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Machine Learning in Robot-Assisted Upper Limb Rehabilitation: A Focused Review

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***Abstract*—Robot-assisted rehabilitation, which can provide repetitive, intensive and high-precision physics training, has a positive influence on motor function recovery of stroke patients. Current robots need to be more intelligent and more reliable in clinical practice. Machine learning algorithms (MLAs) are able to learn from data and predict future unknown conditions, which is of benefit to improve the effectiveness of robot-assisted rehabilitation. In this paper, we conduct a focused review on machine learning-based methods for robot-assisted upper limb rehabilitation. Firstly, the current status of upper rehabilitation robots is presented. Then, we outline and analyze the designs and applications of MLAs for upper limb movement intention recognition, human-robot interaction control and quantitative assessment of motor function. Meanwhile, we discuss the future directions of MLAs-based robotic rehabilitation. This review article provides a summary of MLAs for robotic upper limb rehabilitation and contributes to the design and development of future advanced intelligent medical devices.**

***Index Terms*—Machine learning, upper limb rehabilitation, intention recognition, human-robot interaction, quantitative assessment**

I. Introduction

Stroke is a disorder of cerebral blood circulation caused by blockage of vessels. According to World Health Organization, stroke is one of the most common causes of death and the main cause of adulthood disabilities. Whilst there are more than 2 million new stroke patients, and more than 1.5 million people die from stroke each year in China [1]. With the rapid progress of neurosurgery technologies, the mortality rate of stroke patients is gradually decreasing, but the disability rate remains high. One of the most common symptom of stroke is the restriction of motor activity, which reduces muscle movement and mobility [2]. More than two-thirds stroke patients suffer from impairment upper limb exercise capacity [3]. About 50% of patients have chronically impairment of arm function after stroke [4]. The lack of upper limb function makes it difficult for patients to perform daily living activities independently, which leads to serious family and social issues.

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Traditional treatments that physiotherapists utilize simple equipment or qualitative observations to guide patients have obvious drawbacks of intensive subjectivity and uncertainty. Experiments indicate that robot-assisted rehabilitation can promote the reorganization and compensation of central nervous system, and restore patient's limb motor function by providing precise, repetitive, and task-specific treatments [5]. Robots can accurately track predefined path, perform various training modes according to patient's recovery conditions, objectively record the patient data and assess the ability during exercise. Besides, rehabilitation robots can arouse patient's training willingness through virtual reality or other techniques.

Rehabilitation robots are directly in contact with human, it's thus crucial for robots to acquire patients' data and learn their movement characteristics to ensure the safety and effectiveness of training. Machine learning algorithms (MLAs) learn from experience and predict unknown conditions, which has great potential to improve the intelligence of robot-assisted rehabilitation. Combined with MLAs, robots can explore the inherent movement patterns and predict human intentions. Intelligent methods can learn from past control process, adapt better to dynamic environment and unknown robotic model. Also, the evaluation process can be more objective through index quantification and feature learning. Though existing review articles have discussed various robot-assisted upper limb rehabilitation in terms of the robotic hardware [6], sensing technologies [7], control strategies [8, 9], patient engagement [10], human-robot interaction (HRI) modalities [11], and kinematic assessment [12, 13], etc., the applications of MLAs in robot-assisted rehabilitation has not been fully discussed.

This paper aims to provide a systematic review of the design and applications of MLAs for robot-assisted upper limb rehabilitation. Fig. 1 shows a typical system of robot-assisted upper limb rehabilitation, which can be an end-effector or exoskeleton mounted design. End-effector rehabilitation robots rely on a single attachment point at the end of the human arm, whereas exoskeleton rehabilitation robots interact with human arm through multi-point contact. Whilst MLAs can appropriately sit in several components of the system, such as intention understanding, robotic control and patient assessment, by using the collected human and/or robot data. MLAs can be used in intension recognition with physiological and/or physical signals to predict patient movements; intelligent controller is able to learn from patient status to adjust their reference trajectories or control criteria; a rehabilitation knowledge library can also be established by combining MLAs with conventional medical clinical scales to realize automatic evaluation of patient recovery stage.

This article points out the current research gaps and future directions, and promotes the emergence of more adaptable and intelligent robots to meet the growing demand of rehabilitation. The remaining of this article are organized as follows: Section II overviews the upper limb rehabilitation robots; Section III summarizes the movement intention recognition of patients using MLAs; In Section IV, the intelligent control strategies of upper limb rehabilitation robots are analyzed and discussed; Section V summarizes robot-assisted quantitative assessment methods based on MLAs. Finally, we make a conclusion on MLAs in robot-assisted rehabilitation and the future trends.

