonly known as neuro-plasticity (Frackowiak 2002), 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 (Lindberg *et al.* 2004). 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 (Crespo and Reinkensmeyer 2000, Wang *et al.* 2009). 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.

4.3 Coordination control for rehabilitation robot

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 in doing 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 (Blaya and Herr 2004, Cai *et al.* 2006, Crespo and Reinkensmeyer 2000, Eilenberg *et al.* 2010, Frackowiak 2002, Guadagnoli and Lee 2004, Li *et al.* 2011, Metrailler *et al.* 2007, Riener *et al.* 2005, Sugarman *et al.* 2008). 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 Neuro-Machine Interaction based active rehabilitation robot system 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 Neuro-Machine Interaction based active rehabilitation robot 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 (Li *et al.* 2011, Xiong *et al.* 2012). 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 (Ma and Song 2011, Qian *et al.* 2011, Pennycott *et al.* 2009). Implementation of visual, auditory feedbacks are easy to complete, but high spatial resolution force feedback and realistic haptic sensation are still difficult to reconstruct and input into person. Patient’s active

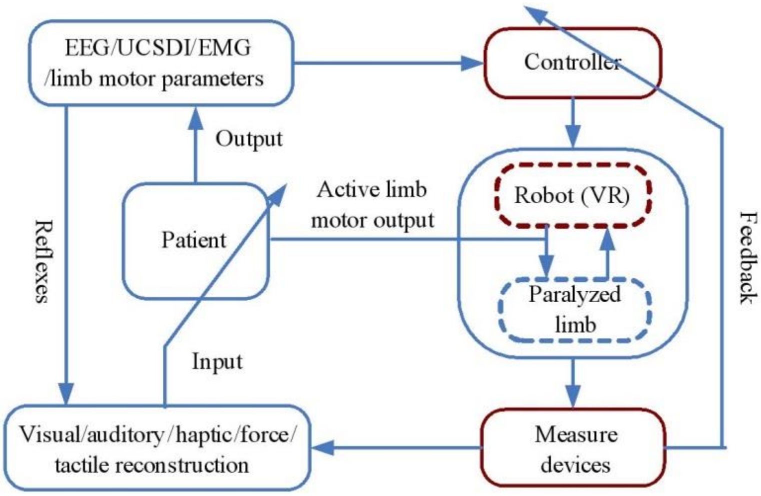

Fig. 4 Scheme of coordination control for rehabilitation robot

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 (Lunenburger *et al.* 2007). 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 3-200Hz, 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 (Wang and Buchanan 2002). The nonlinearity of the kinetics of human limb especially paralyzed limb is another important problem need to be considered for rehabilitation robot control (Shaw *et al.* 2005). 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 (Pan *et al.* 2011, Xu *et al.* 2012, Zajac 1989).

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 kind of Neuro-Machine Interaction based active rehabilitation robot 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 depends 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 perception is 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.

5. Conclusions

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 Neuro-Machine Interaction based active rehabilitation robot has been currently proposed, which measures 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. Noninvasive precise detection of neural signal and realistic sensation feedback are crucial for development of such kind of rehabilitation robot. There are still some grand challenges in developing the Neuro-Machine Interaction based active rehabilitation robot as following: how to precisely detect neural signal noninvasively, how the bilateral interaction especially perception feedback affects the neuromuscular rehabilitation, and how to optimize the coordination control of rehabilitation robot.

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References

Blaya, J.A. and Herr, H. (2004), “Adaptive control of a variable-impedance ankle-foot orthosis to assist drop-foot gait”, *IEEE T. Neur. Sys. Reh.*, **12**(1), 24-31.

Burgar, C.G., Lum, P.S. and Shor, P.C. (2000), “Development of robots for rehabilitation therapy: the Polo Altova/Stanford experience”, *J. Rehabil. Res. Dev.*, **37**(6), 663-673.

Cai, L.L., Fong, A.J., Otoshi, C.K., Liang, Y., Burdick, J.W., Roy, R.R. and Edgerton, V.R. (2006), “Implications of assist-as-needed robotic step training after a complete spinal cord injury on intrinsic strategies of motor learning”, *J. Neurosci.*, **26**(41),10564-10568.

