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Reviewing high-level control techniques on robot-assisted upper-limb rehabilitation

Qing Miao[1,2], Mingming Zhang[2*], Jinghui Cao[3], Sheng Q. Xie[4]

[1] School of Mechanical and Electronic Engineering, Wuhan University of Technology, Wuhan, China

[2*] Department of Biomedical Engineering, Southern University of Science and Technology, Shenzhen

[3] Department of Mechanical Engineering, the University of Auckland, Auckland, New Zealand

[4] School of Electronic and Electrical Engineering, University of Leeds, Leeds, UK

*Corresponding Author: zhangmm@sustc.edu.cn

Qing Miao was born in Hubei of China in 1988. He received the M.E. in Control Science and Control Engineering from Wuhan University of Technology, Wuhan, China, in 2014. He is the Ph.D student in Mechanical and Electrical Engineering from Wuhan University of Technology, Wuhan, China, at present. Since November of 2016, he has been researching as an exchanging Ph.D student in the Department of Mechanical Engineering at University of Auckland. His research includes medical, intelligent control system and rehabilitation robotics.

Mingming Zhang was born in Henan of China in 1985. He received the M.E. in mechatronics from Chongqing University, Chongqing, China, in 2012, and the Ph.D. degree in mechanical engineering from the University of Auckland, Auckland, New Zealand, in 2016. From October of 2015 to July of 2018, he has been working as a research fellow in the Department of Mechanical Engineering at the University of Auckland. Since August of 2018, he joined Department of Biomedical Engineering at Southern University of Science and Technology as an assistant professor. His research includes mechatronics, medical and rehabilitation robotics, biomechanics, and advanced control system. He has published over 20 academic papers and hold five patents.

Sheng Quan Xie received the M.E. and Ph.D. degree in mechatronics from Huazhong University of Science and Technology, Wuhan, China, in 1995 and 1998, respectively, and the Ph.D. degree in manufacturing automation from the University of Canterbury, Canterbury, New Zealand, in 2002. 2003 to 2016, he worked at the University of Auckland as a Chair Professor. Since 2017, he joined University of Leeds where he is currently a Chair Professor in the area of biomechatronics. He has published 2 books, 15 book chapters, and over 200 international journal and conference papers. His current research interests are smart sensors and actuators, medical and rehabilitation robots, microelectromechanical systems, modern control technologies and applications, and rapid product development technologies, methods, and tools. Prof. Xie is an Editor in Chief for the International Journal of Biomechatronics and Biomedical Robotics, and is an Associate Editor for the International Journal of Advanced Mechatronic Systems and the International Journal of Mechatronics and Intelligent Manufacturing.

Jinghui Cao received the B.E. with degree in Mechatronics Engineering with First Class Honours from the University of Auckland, New Zealand in 2013. Since March 2013, he has been working towards a Ph.D degree in the Department of Mechanical Engineering, University of Auckland. His research interests include mechatronics, rehabilitation robotics and motion control.

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Abstract− This paper presents a comprehensive review of high-level control techniques for upper-limb robotic training. It aims to compare and discuss the potentials of these different control algorithms, and specify future research direction. Included studies mainly come from selected papers in four review articles. To make selected studies complete and comprehensive, especially some recently-developed upper-limb robotic devices, a search was further conducted in IEEE Xplore, Google Scholar, Scopus and Web of Science using keywords ('upper limb*' or 'upper body*') and ('rehabilitation*' or 'treatment*') and ('robot*' or 'device*' or 'exoskeleton*'). The search is limited to English-language articles published between January 2013 and December 2017. Valuable references in related publications were also screened. Comparative analysis shows that high-level interaction control strategies can be implemented in a range of methods, mainly including impedance/admittance based strategies, adaptive control techniques, and physiological signal control. Even though the potentials of existing interactive control strategies have been demonstrated, it is hard to identify the one leading to maximum encouragement from human users. However, it is reasonable to suggest that future studies should combine different control strategies to be application specific, and deliver appropriate robotic assistance based on physical disability levels of human users.

Keywords: interactive control; upper-limb; robot; rehabilitation

1. Introduction

Stroke is the second leading cause for acquired disabilities in adults [1, 2], and most of these survivors are left with motor impairments on their upper-limb movements [3]. Other issues like spinal cord injuries [4] and multiple sclerosis [5] can also lead to upper limb control deficits. A variety of robotic devices have been developed for people's upper limb rehabilitation over the past few decades [6-9]. With respect to traditional physical therapy, robot-assisted techniques are able to provide more intensive training by increasing the number of repetitions which a therapist can impose, and allow more intelligent interaction [10].

Many upper-limb rehabilitation robotic systems have been successfully developed with experimental validation with human users. They are either wearable exoskeleton robots (such as the ARMin III [11] and the L-EXOS [12]), or end-effector devices (such as the MIT-MANUS [13] and the hCAAR [14]). These robotic devices can be also classified into unilateral or bilateral systems. While majority of current robot-assisted upper-limb rehabilitation techniques are designed for unilateral training of human limbs, bilateral training has become an emerging form of rehabilitation by stimulating coordinated use of both arms [6]. One example is the hand robotic device developed by Rashedi, et al. [15].

Robot-assisted upper-limb training can provoke motor plasticity and therefore improve motor recovery. Passive training is to control the robotic movement strictly along a desired reference trajectory through position feedback with high gains. In rehabilitation this passive technique is common at early stages of rehabilitation, when the impaired limb is generally unresponsive. However, the efficacy of passive training is known to be limited in stimulating neuroplasticity [16]. To enhance rehabilitation efficacy, especially for late stages of therapy, patients are normally encouraged to be involved with the robotic training with active engagement. It is evident that the low-level trajectory tracking control techniques do not allow for the implementation of interactive training. High-level control strategies are required on robotic devices to achieve more effective rehabilitation training due to enhanced human-robot interaction.