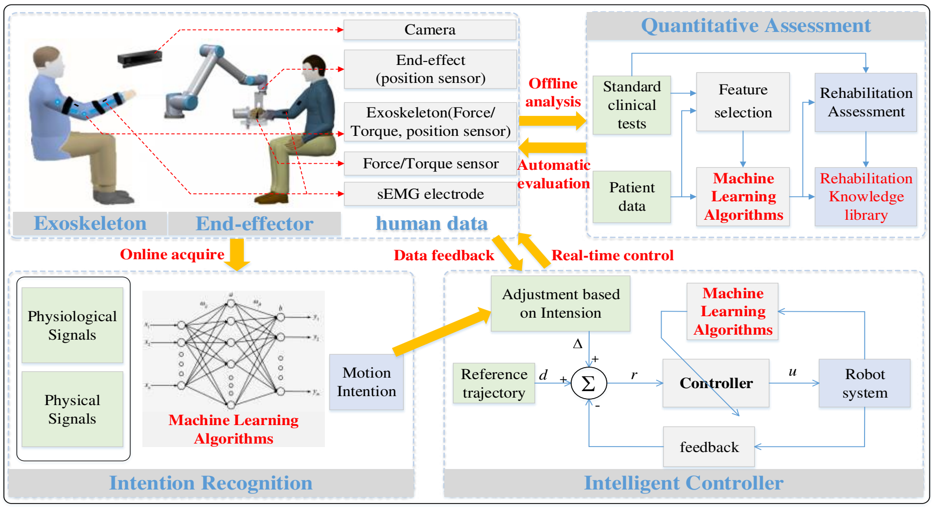
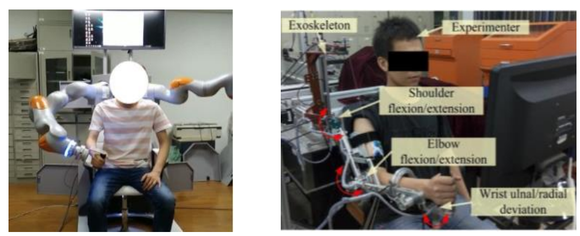


Fig. 1. Machine learning-based robot-assisted upper limb rehabilitation system

II. Overview of Upper Limb Rehabilitation Robots

End-effector robots firstly appeared 30 years ago, which have the advantages of simple structure, convenient control and high-precision [14]. A majority of end-effector robots were designed that time and many rehabilitation experiments with human participants have been conducted in the past two decades. Currently, some end-effector robots have been even applied in clinical robotic rehabilitation or treatments. Typical end-effector robots include MIT-Manus [15], MIME [16], ARMGuide [17], GENTLE/S [18], NeReBot [19], EMUL [20], Braccio di ferro [21] and ACT^{3D} [22], etc. Fig. 2(a) illustrates a new end-effector upper limb rehabilitation robot named EULRR, which consists of a supporting module and a motion assistance module. Two 7 degree-of-freedom (DOF) manipulators were used to support and assist patient's arm to complete rehabilitation training. Each joint was equipped with a torque sensor and a position encoder, which can be used for torque control. The assist-as-needed (AAN) controller allows patient's arm to move freely in a virtual channel and provide assistance while the arm deviates the virtual channel.

Wearable exoskeleton robots can provide assistance for multiple joints of the upper limb to perform safe and flexible rehabilitation training, which has gradually become popular in clinics. However, exoskeleton robots have more complicated mechanical structures and control strategies, so a majority of rehabilitation exoskeletons are still in prototype phase [25]. ETH Zurich has developed the ARMin series [26-30] for upper limb rehabilitation. Other well-known examples include L-Exos [31], CADEN-7 [32], IntelliArm [33], SUEFUL-7 [34], UL-Exo7 [35], Pneu-Wrex [36], RUPERT [37], etc. In Fig. 2(b), the upper limb neurorehabilitation exoskeleton has



(a) EULRR [23] (b) Neurorehabilitation exoskeleton [24]

Fig. 2. Examples of robot-assisted upper limb rehabilitation

seven actuated DOF for shoulder, elbow, and wrist joints. The robot joint positions were measured via potentiometers and two six-axis force/torque sensors were used to detect the interaction force. A neural-fuzzy adaptive controller based on radial basis function neural network (RBFNN) was proposed to guarantee the trajectory tracking accuracy with parametric uncertainties and environmental disturbances.