Carel, C., Loubinoux, I., Boulanouar, K., Manelfe, C. and Rascol, O. (2000), “Neural substrate for the effects of passive training on sensorimotor cortical representation: a study with functional magnetic resonance imaging in healthy subjects”, *J. Cereb. Blood Flow Metab.*, **20**(3), 478-484.

Crespo, L.M and Reinkensmeyer, D.J. (2000), “Review of control strategies for robotic movement training after neurologic injury”, *J. Neuro Eng. Rehabil.*, **6**, doi:10.1186/1743-0003-6-20.

Carey, J.R., Kimberley, T.J., Lewis, S.M., Auerbach, E.J. and Dorsey, L. (2002), “Analysis of fMRI and finger tracking training in subjects with chronic stroke”, *Brain*, **125**(4), 773-788.

Duygun, E., Vishnu, M. and Nilanjan, S. (2005), “A new control approach to robot assisted rehabilitation”, *The 2005 IEEE 9th International Conference on Rehabilitation Robotics*, Chicago, USA, June.

Eilenberg, M.F., Geyer, H. and Herr, H. (2010), “Control of a powered ankle-foot prosthesisbased on a neuromuscular model”, *IEEE T. Neur. Sys. Reh.*, **18**(2), 164-173.

Ferilli, M., Rossini, L. and Rossini, P.M. (2012), "A non-invasive tool for brain-plasiticity-based therapy: transcranial magnetic stimulation in post-stroke rehabilitation", *The fourth IEEE RAS/EMBS International Conference on Biomedical Robotics and Biomechatronics*, Rome, Italy, June.

Frackowiak, R.S.J. (2002), "Imaging neuroscience: Lessons from studies of brain plasticity", *The 5th IEEE EMBS International Summer School on Biomedical Imaging*, London, UK, June.

Glanz, M., Klawansky, S., Stason, W., Berkey, C. and Chalmers, T.C. (1996), "Functional electrostimulation in post-stroke rehabilitation: a meta-analysis of the randomized controlled trials", *Arch. Phys. Med. Rehabil.*, **77**(6), 549-553.

Guadagnoli, M. and Lee, T. (2004), "Challenge point: a framework for conceptualizing the effects of various practice conditions in motor learning", *J. Mot. Behav*., **36**(2), 212-224.

He, B. (2004), *Modeling and imaging of bioelectrical activity-principles and applications*, Kluwer Academic Publishers.

He, B. (2005), *Neural engineering*, Norwell, MA: Kluwer/Plenum.

Huang, H.P., Huang, T.H., Liu, Y.H., Kang, Z.H. and Teng, J.T. (2011), "A brain-controlled rehabilitation system with multiple kernel learning", *The 2011 IEEE International Conference on Systems*, *Man and Cybernetics*, Taipei, Taiwan, October.

Holden, M. (2005), "Virtual environments for motor rehabilitation: review", *Cyberpsychol. Behav*., **8**(3), 187-211.

He, B., Yang, L., Wilke, C. and Yuan, H. (2011a), "Electrophysiological imaging of brain activity and connectivity-challenges and opportunities", *IEEE T. Biomed. Eng.*, **58**(7), 1918-1931.

Johansson, B.B. (2012), "Multisensory stimulation in stroke rehabilitation", *Front. Human Neurosci.*, **6**(60), doi: 10.3389/fnhum.2012.00060.

Johansson, B.B., Haker, E., Arbin, M.V. and Britton, M. (2001), "Acupuncture and trancutaneous nerve stimulation in stroke rehabilitation", *Stroke*, **32**(3), 707-713.

Kahn, L.E., Rymer, W.Z. and Reinkensmeyer, D.J. (2004), "Adaptive assistance for guided force training in chronic stroke", *The 26th Annual International Conference of the IEEE EMBS*, San Francisco, USA, September.

Krebs, H.I., Hogan, N., Aisen, M.L. and Volpe, B.T. (1998), "Robot-aided neurorehabilitation", *IEEE T. Rehab. Eng*, **6**(2), 75-87.

Krebs, H.I., Volpe, B.T., Aisen, M.L. and Hogan, N. (2000), "Increasing productivity and quality of care: robot-aided neuro-rehabilitation", *J. Rehabil. Res. Dev.*, **37**(6), 639-652.

Kwakkel, G., Kollen, B.J. and Wagenaar, R.C. (1999), "Therapy impact on functional recovery in stroke rehabilitation: a critical review of the literature", *Physiotherapy*, **13**, 377-379.