However, the question of what is the most appropriate high-level control technique for robot-assisted upper-limb rehabilitation is not evident. Direct comparisons between different high-level control strategies implemented with the same robotic device are lacking. This review aims to investigate various high-level control techniques already implemented on robotic prototypes, and analyze their potentials in delivering more effective robotic training to human upper limbs. In this review, we focus on the discussion of "high-level" rather than "low-level" control algorithms already implemented on upper-limb rehabilitation robots. The "high-level" concept is defined as control strategies to realize interactive robotic training. From the viewpoint of end users, "high-level" strategies generally refer to these designs that direct human-robot interaction following certain training tasks. A common way is to encourage patients' active engagement with robot-assisted rehabilitation training considering their movement intention or task completion performance.

This review paper is organized as below: following the Introduction, a detailed search and selection process is given, including selected papers, identified databases and keywords, and inclusion/exclusion criteria. Results of different classifications are provided next in tables, followed by Discussion and Conclusion.

2. Search and selection process

Selected studies are mainly from four review papers [6-9]. In 2012, Lo and Xie [8] reviewed 17 typical upper-limb exoskeleton robots for rehabilitation of patients with neuromuscular disorders, and Van Delden, et al. [6] summarized six mechanical and 14 robotic bilateral upper limb training devices. In 2016, Brackenridge, et al. [7] conducted a more comprehensive review on upper-limb rehabilitation devices (141 robotic or mechanical devices), and Proietti, et al. [9] presented a list of 32 upper-limb rehabilitation robotic exoskeletons focusing on control techniques. To ensure selected studies complete and comprehensive, especially some recently-developed upper-limb robotic devices, a search was further conducted in IEEE Xplore, Google Scholar, Scopus and Web of Science using keywords ('upper limb*' or 'upper body*') and ('rehabilitation*' or 'treatment*') and ('robot*' or 'device*' or 'exoskeleton*'). The search is limited to English-language articles published between January 2013 and December 2017. Valuable references listed in relevant publications were also screened.

This review aims to compare and analyze existing upper-limb rehabilitation devices in terms of high-level control strategies. The inclusion criteria include 1) robotic exoskeletons or platform robots developed for human upper limb rehabilitation, 2) implementation of interactive control schemes, and 3) well-developed prototypes that have been successfully prototyped and tested on human subjects. Studies with design analysis, simulation or tests on animals will be excluded. When there are multiple studies with the same robotic system, only those implemented with high-level control are selected. Excluded studies are those 1) with non-automatic mechanical rehabilitation devices, 2) with only mechanical description or design optimization of the robotic device, 3) with only trajectory tracking control implementation, 4) focusing on human finger rehabilitation, and 5) with experimental validation of the robotic system on animals instead of human users. The search and selection process is presented in Figure 1.

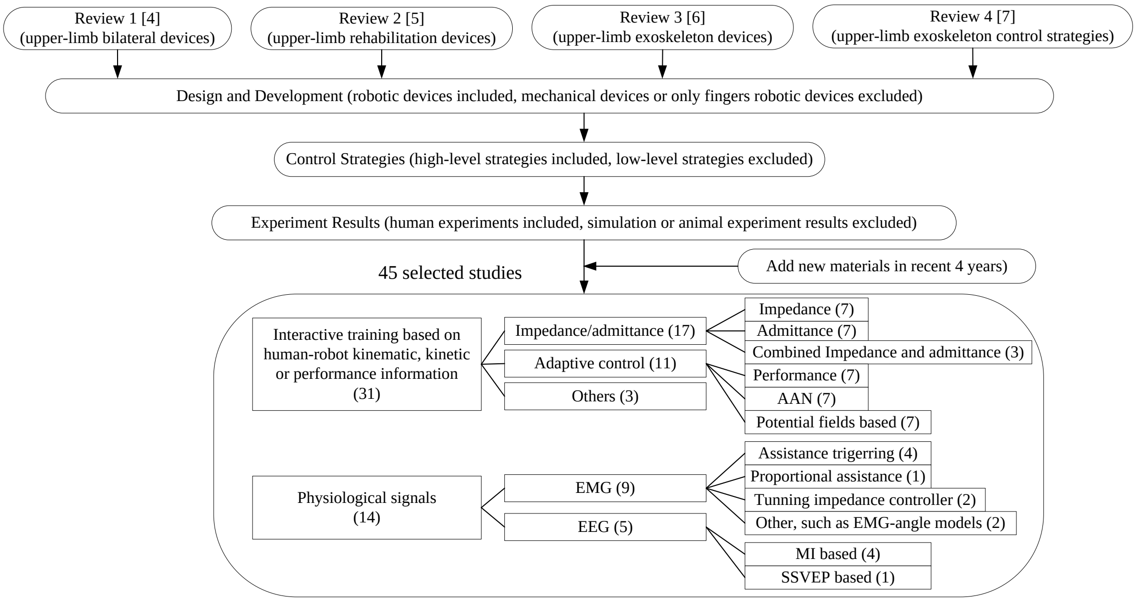

Figure 1. Flow chart of the search and selection process. (AAN: assist-as-needed; EMG: electromyographic; EEG: electroencephalography; MI: motor imagery; SSVEP: steady-state visual evoked potential)