Existing upper limb rehabilitation robots are able to enhance the muscle strength and expand range of movement of affected limb. However, they are not intelligent enough to provide integral rehabilitation training without the guidance of therapists. Due to the uncertainty of human movement, it's difficult for current robots to provide appropriate assistance as patients needed. It is thus important for rehabilitation robot to recognize the motor intentions of patient during training. MLAs are capable of recognizing motion intention through physiological and physical signals to automatically regulate the training according to patient's actual ability. In addition, most of the existing robotic systems still follow the predefined control methods, while intelligent or adaptive controller is more appropriate for personalized rehabilitation. Combing the advanced control theory with MLAs, intelligent control methods can be proposed to adapt better to nonlinear systems and dynamic environment. Last but not least, MLAs are suitable for patient quantitative assessment by preprocessing, learning and classifying patient's data in recovery process. In summary, MLAs can improve the efficiency and reliability of motor function assessment in post-stroke rehabilitation.

III. Machine Learning-based Intention Recognition

During rehabilitation training, the involvement of patients' willingness to actively exercise can strengthen the central nervous system and speed up the recovery. The interactive process between human and robot should be dominated by patient's movement intention, supplemented by the robot assistance. How to incorporate patient's voluntary intention into robotic system is the primary goal for active rehabilitation. A common strategy is to quantify patient's intention with patient's data during the recovery. There are mainly two branches for the digitization of movement intention: 1) via physiological signals, and 2) via physical signals.

A. *via Physiological Signals*

Various physiological signals [38] have been used to obtain the movement intention information of human limbs, including electromyogram (EMG), electroencephalogram (EEG), electrooculogram (EOG) and electrocardiogram (ECG), etc. However, the amplitude of EEG is very small (5-300 μV), which requires signal amplifier with very high gain multiple (about 100dB), while the subtle movement of any small muscle may cause large noises; the learning and calibration process of EOG signal is extremely complicated, which also brings limitations to its application; ECG mostly reflects emotional information but less exercise intention information. In addition, the EMG signal can predict the human's movement before it occurs, so in this section we mainly consider the intention recognition using surface EMG (sEMG) signals, which are easy to acquire, stable and contains rich muscle information. Currently, MLAs have been usually applied in sEMG signal classification, such as Hidden Markov Models (HMMs) [39], Support Vector Machine (SVM) [40], Dynamic Bayesian Network (DBN) [41], Multilayer Perceptron Neural Network (MLPNN) [42] and Linear-based Artificial Neural Network (ANN) [43], etc. Though these methods can reach satisfactory classification accuracy, they can only provide an "on/off" signal, which may lead to non-smooth robot control. The robot actions cannot switch to each other arbitrarily and no further control can be performed during the execution of each action.

TABLE I. Continuous Motion Estimation via sEMG Using Machine Learning Methods

Types	Methods	Representative work	Aims	Features	Prediction results
Angle estimation	SVM	Siddiqi (2015)	Prediction of thumb angle during flexion motion	AR(2)-Vr. +MWAMP+SSI	Average accuracy: 86.53%
	GRNN	Liu (2018)	Knee joint angle prediction based on muscle synergy theory	WL	Mean R^2: 0.933
	TDRNN	Xin (2017)	Prediction of hand and wrist in 3-DOF	RMS	R^2 ranges between 0.81 and 0.94
	NARX MLPNN	Retheep (2017)	Estimation of elbow movement velocity and elbow joint angle	IEMG+ZC	R value: 0.9641 (angular prediction) and 0.9347 (velocity estimation)
	LS-SVR	Li (2015)	Estimation of joint angles of knee and hip	IAV	RMSE is smaller than 5°
	PCA(ICA) and ANN	Zhang (2017)	Simultaneous and continuous estimation for 4-DOF shoulder and elbow joint	MAV	Average estimation accuracy 91.12% (90.23%)
Force/ Torque estimation	ANN	Bahareh (2013)	Force estimation of wrist and hand	MAV	Average RMSE: 0.76 ± 0.42 and average of R^2: 0.84 ± 0.08
	TDNNs	Claudio (2014)	Online elbow joint torque prediction	MAV	RMSE(shoulder): 2.17 RMSE(elbow): 1.19
	BPNN	Peng (2015)	Torque estimation to obtain human motion intention	MVC	RMS(hip): 3.71 RMS(knee): 2.92

Features: AR(2)-Vr. +MWAMP+SSI: 2nd order Auto-regressive + Modified Willison Amplitude + Simple Square Integral (SSI) giving;
ML: wave-length; IEMG: integrated EMG; ZC: Zero crossing; IAV: Integral absolute value; MAV: mean absolute value; MVC: maximum voluntary contraction; PCA: principal component analysis; ICA: independent component analysis;
Criterion of errors: RMSE: root mean square error; CC: correlation coefficient; R^2: coefficient of determination; RMS: root-mean-squared; R value: correlation coefficient.