Kwakkel, G., Wagenaar, R.C., Twisk, J.W., Lankhorst, G.J. and Koetsier, J.C. (1999), "Intensity of leg and arm training after primary middle-cerebralartery stroke: a randomised trial", *Lancet*, **354**, 191-196.

Lang, A.K., Luft, A.R., Sawaki, L., Burstein, A.H., Sohn, Y.H. and Cohen, L.G. (2002), "Modulation of human corticomotor excitability by somatosensory input", *J. Physiol.*, **540**(2), 623-633.

Lenzi, T., Rossi, S.D., Vitiello, N. and Carrozza, M.C. (2012), "Intention-based EMG control for powered exoskeletons", *IEEE T. Biomed. Eng.*, **59**(8), 2180-2190.

Li, T., Song, A.G. and Fei, S.M. (2011), "Master-slave synchronization for delayed lurie systems using time-delay feedback control", *Asian J. Control*, **13**(6), 879-892.

Li, T., Song, A.G., Xue, M. and Zhang, H. (2011), "Stability analysis on delayed neural networks based on an improved delay-partitioning approach", *J. Comput. Appl. Math.*, **235**(9), 3086-3095.

Lindberg, P., Schmitz, C., Forssberg, H., Engardt, M. and Borg, J. (2004), "Effects of passive-active movement training on upper limb motor function and cortical activation in chronic patients with stroke: a pilot study", *J. Rehabil. Med.*, **36**(3), 117-123.

Lum, P.S., Burgar, C.G. and Loos, M.V. (1997), "The use of a robotic device for post-stroke movement therapy", *The Conference on Rehabilitation Robotics*, Bath, U.K., 107-110.

Lum, P.S., Burgar, C.G., Shor, P.C. and Majmundar, M. (2002), "Robot-assisted movement training compared with conventional therapy techniques for the rehabilitation of upper-limb motor function after stroke", *Arch. Phys. Med. Rehabil.*, **83**(7), 952-959.

Lunenburger, L., Colombo, G. and Riener, R. (2007), “Biofeedback for robotic gait rehabilitation”, *J. Neuro Eng. Rehabil.*, **4**(1), doi: 10.1186/1743-0003-4-1.

Ma, J.Q. and Song, A.G. (2011), “Development of a novel two-axis force sensor for Chinese massage robot”, *The 3rd International Conference on Precision Instrumentation and Measurement*, Xiangtan, China, July.

Marshall, R.S., Perera, G.M., Lazar, R.M., Krakauer, J.W., Constantine, R.C. and DeLaPaz, R.L. (2000), “Evolution of cortical activation during recovery from corticospinal tract infarction”, *Stroke*, **31**(3), 656-661.

Mauro, A.D., Carrasco, E., Oyarzun, D. and Ardanza, A. (2012), “Advanced hybrid technology for neurorehabilitation: the HYPER project”, *Advances in Robotics & Virtual Reality*, Springer-Verlag Berlin Heidelberg, 89-108.

Metrailler, P., Brodard, R., Stauffer, Y., Clavel, R. and Frischknecht, R. (2007), “Cyberthosis: rehabilitation robotics with controlled electrical muscle stimulation”, *Rehabilitation robotics*, 303-318.

Michel, V.E.G., Driessen, B.J.F. and Michel, D. (2005), “A motorized gravity compensation mechanism used for active rehabilitation of upper limbs”, *The 2005 IEEE 9th International Conference on Rehabilitation Robotics*, Chicago, USA, June.

Nudo, R.J., Plautz, E.J. and Frost, S.B. (2001), “Role of adaptive plasticity in recovery of function after damage to motor cortex”, *Muscle Nerve*, **24**(8), 1000-1019.

Olafsson, R., Witte, R.S., Huang, S.W. and Donnell, M.O. (2008), “Ultrasound current source density imaging”, *IEEE T. Biomed. Eng.*, **55**(7), 1840-1848.

Olafsson, R., Witte, R.S., Jia, C.X., Huang, S.W., Kim, K. and Donnell, M.O. (2009), “Cardiac activation mapping using ultrasound current source density imaging (UCSDI)”, *IEEE T. Ultrason. Ferr.*, **56**(3), 565-574.