More specifically about the selection process, studies with non-automatic mechanical devices rather than robotic ones for upper-limb rehabilitation are excluded, such as the T-WREX [17] that passively counterbalances the arm weight using elastic bands. Studies with only mechanical description or design optimization of the robotic device are excluded, such as some upper-limb powered exoskeletons [18-20], the Pneu-WREX [21], the Wrist Gimbal [22], and the 6-REXOS [23], the optimization of a redundant shoulder exoskeleton [24], the BONES [25, 26], and the MEDARM [27, 28]. Studies such as [29, 30] were also excluded due to the lack of experimental validation with human users, although advanced control techniques were proposed. Studies focusing on finger rehabilitation are excluded, such as the Haptic Knob [31], the intelligent hand motion system [32], the intention-driven hand robotic system [33], the FINGER [34], the pneumatically-controlled glove [35], and the electromyographic (EMG) controlled hand exoskeletons [36, 37]. Studies are excluded if solely involving trajectory tracking control techniques, four examples are the Hybrid-PLEMO [38], the ETS-MARSE [39], the robot arm [40], and the ExoRob [41]. Studies with advanced adaptive control algorithms aiming to achieve stable, accurate, and robust trajectory tracking are excluded, such as an impedance identification based adaptive control method [42], a neural proportional–integral–derivative (PID) control [43], a robust sliding base control [44], an adaptive controller combining a PID-based feedback controller and an iterative learning controller based feedforward controller [45], and an observer based adaptive control [46]. Studies are selected with higher-qualified high-level control techniques in the case of multiple studies with the similar robotic system. For instance, studies [12, 47] are included compared with those [48, 49]. Studies introducing newer prototypes with the same control strategy were selected with respect to those with old versions. It should be noted that these studies presenting high-level control strategies of the old prototypes will be still cited to support comparison and analysis.

3. Results

After a comprehensive search and selection, a total of 45 studies are selected based on predefined inclusion and exclusion criteria. In Table 1 are 31 rehabilitation studies that implement interactive training based on human-robot kinematic, kinetic or performance information, of them seven studies [12, 50-55] based on impedance, seven studies [56-62] based on admittance, three studies combining impedance with admittance [63-65], four studies [14, 66-68] for adaptive control based on performance, six studies [69-74] with assist-as-needed (AAN) strategy, one study [75] with potential fields based adaptive control, and three other studies [76-78]. Table 2 presents 14 studies with interactive training based on physiological signals, of them nine studies [13, 79-86] based on EMG signals and five studies [47, 87-90] based on electroencephalography (EEG) signals. Further to divide EMG related research, four studies[13, 79-81] tried to trigger robotic assistance by detecting participants' movement intention using EMG signals, one study [82] linked EMG signals to robotic assistance, two studies[83, 84] linked EMG signals to impedance control parameters, another two studies[85, 86] represent others, such as EMG-angle models. For EEG related research, four studies [47, 88-90] used EEG signals to detect motion intention based on motor imagery (MI) but the one [87] using the steady-state visual evoked potential (SSVEP) method.

Table 1. Thirty-one studies implementing human-robot interaction training based on kinematic, kinetic or performance information.

Studies	Joints	Control Strategies	Features	Training Tasks	Performances
Impedance/admittance control (* impedance, **admittance, ***combined impedance and admittance)					
Haptic device [50]*	Forearm Wrist	Impedance control.	In patient-in-charge mode, it required low impedance. In robot-in-charge mode, it needed high robot impedance.	Play games in virtual reality in eight different directions.	Experimental results suggest that the developed device can be used as a good haptic interface.
L-EXOS [12]*	Shoulder Elbow	Impedance control.	Leave the patient the possibility to actively conduct the task and being passively guided by the robot only when he/she is unable to complete the reaching task.	Reaching movements.	The evaluation on eight post-stroke patients showed a significant reduction of the performance error (paired $t-\text{test}, p < 0.02$).
IntelliArm [51, 52]*	Shoulder Elbow Hand	Zero resistance regulation control [51]. Internal model based impedance control [52].	The feedback loop of measured force and torque was constructed at each joint to regulate zero force/torque [51]. It was accurate and robust due to dynamics estimation error correction using the internal model control structure and efficient estimation of nonlinear dynamics using time-delay estimation [52].	Perform voluntary movement training with zero resistance [51]. Active reaching training after passive stretching [52].	Feasibility of the integrated capabilities of the robotic system was demonstrated through experiments with stroke survivors and healthy subjects.
Rehab-Exos exoskeleton [53]*	Shoulder Elbow Wrist	Interaction torque control based on impedance.	The centralized torque control is based on a full dynamics model of the exoskeleton, calculates the kinematics and dynamics of the system and estimates the feed-forward contribution for the compensation of dynamic loads measured by joint torque sensors.	Track desired trajectories.	Tests have been carried out to validate the desired torque tracking in haptic interaction tasks.
RiceWrist [54]*	Forearm Wrist	Impedance force control.	In the case of the forearm, the task-space and the joint-space are the same and hence the impedance controller is simply a joint-space controller.	Free motion and steady contact with the visual wall.	RiceWrist is a modification of the MAHI exoskeleton [91]. It exhibits low friction, zero-backlash and high manipulability.
LIMPAOT [55]*	Shoulder Elbow	Impedance control.	The impedance control contains the gravitation vector used to compensate for gravitational effects.	Tracking a cycloidal joint angle reference	The impedance controller ensures tracking of a cycloidal joint angle reference.
Support robot [56]**	Shoulder Elbow	Admittance control	For resistance force control.	Move the upper limb along the guided trajectory made by the therapist.	Training on subjects verified the effectiveness of the control algorithm of these systems.
MEMOS [57]**	Shoulder Elbow Wrist	Stiffness control based on admittance.	The selection of parameters like task duration, maximum speed, force threshold could be changed for each patient.	Track a figure in a horizontal plane.	Results showed that the robotic system is able to help chronic hemiparetics to reduce their impairments.
iPAM robot [58]**	Shoulder Elbow Wrist	Admittance control.	It allowed the charactistics of assistance to be altered in each degree of freedom (DOF) of the human arm independently.	Perform the cycle task for 15 times.	Results demonstrated the control suitability depending on the severity of patient disability.
Wrist robot [59]**	Wrist	Admittance control.	Implement several rehabilitation exercise by adjusting impedance parameters appropriately.	Perform isometric, isotonic, passive isokinetic exercise and active isokinetic exercise.	The validity of the proposed system is confirmed through experiments.
Gentle/G [60]**	Shoulder Elbow Hand	Admittance control	When combining Gental/G [92] with the Gentle/S robot [93] a total of 6 active and 3 passive DOFs are available, and virtual exercises are designed to be highly interactive and motivational.	Reach-grasp-transfer-release movements.	Results indicate the benefits of functional reach and grasp therapy as performed by the Gentle/G robotic system.
EXO-UL7 [61]**	Shoulder Elbow Forearm Wrist	Admittance control	Two different admittance controllers: one used the force to create trajectories, and the other resolves the interaction forces into joint torque equivalents before creating trajectories in joint space.	Perform tasks of inserting the peg into the hole.	Task space based admittance control was about 11% lower in mean interaction energy for the peg in the hole task compared to joint space control. Task completion time increased with both controllers compared to back-driving the device.
Bimanual robot [62]**	Shoulder Elbow	Admittance control	The parameters of admittance control could be adjusted based on training mode.	Perform tracking exercises developed to stimulate motor learning.	Results showed the system is suitable for motor learning experiments during unimanual and bimanual movements.
HEnRie [65]***	Elbow Hand	High level impedance control and low level admittance one	A virtual physiotherapist to stimulate and guide the patient through the rehabilitation process.	Perform 17 repetitions of the reaching and grasping tasks.	HEnRiE allows training of complex reaching and grasping movements.
ARMin [64].***	Shoulder Elbow Wrist	Patient-cooperative control based on impedance and admittance.	Axes 1 and 2 are admittance controlled, and axes 3 to 6 are impedance controlled.	Fulfill a task and gets patient-cooperative support in a ADLs game.	The latest ARMin system is commercially available.
Upper-limb exoskeleton [63]***	Shoulder Elbow	Impedance/admittance control.	Gravity and friction compensation algorithms are developed to make the use's interaction with the robot feel light.	Perform upper limb voluntary movements.	Experimental results demonstrated the feasibility impedance and admittance control for both the robot elbow and shoulder joint.