Therefore, how to continuously estimate the joint angle and force/torque is the key to achieve uninterrupted and smooth control of rehabilitation robots. Attributing to the nonlinear processing capabilities, MLAs are particularly suitable for continuous motion estimation, while Table I shows the characteristics of MLAs-based methods. The joint angle estimation based on sEMG can promote continuous smooth control towards the trajectory of rehabilitation robots. Siddiqi et al. [44] used SVM to predict thumb angle of bending motion and adopted "piecewise-discretization" method for continuous angle prediction. Liu et al. [45] used a generalized neural network (GNN) to estimate the joint angle of the lower limb knee joint during continuous movement. Xin et al.[46] used sEMG to predict the joint angle of wrist flexion and extension movement through a time-delay recurrent neural network (TDRNN). Retheep et al. [47] proposed a Nonlinear Auto Regressive with eXogenous (NARX) input structure based multiple layer perceptron neural network (MLPNN) model to estimate the elbow joint angle and angular velocity. With the rising demand of multi-DOF rehabilitation equipment, multiple joint angles need to be estimated. Li et al. [48] derived the dynamic relationship between the joint angle and the level of muscle activation on the basis of least squares support vector regression (LS-SVR), which could estimate the angles of the hip and knee joints. Zhang et al. [49] proposed a simultaneous estimation method based on ANN, principle component analysis (PCA) and independent component analysis (ICA) to calculate the shoulder and elbow joint angles that coordinate the movement of the upper limbs.

Muscle force and joint torque can reflect human activation status, and the accurate estimation of force and torque helps quantify the patient's movement intention. Bahareh et al. [50] mapped muscle activation coefficient to joint force with ANN, and estimated the joint force of wrist and hand movements. Claudio et al. [51] proposed a sEMG-based torque prediction method based on time-delay neural networks (TDNNs). Peng et al. [52] established two three-layer BPNN sEMG-based models to estimate the torques of the hip and knee joints.

B. via Physical Signals

Intention estimation based on physical signals is generally carried out with human-robot kinematic and dynamic data such as force and position, and a mapping model can be established to quantify the active movement intention. Some researchers regard human motion intention as a stochastic process. Ding et al. [53] proposed a method based on HMMs and used probability density function to build kinematic or dynamic models of human arm for long-term prediction. Dirk et al. [54] used Hybrid Dynamic Bayesian Network (HDBN) to model human intention, and proposed a multi-level approach towards intention, activity and motion recognition. Zhu et al. [55] combined a NN for gesture spotting and a hierarchical hidden Markov model (HHMM) for context-based recognition.

TABLE II. INTENTION ESTIMATION VIA PHYSICAL SIGNALS USING MACHINE LEARNING METHODS

Types	Methods	Representative work	Aims	Signals	Prediction results
Stochastic methods	HMMs	Ding (2011)	Online prediction of human arm's behavior	Position of arm joints (shoulder, elbow, wrist) from motion capture	Computational time is around 0.04s with the threshold δ = 0.9996
	HDBN	Dirk (2011)	Motion recognition on a data set of complex kitchen tasks	Images from a monocular camera	Average recognition rate of 67.2%
	HHMM	Zhu (2008)	Daily activity recognition	Inertial sensors attached to one foot and the waist	Test accuracy: 98.3%
Neural networks	Supervised NN	Ge (2011)	Motion intention estimation for physical HRI	Interaction force, position and velocity	The desired mean-square error 10^{-8}
	RBFNN	Li (2014)	Online motion intention estimation for human-robot collaborating	Force/torque sensor	Robot moves toward human's intended position
	ELM	Khan (2017)	Estimation of Desired Motion Intention when picking up a cup with upper limb exoskeleton	Position, velocity and force data	RMS Error = 4.2° with Standard Deviation = 6°

Considering the nonlinear and time-varying characteristics of human limbs, NN has been combined with the intention estimation method, due to its excellent approximation ability for unknown complex nonlinear system. Ge et al. [56] used a supervised NN to estimate the offline expected trajectory of the human limb. Specifically, they acquired the interaction force, position and speed of contact point to train the human limb model, and then estimated patient movement intentions. Nonetheless, offline estimation has two shortcomings: patients may change their intentions during interactive process which leads to retraining of models; and human fine movements are difficult to recognize during practical training. Li et al. [57] defined the desired trajectory of human as motion intension and used RBFNN to ensuring the accuracy of online estimation in spite of the change of human motion intention, which could overcome the nonlinear and time-varying property of the limb model. However, the weights refreshing relied heavily on the radial basis function parameters for convergence, and the adjustment of parameters was time-consuming. Khan et al. [58] used extreme learning machine (ELM) to predict human movement intentions, in which the hidden layer biased weights were randomly chosen, and the output weights were determined by a generalized inverse operation of the hidden layer matrix, so as to reduce the learning time. The MLAs-based intention estimation methods via physical signals are summarized in Table II.