Olafsson, R., Witte, R.S., Kim, K., Ashkenazi, S. and Donnell, M.O. (2006), “Electric current mapping using the acoustoelectric effect”, *Medical Imaging 2006: Ultrasonic Imaging and Signal Processing*, San Diego, USA, February.

Pan, L.Z., Song, A.G. and Xu, G.Z. (2011), “Robot-assisted upper-limb fuzzy adaptive passive movement training and clinical experiment”, *Appl. Mech. Mater.*, **130**, 227-231.

Parker, J., Mountain, G. and Hammerton, J. (2011), “A review of the evidence underpinning the use of visual and auditory feedback for computer technology in post-stroke upper-limb rehabilitation”, *Disabil. Rehabil.*, **6**, 465-472.

Pennycott, A., Hunt, K.J., Jack, L.P., Perret, C. and Kakebeeke, T.H. (2009), “Estimation and volitional feedback control of active work rate during robot-assisted gait”, *Control Eng. Pract*, **17**(2), 322-328.

Platz, T., Winter, T., Muller, N., Pinkowski, C., Eickhof, C. and Mauritz, K.H. (2001), “Arm ability training for stroke and traumatic brain injury patients with mild arm paresis: a single-blind, randomized, controlled trial”, *Arch. Phys. Med. Rehabil.*, **82**(7),961-968.

Qian, Y., Song, A.G. and Yan, R.Q. (2011), “Design and realization of an array pulse detecting tactile sensor”, *Instrumentation and Measurement Technology Conference (I2MTC)*, Hangzhou, China, May.

Reinkensmeyer, D.J., Kahn, L.E. and Arerbuch, M. (2000), “Understanding and treating arm movement impairment after chronic brain injury: progress with the ARM Guide”, *J. Rehabil. Res. Dev.*, **37**(6), 653-662.

Ridding, M.C., Brouwer, B., Miles, T.S., Pitcher, J.B. and Thompson, P.D. (2000), “Changes in muscle responses to stimulation of the motor cortex induced by peripheral nerve stimulation in human subjects”, *Exp. Brain Res.*, **131**(1), 135-143.

Riener, R., Lunenburger, L., Jezernik, S. and Anderschitz, M. (2005), “Patient-cooperative strategies for robot-aided treadmill training: first experimental results”, *IEEE T. Neur. Sys. Reh.*, **13**(3), 380-394.

Riener, R., Nef, T. and Colombo, G. (2005), “Robot-aided neurorehabilitation of the upper extremities”, *Med. Biol. Eng. Comput.*, **43**(1), 2-10.

Saposnik, G. and Levin, M. (2011), “Virtual reality in stroke rehabilitation: a meta-analysis and implications for clinicians”, *Stroke*, **42**(5), 1380-1386.

Shaw, S.E., Morris, D.M., Uswatte, G., McKay, S., Meythaler, J.M. and Taub, E. (2005), “Constraint-induced movement therapy for recovery of upper-limb function following traumatic brain injury”, *J.*