Adaptive control (* performance based, **AAN, *** Potential fields based)					
Bimanual robot [66]*	Shoulder Elbow Wrist	Adaptive assistance control	Allow the paretic arm to contribute as much as possible toward tracking the reference object.	Tracking exercises.	Trials on four stroke patients show promising results. After eight training sessions, the subjects were able to apply forces with the paretic arm similar to the forces of the unaffected arm.
IIT-wrist robot [67]*	Forearm Wrist	Performance based adaptive control.	The level of difficulty was managed by the controller modulating two parameters as a function of the performance: a) frequency of the target motion; b) level of the robot assistance.	Mono-dimensional tracking of a sinusoidally moving target.	Preliminary results show that robotic therapy may improve motivations in patients and provide tangible results even in a short term experience
RUPERT [68]*	Shoulder Elbow Wrist	Adaptive active-assist mode and adaptive co-operative mode.	The active-assist therapy utilizes the measure of a subject's motor ability and real-time movement kinematics to initiate robotic assistance at the appropriate time. The adaptive co-operative mode is to enable task completion instead of completing the task for the subject.	Reaching movements to different target locations.	The results on three stroke subjects demonstrated that the device can be used for administering robot-assisted therapy, in a manner that encourages voluntary participation.
hCAAR [14]*	Shoulder Elbow Wrist	Active non-assist for assessment and active assisted bimanual mode for training.	The assistance levels adjust according to the performance in the assessment exercise.	Each game involves a series of linear movements.	Seventeen participants used the robotic device independently for eight weeks in their own homes with significant improvements in the kinematic and clinical outcomes.
PASCAL robot [69]**	Shoulder Elbow	AAN path control.	(1) Virtual tunnel to stay close to the desired path; (2) Minimum and maximum speed restrictions; (3) Direction-dependent supportive flux along the path; (4) Gain-scheduling control to ensure the target is reached.	Move to one of eight different targets located at a distance of 10 cm around a starting position.	Results showed that the AAN controller covers the support range from a passive arm that needs full assistance to a completely active movement.
Pneu-WREX [70, 71]**	Clavicle Shoulder Elbow	Model based AAN control with forgetting [70, 71].	Lookup table forming a model of the patient's ability [70], and real-time computer modeling of weakness optimizes robotic assistance [71].	Reaching movements [70, 71]	Results demonstrated the ability of the orthosis to complete reaching movements with graded assistance and to adapt to the effort level of the subject, with improved movement ability [70, 71].
RiceWrist-S [72]**	Forearm Wrist	Model based AAN control.	Model-based sensorless force estimation to determine subject capability.	Perform a target-reaching task in a visual interface.	The RiceWrist-S is a 3-DOF serial mechanism [94]. The AAN controller and accompanying algorithms were demonstrated experimentally with subjects.
Upper-limb robot [73]**	Arm Wrist	AAN control.	It handles human–robot interactions in such a way that correct movements are encouraged and incorrect ones are suppressed to make the training process more effective.	Trajectory tracking.	The control allows parameter adjustment to provide flexibility for therapists to adjust and fine tune depending on the conditions of the patients and the progress of their recovery.
NTUH-ARM [74]**	Shoulder Elbow	AAN control.	It defined a smooth motion trajectory as basis to determine the timing to switch on/off the assistance.	Smooth trajectory with continuous positioning and velocity using the cubic spline method.	Results with six patients are positive and the assessment by physical therapists also reveals promising results.
Upper-limb robot [75]***	Shoulder Elbow Wrist	Potential fields based adaptive control.	The control modified the robot behavior in accordance with a force field defined along its workspace, trying to mimic the corrective actions done by the therapists.	Track the path conducted by a therapist.	Results showed that the controller based on potential fields achieve a stable and safety behavior of the robot with an acceptable accuracy.
Others					
Upper-limb robot [76]	Shoulder Elbow	Hybrid Position/force control incorporating fuzzy logic.	Constrain the movement in the desired direction and to maintain a constant force along the moving direction.	Planned linear or circular trajectories	Results on normal and stroke subjects showed that the robot can guide subjects through linear and circular movements under predefined external force levels.
Forearm robot [77]	Forearm	Fuzzy logic torque control.	Fuzzy PI tuner was used to compensate the nonlinear dynamics of the robot and the unknown disturbing torque from the subject.	Trajectory tracking	Results showed that in active mode the robot could maintain constant assistant or resistant torque.
ULERD [78]	Elbow Wrist	A method to detect the motion of the human forearm using elastic materials.	It is useful with the lack of backdrivability and accurate detection of the contact force between the human and the device	Perform elbow flexion and extension.	Results indicated that the proposed method of exerting resistance can be implemented and is effective for use with the ULERD.