C. Discussion on MLAs-based recognition

It is significant to understand patient movement intention during rehabilitation. As for physiological signals, especially sEMG, great progress has been made by applying MLAs into discrete classification to achieve high accuracy. However, discrete commands make the robot trajectory discontinuous. While continuous motion estimation based on ANN are necessarily required to make the robot move more smooth and safe. ANN shows strong nonlinear characteristics, and many NNs of different structures have been used to estimate continuous motion signals, such as angle and force/torque. However, the structure of the NN has a relatively large impact on the estimation results, sometimes it is difficult to define a suitable network structure, and the determination of parameters also largely depend on the training data. Besides, NN currently has many shortcomings: low calculation speed, poor generalization capacity and local minimum [59].

Physical signals (including joint angle, angular velocity, acceleration, force, and torque, etc.) can be directly obtained by physical sensors. Stochastic methods or NNs are often used to approximate the kinematics and dynamics models of human limbs, so as to extract the patient motion intention. Stochastic method defines the intentions into several states, which is suitable for recognition of actions with small changes [60]. NNs possess excellent universal approximation ability to nonlinear and time-varying properties of human limb models. For both physiological and physical signals, MLAs will play important roles in nonlinear signal processing. However, the majority of current researches on MLAs still have certain limitations, which only work for specific tasks. Consequently, MLAs need to be further developed to cater for the characteristics of the signals to be processed, while the learning speed and accuracy of real-time intention estimation need to be improved. Deep learning, as current hot issue of MLAs, has been applied into EEG analysis [61, 62]. Due to the huge demand for patient samples and consumption of training time, new deep learning structures are expected to proposed to achieve faster and more accurate recognition. In addition, it's an important area to estimate patient intention by combining multiple signals, which adopts appropriate MLAs according to the properties of different signals to enhance the reliable of intention recognition.

IV. MACHINE LEARNING-BASED HUMAN-ROBOT INTERACTIVE CONTROL

To facilitate personalized training, rehabilitation robots should be able to adjust the assistive trajectory or force according to the condition of patients, and guide the patient to move actively during exercise. Appropriate human-robot interactive control strategies are crucial to achieve motor function reconstruction for patients after stroke with rehabilitation robots. In rehabilitation, the robot compliance is also important which can adapt to the external constraint environment. The compliance can be passive or active [63]. Passive compliance uses specific compliant actuators to make the robot comply with environmental changes. Active compliance refers to the design of appropriate control strategies to adjust the contact force between the human and robot. By combining with advanced control theory, robots can be adjusted to cope with complex environments adaptively.

TABLE III. NEURAL NETWORK-BASED ADAPTIVE INTERACTIVE CONTROL METHODS

Control method	Representative work	Aims	Control results
Adaptive impedance control	Huang (2004)	Position/force tracking adaptively tuned with position error	Positions converge to desired values with force errors bounded, torques in reasonable ranges
Adaptive admittance control	Choi (2009)	Adaptive task scheduling and adaptive modification of difficulty	The simulations with different difficulties successfully followed the desired model
Adaptive impedance control based on ANN	Tsuji (2005)	Tracking control using one NN to adapt individual differences and identifying nonlinear characteristic	Adaptive adjustment of the parameters to improve the effectiveness of the tracking performance
Hierarchical neuro- fuzzy adaptive impedance control	Kiguchi (2008)	Adapt to physical and physiological condition of any user to realize the desire motion	The exoskeleton system effectively assists the upper-limb motion with the activation levels of the EMG signals reduced
Adaptive impedance control based on EDRFNN	Xu (2011)	Regulate desired impedance between robot and impaired limb in real time	EDRFNN controller has good position tracking performance even in the presence of variable assistive force
Adaptive impedance controller based RBFNN	Khan (2015)	Extraction of desired motion intention and development of impedance control for assistance	Asymptomatic tracking of desired reference impedance model

A. *Neural Network-Based Adaptive Interactive Control*

Adaptive functional training allows controller parameters or task difficulty index to be modified according to patient's performance, rather than imposing a predetermined mode. The adaptive algorithm can feed back the output of control system to the input and change it with certain rules to overcome the difficulties caused by uncertainty of the time-invariant model. Huang et al. [64] developed an adaptive impedance control scheme for a constrained robot to achieve asymptotic convergence of the robot's position tracking error and the boundedness of constraint force error. Choi et al. [65] adopted adaptive admittance control to select the task and set the task difficulty adaptively according to patient's previous data. Adaptive control methods can revise the assistive trajectory or force according to patient's performance, thus making the interaction between robot and human safer and compliant. However, because of the individual differences, such as arm's length and range of motion, impedance parameters are still tentative and cannot be easily extended to other participants.