Rehabil. Res Dev., **42**(6),769-778.
Sonde, L., Kalimo, H., Fernaeus, S.E. and Viittanen, M. (2000), "Low TENS treatment on post-stroke paretic arm: a three-year follow-up", *Clin. Rehabil.*, **14**(1), 14-19.
Sugarman, H., Dayan, E., Lauden, A., Eichler, A.W. and Tiran, J. (2008), "Investigating the use of force feedback joysticks for low-cost, robotmediated therapy", *Int. J. Disabil. Human Dev.*, **7**(1), 95-100.
Sumi, C. (2009), "Expression for noninvasive measurement of internal map of local Joule heat consumption using acousto-electric effect", *Acoust. Sci. Technol.*, **30**(4), 310-312.
Taub, E., Uswatte, G. and Elbert, T. (2002), "New treatments in neurorehabilitation founded on basic research", *Nature Rev. Neurosci*, **3**(3), 228-236.
Tan, H.G., Zhang, H.H., Wang, C.C., Shee, C.Y., Ang, W.T. and Guan, C.T. (2008), "Arm flexion and extension exercises using a brain-computer interface and functional electrical stimulation", *The Sixth IASTED International Conference on Biomedical Engineering*, Innsbruck, Austria, February.
Wang, C., Phua, K.S. and Ang, K.K. (2009), "A feasibility study of non-invasive motor-imagery BCI-based robotic rehabilitation for stroke patients", *The 4th IEEE International Conference on Neural Engineering*, Antalya, Turkey, April.
Wang, L. and Buchanan, T.S. (2002), "Prediction of joint moments using a neural network model of muscle activations from EMG signals", *IEEE T. Neur. Sys. Reh.*, **10**(1), 30-37.
Wang, Z.H., Olafsson, R., Ingram, P., Li, Q. and Witte, R.S. (2011), "Four-dimensional ultrasound current source density imaging of a dipole field", *Appl. Phys. Lett.*, **99**(11), 113701.
Weiller, C. (1998), "Imaging functional recovery from stroke", *Exp. Brain Res.*, **123**(1), 13-17.
Weiss, P., Kizony, R., Feintuch, U. and Katz, N. (2006), "Virtual reality in neurorehabilitation", *Textbook Neur. Repair Neurorehabil.*, **2**, 182-197.
Witte, R.S., Olafsson, R. and Donnell, M.O. (2006), "Acousto-electric detection of current flow in a neural recording chamber", *The IEEE Int. Ultrason. Symp.*, 5-8.
Witte, R.S., Olafsson, R., Huang, S.W. and Donnell, M.O. (2007), "Imaging current flow in lobster nerve cord using the acousto-electric effect", *Appl. Phy. Lett.*, **90**(16), 163902.
Xiong, P.W., Song, A.G., Qian, K., Zhang, L.X. and Xu, X.N. (2012), "Operation modes and control schemes for a telerobot with time delay", *Int. J. Adv. Robot. Syst.*, **9**(57), doi: 10.5772/50649.
Xu, B.G., Peng, S., Song, A.G., Yang, R.H. and Pan, L.Z. (2011), "Robot-aided upper-limb rehabilitation based on motor imagery EEG", *Int. J. Adv. Robot. Syst.*, **8**(4), 88-97.
Xu, G.Z., Song, A.G. and Li, H.J. (2011a), "Control system design for an upper-limb rehabilitation robot", *Adv. Robot.*, **25**(1), 229-251.
Xu, G.Z., Song, A.G. and Li, H.J. (2011b), "Adaptive impedance control for upper-limb rehabilitation robot using evolutionary dynamic recurrent fuzzy neural networks", *J. Intell. Robot Syst.*, **62**(3), 501-525.
Xu, G.Z., Song, A.G., Pan, L.Z., Li, H.J., Liang, Z.W., Zhu, S.H., Xu, B.G. and Li, J.F. (2012), "Adaptive hierarchical control for the muscle strength training of stroke survivors in robot-aided upper-limb rehabilitation", *Int. J. Adv. Robot. Syst.*, **9**(122), 2071-2083.
Yang, R.H., Song, A.G. and Xu, B.G. (2010), "Feature extraction of motor imagery EEG based on wavelet transform and higher-order statistics", *Wavelets Multiresolution Inform. Process.*, **8**(3), 373-384.
Yang, R.H., Li, X., Liu, J. and He, B. (2011), "3D current source density imaging based on the acoustoelectric effect: a simulation study using unipolar pulses", *Phys. Med. Biol.*, **56**(13), 3825-3842.
Yang, R.H., Li, X., Song, A.G., He, B. and Yan, R.Q. (2012a), "A 3D reconstruction solution to current density imaging based on acoustoelectric effect by deconvolution: a simulation study", *IEEE T. Biomed. Eng.*, **59**(12), doi: 10.1109/TBME.2012.2228641.
Yang, R.H., Li, X., Song, A.G,, He, B. and Yan, R.Q. (2012b), "Three-dimensional noninvasive ultrasound Joule heat tomography based on the acousto-electric effect using unipolar pulses: a simulation study", *Phys. Med. Biol.*, **57**(22), 7689-7708.
Zajac, F.E. (1989), "Muscle and tendon: Properties, models, scaling, and application to biomechanics and motor control", *Crit. Rev. Biomed. Eng.*, **17**(4), 359-411.
Zhang, H. and Wang, L.H. (2004), "Acousto-electric tomography," *Photons plus Ultrasound: Imaging and Sensing*, San Jose, USA, January.

Zhang, Y.B., Wang, Z.X., Ji, L.H. and Bi, S. (2005), "The clinical application of the upper extremity compound movements rehabilitation training robot", *The 2005 IEEE 9th International Conference on Rehabilitation Robotics*, Chicago, USA, June.

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