Table 2. Fourteen studies implementing human-robot interaction training based on physiological signals.

Studies	Joints	Control Strategies	Features	Training Tasks	Performances
Physiological control — EMG signals (* triggering robots by detecting motion intention, ** linked to robotic assistance, *** linked to impedance control parameters, **** representing others, such as EMG-angle models)					
MIT-MANUS [13]*	Shoulder Elbow Wrist	Speed, time or EMG signals to initiate robot assistance for performance-based robot therapy.	EMG activity increases above the threshold.	Reaching movement tasks.	The effectiveness of the algorithm is vague, but with one strong benefit: a significant reduction in arm tone.
Upper-limb robot [79]*	Shoulder Elbow Wrist	EMG signals for patients' movement intention detection.	Levenberg-Marquardt algorithm based back propagation neural network is used to recognize six rehabilitation motions.	Perform six upper-limb activities of daily living (ADLs) motions.	Results on healthy subjects demonstrated the effectiveness of the proposed method.
Exoskeleton arm [80]*	Elbow Wrist	EMG signals for users' motion intention detection.	The difference of the EMG-based estimated muscle force between the agonist and antagonist muscles is considered as the reference input in the controller.	Perform flexion and extension movements of the elbow and the wrist.	The effectiveness of the proposed approaches has been verified on five subjects.
InMotion[2] [81]*	Shoulder Elbow	The onset of a patient's attempt to move is detected by monitoring EMG signals in selected muscles.	EMG based game parameters can be adapted to train specific muscles and to deliver robotic treatment even when the patient is only able to generate weak bursts of muscular contractions. EMG signals can be useful to better understand patient recovery from stroke.	Perform point-to-point movements in a horizontal plane.	Experiments were conducted to evaluate the potential of EMG-triggered and robot-assisted therapy, however its clinical effectiveness was not evaluated in this study.
Elbow robot [82]**	Elbow	EMG signals for assistive control.	Provide continuous assistive torque in proportion to the amplitude of the subject's EMG signal from the triceps and enable stroke subjects to perform training beyond their initial voluntary range of motion (ROM).	Control elbow movement to track and match the target pointer that was displayed in real time.	Results on eight chronic stroke patients showed improvements in upper limb functions in terms of clinical scales and robot-measured parameters.
Upper-limb exoskeleton [83]***	Shoulder Elbow Wrist	EMG signals based impedance control.	The estimated joint stiffness through EMG signals is utilized to design the optimal reference impedance model.	The designed trajectories were selected as 0.5*sin(t).	The robustness of the proposed approach has been verified using a real robotic exoskeleton and a human operator.
SUEFUL-7 [84]***	Shoulder Elbow Forearm Wrist	EMG signals based impedance control.	Impedance parameters were adjusted in real time by considering the upper-limb posture and EMG activity levels based on a neuro-fuzzy modifier.	Perform cooperative ADLs motions.	Results with two young subjects showed the effectiveness of the proposed robotic system.
Elbow exoskeleton [85]****	Elbow	An EMG-angle model was constructed for pattern recognition, i.e. using EMGs to predict elbow joint angle.	Elbow joint angle can be predicted from EMG signals by using the back-propagation neural network as the classifier. Thus the nervous system can adapt the exoskeleton control for different motions.	Perform elbow flexion and extension movements by holding a 1-kg load.	Results with six healthy subjects indicated that the exoskeleton could be controlled by the user's motion intention in real time based on EMG signals.
W-EXOS [86]****	Forearm Wrist	EMG-based fuzzy-neuro control to realize natural and flexible motion assistance.	Multiple fuzzy-neuro controllers are used owing to muscles activation levels changing in accordance with the angles of motions.	Perform wrist flexion and extension and forearm pronation with assistance.	Results with two young subjects show that the W-EXOS is able to assist wrist and forearm motion of physically weak individuals.
Physiological control —EEG signals (* detecting motion intention based on SSVEP, ** detecting motion intention based on motor imagery (MI))					
BOTAS [87]*	Shoulder Elbow Wrist Fingers	A SSVEP based brain-computer interface (BCI) using EEG signals.	The BCI was used to trigger predefined movements.	Grasping-a-ball and a carrying-the-ball movement.	Twelve able-bodied subjects were able to control BOTAS successfully using SSVEP.
L-EXOS [47]**	Shoulder Elbow	Gaze-BCI-driven control. BCI: brain computer interface	At the level of action plan, a kinect-based vision system was employed to track objects, and an eye-tracker was used for target selection. At the level of action generation, an EEG-based BCI was used to control the movement through the motor imagery (MI) paradigm.	Assist the patient in reaching and grasping of real objects by online capturing his/her intention of movement.	Results showed that subjects were able to operate the exoskeleton movement by BCI with a classification error rate of $89.4 \pm 5.0\%$ in the robot-assisted condition.
BRAVO Exoskeleton [88]**	Shoulder Elbow Wrist	Movement intention detection based on MI-BCI.	MI-BCI was used to trigger the robot movement.	Perform reaching/grasping/releasing tasks.	The average elapsed time of 3.45±1.60 s indicates that patients were able to volitionally trigger task execution through the MI-BCI.
ArmeoPower [89]**	Shoulder Elbow Wrist	Movement intention detection based on MI-BCI.	Link three-dimensional robotic training to the participants' efforts.	Reaching movements.	Results showed that the proposed BCI can link three-dimensional robotic training to the participants' efforts and allow for task-oriented practice of ADLs.
MAHI Exo-II [90]**	Elbow, Forearm, Wrist	Movement intention detection based on MI-BCI.	Several BCI features were optimized to increase system performance in the presence of single-trial variability of MRCPs in the injured brain.	Initiate elbow flexion or extension of the exoskeleton to reach the target.	Evidences show the closed-loop EEG-based BCI can be optimized to perform well across multiple days without system recalibration.