Human-robot interactive control schemes incorporating MLAs (such as NNs) have been introduced to rehabilitation robots recently. In Table III we summarize the NN-based adaptive impedance control methods. Tsuji et al. [66] used ANN to establish an adaptive training system based on human characteristics, utilizing a NN to adjust the control parameters to cope with individual differences. Kiguchi et al. [67] further proposed a hierarchical neuro-fuzzy impedance controller for a robotic rehabilitation system, in which the desired impedance control parameters were regulated by the EMG signals of limbs. Xu et al. [68] developed an adaptive impedance controller based on evolutionary dynamic fuzzy neural network (EDRFNN) to regulate the desired impedance between robot and impaired limb in real-time according to physical recovery condition. Khan et al. [69] proposed an adaptive impedance controller based on RBFNN for the upper limb dynamic exoskeleton to follow human movement actively. Meng et al. [70] proposed a robust iterative learning feedback tuning technique for repetitive training control, which can learn from previous control data to adjust controller parameters. Ai et al.[71] further proposed high-order model-free adaptive iterative learning controller to achieve fast convergence speed. NN-based intelligent controllers possess superior performance because they can adapt to patients through learning. However, due to the inevitable NN reconstruction error, the control trajectory is limited to unified ultimate bounded stability [72]. Furthermore, there will be a trade-off between the robot impedance and the tracking accuracy. It is necessary to develop an advanced controller by combining with MLAs which can automatically adjust the control criteria for different training tasks.

TABLE IV. REINFORCEMENT LEARNING-BASED INTERACTIVE CONTROL METHODS

Control method	Representative work	Aims	Function of Reinforcement learning
Impedance control using eNAC algorithm	Byungchan (2010)	Motor skill learning for robotic contact tasks	Determine the impedance parameters and optimize the performance of the contact task
RL-based input and reference compensation	Pane (2019)	Precise reference tracking on a 6-DOF robotic manipulator	Compensate unmodeled aberrations to enhance the performance of nominal tracking controller
AHC based on actor-critic	Meng (2014)	Assist person to achieve functional task on assisted-as-needed principle	Evaluate the patient's performance and change its assistance/resistance automatically
Adaptive impedance- based control combining with IRL	Hamidrezaet (2016)	Assist human to perform a task with minimum workload demands	Transform the problem of finding the optimal parameters of robot impedance model into a LQR problem and solve LQR problem
Variable impedance control based on model-free RL	Li (2019)	Control the contact force accurately in the unstructured environment	Predict the uncertainties of the states and search the optimal control strategy and regulate the target stiffness and damping directly
Variable admittance control based on fuzzy Sarsa (λ) learning	Wang (2019)	Surgical arms adjusted manually to their expected configuration before robotic-assisted surgery	Acclimatize various operating characteristics through enough online learning

B. Reinforcement Learning-Based Interactive Control

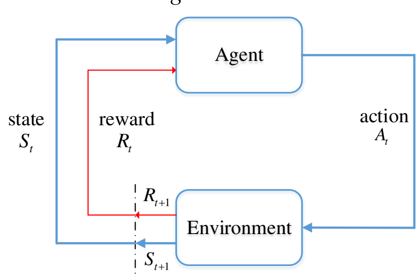


Fig. 3. Structure of typical reinforcement learning scheme

Reinforcement learning (RL) is a branch of machine learning, which focuses on goal-directed learning from experience. As shown in Fig. 3, the state signal represents the state of agent such as the Cartesian position of robot, the action signal describes the influence of the agent to the environment, and the reward signal gives positive or negative feedback to the agent [73]. The principle of RL is to find out a suitable policy to maximize the reward function generated by agent when interacting with the environment by trial-and-error search policy. Thus, incorporating RL into robot control can improve control performance and provide a new way towards the optimization decision of a complex system with unknown model. Actually, RL-based control methods have been applied to interactive control of robotic arms, such as the biological arm control [74], robotic arm navigation [75], and robotic arm tracking control with uncertainty [76].