4. Discussion

The efficacy of robot-assisted physical therapy can be enhanced when active engagement is involved by the patient, while passive training is not capable of inducing motor learning [47]. Encouraging human users to perform self-initiated movements is thought to be an essential requirement to achieve effective cortical reorganization [47]. Over the past few decades, a variety of high-level control strategies have been proposed to modulate the robot assistance according to kinematic, kinetic, performance, or either physiological information measured during task execution, such as trajectory tracking error, interaction force/torque, EMG, and EEG activity, as summarized in Table 1 and 2.

4.1 Impedance/admittance control

Human-robot interactive tasks cannot be completely handled by just motion control. Position control generally rejects external forces or torques from human users as disturbances. An impedance control scheme is generally considered as the basis of interactive robotic training. It has been widely adopted with rehabilitation robots for enhanced training safety, comfort, and efficacy. There are two methods of implementing impedance control based on controller causality: impedance control (force/torque based method) and admittance control (position based method). The impedance controller takes a displacement as input and reacts with a force, and the admittance control accepts force and reacts with the position.

Impedance control has been commonly used with a variety of rehabilitation robotic systems to realize interactive training. Seven of selected studies in Table 1 [12, 50-55] implemented interactive training based on impedance. Frisoli, et al. [12] developed an impedance controller on a force-feedback exoskeleton for upper-limb rehabilitation, which allows the patient for active training and being passively guided when he/she is unable to complete the reaching task. Oblak, et al. [50] developed an impedance controller on an universal haptic device to allow patient-in-charge training where the interaction forces are controlled towards zero with a low impedance. Experimental results suggest that this robotic system can be used as a haptic interface between a computer and a human user. Park, et al. [51] developed an IntelliArm that realized zero resistance regulation control through a direct interaction torque feedback. While this does not use the impedance law, this results in a consant interaction torque control, such as zero torque for active training. More recent, the same group proposed an internal model based impedance method to control the robot to be backdrivable [52]. The introduction of the model based control structure improved the control accuracy and robustness through dynamics estimation error correction, with positive experimental results on both healthy subjects and stroke survivors. Solazzi, et al. [53] used an impedance strategy to control contact forces/torques not only at the end-link handle, but also at intermediate links, based on a full dynamics model of the exoskeleton. Similarly, a force control was implemented on the RiceWrist based on a task-space impedance law [54]. Otten, et al. [55] constructed a cascade controller on the hydraulically powered LIMPACT, of which the impedance controller contains the gravitation vector and a state feedback controller to regulate joints' position and velocity.

In general, impedance control has showed great potential for interactive training with a variety of rehabilitation robots. While the issue of poor accuracy in free-space due to friction and other unmodeled dynamics exists, this can be mitigated through inner-loop torque control or the use of low-friction components.

In contrast, while admittance control may result in contact instability with stiff environments, it provides better performance when interacting with soft environments [95]. Admittance control generally requires high transmission ratios such as harmonic drives for precise motion control. Seven studies [56-62] employed admittance control for interactive training for robot-assisted upper limb rehabilitation. This kind of control method aims to compute position and velocity of the robot based on human-robot interaction force or torque. Furuhashi, et al. [56] used admittance control on a rehabilitation support robot for teaching function and muscle tests. For the MIME, Micera, et al. [57] implemented stiffness control to adjust the resistance of the robotic system during the tracking tasks. Stiffness control was achieved by considering only the proportional component. In a more complex system, Jackson, et al. [58] used admittance control to modulate the input trajectory for each DOF as a function of measured force or torque. Similar control design is also applied on a wrist device [59], the Gentle/G [60], the EXO-UL7 [61], and bimanual robot [62].

There are another there studies [63-65] with the implementation of both impedance and admittance control schemes. Lo [63] respectively employed impedance control and admittance control to implement interactive training strategy on a robotic elbow joint and a shoulder mechanism. For the HEnRie, Mihelj, et al. [65] developed a task level controller where the physical model of the virtual environment is impedance based, while the robot joint level control is admittance based. Oldewurtel, et al. [64] proposed a patient-cooperative training scheme based on admittance control of Axes 1 and 2, and impedance control of Axes 3 to 6.

4.2 Adaptive control

Impedance and admittance control can be simply implemented with intuitive properties, unfortunately, these approaches fail to incorporate the time-varying capabilities of a human user and may thus intervene incorrectly. For instance, as robot-assisted rehabilitation training progresses, the participant may require less assistance than is provided. To provide appropriate robotic assistance in response to temporal variabilities in subject performance, several adaptive control schemes have been proposed.

Four studies [14, 66-68] implemented adaptive control, where the adaptation of controller parameters replies on online measurement of the participant's training performance. Sivan, et al. [14] controlled the hCAAR to provide assistance when the user’s voluntary upper limb movement is insufficient to complete the prescribed task. The assistance levels were adjusted according to the performance in the assessment exercises. Trlep, et al. [66] proposed a control strategy with adaptive assistance on a bimanual robot, aiming to adjust the contribution of the healthy arm and thus reduce the load on the paretic side. To achieve smoother and more precise motor patterns on the IIT-wrist robot, Masia, et al. [67] evaluated online performance and modulated both assistance and difficulty of training tasks. Balasubramanian and He [68] implemented two adaptive robot-assisted therapy modes (co-operative mode and active-assist mode). The adaptive active-assist mode completes training tasks when the participant fails to do so voluntarily. It initiates robotic assistance by measuring subjects’ motor ability and their real-time movement kinematics. The adaptive co-operative mode is based on the idea of enabling task completion instead of completing the task for the subject. Both modes were designed to adapt to the participant’ motor ability for enhanced training efficacy.

Providing too much assistance may have negative consequences for learning, thus a commonly stated goal in active exercise is to provide AAN, which means to assist the participant only as much as is needed to accomplish the task [96]. This kind of control strategy is expected to maximize robot-assisted training efficacy, and has been successfully implemented on some upper-limb robotic systems [69-74]. Keller, et al. [69] designed an AAN strategy by combining a path controller with additional speed restrictions to support, when the arm speed is too slow, and to resist, when the speed is too fast. Similar high-level control to assist only as needed in reaching exercises were also implemented on the Pneu-WREX [70, 71]. This controller allows voluntary movements toward the task target while resisting movements away from it. As each target position is reached, the controller builds an internal model of the participant’s capability, and learns the forces required for movement completion. Pehlivan, et al. [72] proposed a mAAN controller through sensorless force estimation to dynamically determine subject inputs without considering the nature of subject capabilities, and computes a corresponding assistance torque. Another two studies with the AAN strategy also showed promising results [73, 74]. In [73], the controller handles human–robot interactions in a way that correct movements are encouraged and incorrect ones are suppressed to make the training process more effective. Chen, et al. [74] defined a smooth motion trajectory as a basis to determine the timing to switch on/off the assistance. In a different way, Díez, et al. [75] proposed a potential fields based control method to modify the robot behaviour in accordance with a force field defined along its workspace, trying to mimic the corrective actions done by the therapists.

Some other methods have been also adopted for interactive training on upper limb rehabilitation robots [76-78]. Ju, et al. [76] developed a position/force controller incorporating fuzzy logic on a robotic system to constrain the movement in the desired direction and to maintain a constant force. Kung, et al. [77] developed a fuzzy logic tuned torque controller to generate assistant and resistant torque on a forearm rehabilitation robot. Song, et al. [78] used elastic components to detect human motion in the ULERD system for resistance training. It was demonstrated that this method could be used commonly in the field of human-robot interaction where the robot is of high friction, non-backdrivability, and difficult measurement of contact force.

4.3 Physiological control －EMG signals

Physiological signals can be used to avoid slacking and provide robotic assistance. Traditional control concepts have been extended into the consideration of human motion intention during the robotic training. EMG signals recorded from selected muscles have been used as an indicator of training patterns. Four studies [13, 79-81] adopted EMG signals to trigger the robotic motion based on patients' movement intention detection. Of them, Krebs, et al. [13] proposed a performance-based impedance control algorithm, which is triggered via speed, time, or EMG data, determining optimal subject-specific therapy. The game is triggered when the EMG activity increases above the threshold. Li, et al. [79] used a back propagation neural network to recognize six upper-limb rehabilitation motions. Li, et al. [80] collected EMG signal data of selected muscles to reflect the user's motion intention, where the difference of the EMG-based estimated muscle force between the agonist and antagonist muscles is considered as the reference input in the controller. To achieve a similar goal, Dipietro, et al. [81] used EMG signals to detect patients' attempt to trigger the robotic training. The recorded EMG signals were also used to understand the process of recovery from stroke. In general, preliminary tests of these proposed EMG-based triggering control strategies have been verified on human users with great potential for clinical applications.

EMG signals, an indicator of human users' effort generation, can be used for adjusting robotic assistance. Song, et al. [82] collected EMG signals from medial triceps brachii of the affected arm for proportional control to provide continuous robotic assistance, as in Equation (1) of Table 2. Results on eight chronic stroke patients showed improvements in upper limb functions in terms of clinical scales and robot-measured parameters. The EMG signal can be also used or tune control parameters for adaptation. Gopura, et al. [84] developed an impedance controller on the SUEFUL-7 by considering upper limb posture and EMG activity levels. Li, et al. [83] proposed an EMG-driven musculoskeletal human forearm model to account for joint stiffness, and then designed the optimal reference impedance model.