In recent years, RL has been applied to intelligent control of manipulators in HRI scenarios. Some representative works of RL-based control schemes are demonstrated in Table IV. Taking the actor-critic as an example, such a typical RL algorithm integrates value-based method with policy gradient. Actor is a policy function used to generate actions and interact with the environment; and the critic is a value function used to evaluate the performance of the actor and guide the next stage of the actor. Byungchan et al. [77] combined impedance control with RL based on equilibrium point control theory to determine the impedance parameters for contact tasks, in which the state vectors were the joint angles and velocities, the action vectors changed the stiffness matrix in Cartesian space and the rewards were designed to minimize two performance indexes. The optimal impedance parameters were searched through episodic natural actor-critic (eNAC) algorithm based on the recursive least-squares filter. Pane et al. [78] established input compensation and reference compensation methods with actor-critic method to promote the performance of the nominal tracking controller. Each joint of the 6-DOF robot arm was equipped with an actor-critic compensator to reduce the number of learning parameters and simplify the model of learning algorithm. Meng et al. [79] proposed an adaptive inverse optimal hybrid control (AHC) algorithm combining inverse optimal control and actor-critic learning to provide global asymptotically tracking for unknown nonlinear robots with uncertain human dynamics.

Apart from actor-critic framework, other RL methods have also been applied to the manipulator interaction controller. Hamidrezaet et al. [80] built an intelligent interaction system which adjusted the robot behavior automatically to help people accomplish cooperative tasks. The optimization of robot impedance parameters was transformed into a linear quadratic regulator (LQR) problem, which was then solved by integral reinforcement learning (IRL). Li et al. [81] proposed a variable impedance controller with model-based RL algorithm to enable the robot to learn the parameters effectively and control the contact force accurately in an unstructured environment. Wang et al. [82] proposed a new strategy based on fuzzy Sarsa (λ) learning algorithm for surgical assisting robots, and incorporated it into the virtual parameter adjustment strategy to complete the operation in physical HRI.

C. Discussion on MLAs-based control

Rather than performing monotonous tasks repeatedly like industrial robots, rehabilitation robots interact with human and provide suitable assist trajectory or force according to the conditions of patients. It is still a rigorous problem to implement autonomous control of rehabilitation robots. Intelligent control combined with MLAs empower robots the ability of learning, which is potential to handle this problem.

NN-based adaptive controller allows the rehabilitation robots to find the optimal control parameters through training and learning from patient's data, and NN can cope with the nonlinearity of robot dynamics and the uncertainty of patient's limb movement [83]. However, the interactive objects of rehabilitation robots are patients instead of inanimate objects, which needs a high requirement for safety and instantaneity. In addition, the properties of each patient are unique, including basic physical parameters of the body such as length of arm and height, the recovery speed of different patients. New ideas and methods (such as data augmentation and optimization technologies) need to be proposed to tackle the deficiencies of NN-based adaptive controller, e.g. insufficiency of sample and slow calculation speed, to improve the safety and instantaneity and achieve personalized rehabilitation.

RL controllers are proposed by learning from experience, which try to develop an optimal policy to maximize reward by adjusting action to environment. Nonetheless, RL controllers are not yet mature to satisfy researchers' expectation [84]. There are not many applications of RL algorithms in upper limb robotic rehabilitation, and most of them are still in simulation stage. In addition, the structure of RL controllers also need further development and improvement. It's time-consuming to define suitable reward function to avoid unexpected goal, and the cost of trial-and-error search is too high. Even so, we are looking forward to new technologies to settle the weaknesses of RL controllers, such as bionics, optimization, simulation, and digital twin technology.

V. MACHINE LEARNING-BASED QUANTITATIVE ASSESSMENT

The decline of motor function caused by stroke will greatly reduce the patient's muscle strength and agility, including paralysis, loss of motor coordination, abnormal muscle tone and loss of somatosensory and so on [85]. Through clinical evaluation, physiotherapists can track the patient's recovery progress and customize the training schemes. One of the most common assessment methods is performed by experienced experts using chart-based standard clinical tests. Fugl-Meyer Assessment (FMA) [86] is a popular test to evaluate upper limb motor function for patients after stroke. It involves 33 tests for various joints such as shoulders/elbows/forearms, wrists, hands, and exhibits high inter-rater and intra-rater reliability. Other scales, like Wolf Motor Function Test (WMFT) [87] and Motor Activity Log-30 (MAL) [88], have similar functions. However, these scales can only output a rough score, which cannot reflect patients' specific recovery conditions. In addition, the whole evaluation process is under therapist's guidance, which are time-consuming, complicated and labor intensive to complete a set of tests.