EMG signals have been applied for robot-assisted rehabilitation applications in different forms. In [86], to achieve natural and flexible motion assistance, an EMG-based fuzzy-neuro control was developed by combining flexible fuzzy control and adaptive neural network control. Experimental results with two young subjects support the W-EXOS' function in assisting wrist and forearm motion for individuals with physical disabilities. Another study [85] developed an EMG-angle model for pattern recognition during the robotic training. The elbow angle was predicted in real time from EMG signals, and then the angle was input to the controller as the desired trajectory.

While EMG-based control strategies have been widely used with robot-assisted applications, there are some challenges in reliably and accurately collecting EMG signals. For instance, these physiological signals are sensitive to the electrode placement, interference from neighboring muscles signals, and skin properties. However, the use of EMG signals to trigger robotic action offers several advantages: 1) allowing robot-assisted therapy to be customized based on specific muscles; 2) providing a means to verify that patients are actually attempting to generate voluntary movements rather than engaging their trunks to initiate movements; 3) triggering the robot earlier than based on kinematic signals; 4) allowing highly-impaired subjects to activate robot assistance even when they are unable to produce sufficient movement of triggering; 5) providing data to understand the process of recovery and patient's motor abilities. These recapitulative points have been also identified by Dipietro, et al. [81].

4.4 Physiological control －EEG signals

BCI technologies have been also developed by extracting neurophysiological signals from the brain to control robotic devices. The scientific interest in using BCI is corroborated by the fact they can be used even in the earliest phase of stroke recovery, when the injured human upper limb is not able to infer movement intention to guide the robotic training from any of the available peripheral biometric measurements, such as EMG activity and joint displacements.

SSVEP signals are natural responses to visual stimulation at specific frequencies, which mostly requires less training than motor imagery systems. Sakurada, et al. [87] developed a non-invasive SSVEP signal based control method to trigger grasping/carrying ball training movements. Result showed that the participants managed to control the BOTAS. In contrast, motor imagery (MI) based BCI technologies represent a promising rehabilitation approach for sensorimotor training, and is advancing very rapidly with encouraging results. Barsotti, et al. [88] used the MI method to detect patients' movement intention to trigger a full upper limb robotic exoskeleton for reaching and grasping/releasing exercises. The feasibility of the proposed system was verified with three chronic stroke patients. Brauchle, et al. [89] developed a similar MI-BCI on the ArmeoPower where EEG signals were analyzed to control the visualization engine. It was suggested that the proposed BCI technique could successfully link three-dimensional robotic training to the participants' efforts and allow for task-oriented practice of ADLs. Bhagat, et al. [90] analyzed movement related cortical potentials (MRCPs) measured over an optimized set of EEG electrodes to detect patients' intention triggering the motion of an upper-limb exoskeleton (MAHI Exo-II). Several BCI features were optimized to increase system performance, and evidences show that the closed-loop EEG-based BCI can be designed and optimized to perform well across multiple days without system recalibration. With respect to SSVEP based BCI technologies, the MI-BCI generally require a longer period of training session for better identification performance.

BCIs can detect intent by simultaneously combining information from different types of input signals, such as eye movements for enhanced safety of rehabilitation robots. Integrating an eye-tracking system into a MI-BCI, Frisoli, et al. [47] proposed a gaze-independent BCI-driven control scheme on the L-Exos to provide active assistance in reaching and grasping of real objects by online capturing his/her intention of movement. Experimental results from three healthy volunteers and four chronic stroke patients showed that all participants were able to operate the exoskeleton with a classification error rate of $89.4 \pm 5.0\%$. This indicates the high potential of the proposed gaze-BCI-driven robotic assistance for neurorehabilitation of patients with motor impairments after stroke.

In general, a variety of signal features and classification algorithms have been verified with satisfactory accuracy. As a result, the training time has been significantly reduced, which has led to more widespread BCI applications in the daily life of disabled people. However, more research should be devoted to investigating various signal acquisition methods and their performance, as well as identifying electrophysiological and metabolic signals that are best able to encode user intent.

4.8 Limitations of this review

An attempt was made to ensure a complete and comprehensive search and selection relating with high-level control techniques of upper-limb robotic systems. An important assumption is that the four review papers [6-9] include most typical upper-limb robotics systems reported before the year of 2013. However, other research may exist in which upper-limb/body was not identified as a key term within the article. For instance, some articles about upper-limb rehabilitation robots are probably described in terms of upper-extremity. Studies written not in English have been excluded, leading to potential incomplete search.

5. Conclusion

This paper reviews a variety of high-level control techniques that have been used for robot-assisted upper limb rehabilitation. The main purpose of interactive strategies is to encourage human users' engagement and promote enhanced training efficacy. Comparative analysis shows that high-level interaction control strategies can be implemented in a range of methods, mainly including impedance/admittance algorithms, adaptive control techniques, and physiological signal control. To summarize in the field of control strategies for interactive rehabilitation training, 1) the impedance and admittance method is simply implemented with intuitive properties; 2) adaptive control is needed when incorporating time-varying capabilities of human users; and 3) physiological signal control is an effective way of avoiding slacking and providing robotic support only when the brain is particularly responsive to peripheral input.

Even though the potentials of existing interactive control strategies have been demonstrated, it is hard to identify the one leading to maximum encouragement from human users. This is due to the lack of studies with direct comparison among various control algorithms. However, it is reasonable to suggest that future studies should combine different control strategies to be application specific, and deliver appropriate robotic assistance based on physical disability levels of human users.

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