Robotic rehabilitation system can quantitatively record medical data reflecting the pathological characteristics of the affected limb, and make scientific assessments of the motor function. There are some common measurement methods for quantitative assessment. Inertial sensors[89] and physiological sensors are usually mounted on people through wearable devices to record the kinematics data or biological signals; mechanical measurement systems[90] monitor movement or interactive force/torque using sensors installed on the robot, and image processing system[91] focuses on the evaluation of coordination between joints through cameras or motion capture systems.

The prerequisite for quantitative evaluation is to set up an appropriate correlation between patients' data and the clinical assessment scale indicators. Zariffa et al. [92] used multiple linear regression to identify the relationship of sensor data and the manual clinical assessment scales to search combination of predictors with highest correlation; Zollo et al. [93] adopted linear regression analysis to explore the connection of data from wearable sensors with clinical scales to find the most relevant variables to limb movements.

It is important for quantitative evaluation to automatically rate and judge patients' states of weakness. MLAs are competent for this task due to their superior data processing and multi-objective decision making abilities. Silvia et al. [94] used random forest (RF) algorithms to estimate the scores of FMA through wearable sensor data. Tahir et al. [95] proposed an activity recognition system based on gyroscope sensors, and used PCA to exclude redundant features. Different classifiers such as probabilistic neural network (PNN), k nearest neighbor (KNN) and SVM were used to assess walking activities. Yu et al. [96] designed quantitative evaluation framework for remote rehabilitation, which is composed of two accelerometers and seven flex sensors to monitor the motor function of upper limb, and established an ensemble regression model based on ELM to map kinematics and kinetics data to FMA scores. Some work obtains kinematics data indirectly through image information. Ilktan et al. [97] used RGBD cameras to monitor the rehabilitation training, and the observable nodes of Bayesian network was built to learn the image features to predict motion and posture. Otten et al. [98] proposed a framework for automatic upper limb movement assessment using low-cost Kinect sensor to collect movement data, and then adopted SVM to grade the patient's upper limb motor function. Liao et al. [99] proposed a framework based on deep learning to automatically assess the quality of rehabilitation training, containing quantitative movement indicators, scoring functions, and a deep neural network model to quantify movement scores.

Robot-assisted rehabilitation system can measure the subject's data throughout the treatment process, make motor function assessment, and provide feedback to the therapists and patients. Quantitative evaluation can not only improve the reliability of determining states of patients, but also will greatly reduce the time required to assess patients' movement ability. Quantitative rehabilitation assessment methods rely heavily on machine learning methods. The correlation between patient data and medical scales need to be built through multiple linear regression or other algorithms to select characteristic variables. Automatic scoring is a core part of quantitative evaluation, and MLAs such as NN and SVM are very appropriate for this task. Nevertheless, due to the variety of patient data, the inter-cross and intra-cross analysis methods also pose great challenges to MLAs. Besides, many medical indicators are difficult to quantify due to complex and changing motor symptoms, and quantitative assessment methods have not been widely used in clinical rehabilitation, so advanced technologies are needed to analyze medical indicators more deeply to digitize them. After accumulating sufficient patients' data and their evaluation results, a rehabilitation evaluation knowledge library can be established based on MLAs so as to automatically evaluate the state of recovery during robot-assisted rehabilitation.

VI. Conclusion

In the past few decades, upper limb rehabilitation robots and machine learning methods have shown encouraging effects and efficiency in clinical rehabilitation. This article reviews the robot-assisted upper limb training schemes and how MLAs can be applied to motion intention recognition, human-robot interactive control and quantitative assessment of motor functions in rehabilitation. Robotic rehabilitation has increasingly emphasized the importance of patient's active participation, which can strengthen the central nervous system and promote recovery by recognizing the intention of patients based on MLAs to promote the training of basic skills, mobilizing the patient's willingness to actively exercise. Furthermore, it's necessary for rehabilitation robot to ensure the smoothness and flexibility during human-robot interaction process. MLAs-based controllers are able to adjust the parameters adaptively to satisfy the individual differences of patients. In addition, MLAs can play important roles in developing comprehensive evaluation methods to provide patients with objective, quantitative and timely evaluation and assessment. Machine learning methods can promote the feasibility and intelligence of rehabilitation robots. Future intelligent rehabilitation robots are expected to analyze and learn the data during patients' recovery process through machine learning to realize intelligent recognition of patients' movement intention, amalgamate RL with HRI control to implement self-adjusting and autonomous control strategy, combine big data in the rehabilitation process with medical theories to establish a professional rehabilitation knowledge library to accomplish intelligent assessment.

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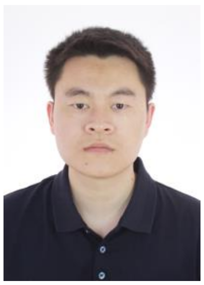

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