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Power Assist Rehabilitation Robot and Motion Intention Estimation

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ABSTRACT

This article attempts to review papers on power assist rehabilitation robots, human motion intention, control laws, and estimation of power assist rehabilitation robots based on human motion intention in recent years. This paper presents the various ways in which human motion intention in rehabilitation can be estimated. This paper also elaborates on the control laws for the estimation of motion intention of the power assist rehabilitation robot. From the review, it has been found that the motion intention estimation method includes: Artificial Intelligence-based motion intention and Model-based motion intention estimation. The controllers include hybrid force/position control, EMG control, and adaptive control. Furthermore, Artificial Intelligence based motion intention estimation can be subdivided into Electromyography (EMG), Surface Electromyography (SEMG), Extreme Learning Machine (ELM), and Electromyography-based Admittance Control (EAC). Also, Model-based motion intention estimation can be subdivided into Impedance and Admittance control interaction. Having reviewed several papers, EAC and ELM are proposed for efficient motion intention estimation under artificial-based motion intention. In future works, Impedance and Admittance control methods are suggested under model-based motion intention for efficient estimation of motion intention of power assist rehabilitation robot. In addition, hybrid force/position control and adaptive control are suggested for the selection of control laws. The findings of this review paper can be used for developing an efficient power assist rehabilitation robot with motion intention to aid people with lower or upper limb impairment.

1. Introduction

According to the World Health Organization, over 15 million individuals are attacked by stroke each year, with approximately six million becoming incapacitated. The impairments range from completely paralyzed limbs to weakening [1]. Robot arm power aid is stretching therapists' limits these days [2]. They help people with arm impairment and injuries caused by accident-related spinal injuries, cerebrovascular illnesses, muscular dystrophy, and limb paralysis. The employment of robotic arms as a substitute for human caregivers is a viable option [3]. Rehabilitation is the process of dealing with the effects of a stroke [4][5]. Stroke patients, accident sufferers, the elderly, athletes, and employees in physically demanding occupations are all at risk of losing their upper limb capacity to do daily tasks [6].

There are different classes of robotic systems [7] that can be used in various applications such as manufacturing process [8], artistic painting and drawing, welding [9] as well as rehabilitation, as shown in Fig. 1. Robotic devices used for rehabilitation are known as rehabilitation robots. End-effector and exoskeleton rehabilitation robots are the two types of upper extremity rehabilitation robots [10], as shown in Fig. 2. These robots can do rehabilitation training tasks to assist patients in completing certain rehabilitation exercises [11][12] and perform varieties of movements [13][14]. At the same time, it provides a repeated and rigorous physical treatment that relieves the physical therapists of a significant amount of work [15]. End-effector systems, which use footplates or handles to create limb motion in space without needing alignment between the patient and robot joints, do so with footplates or handles [16][17].

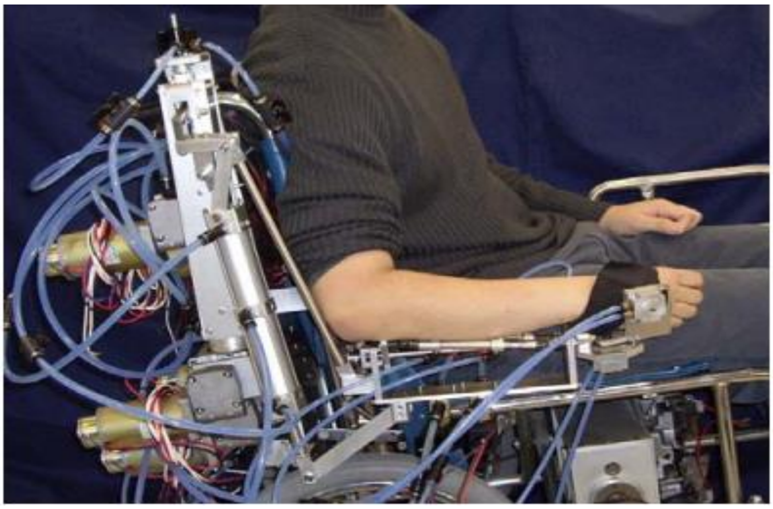

Fig. 1. Rehabilitation Arm [3]

Fig. 2. End-effector (left) and exoskeleton (right) rehabilitation robot device [6]

Each joint in the exoskeleton system is steered along a preprogrammed course by a one-to-one interface between robots and human joints [18]. Based on the number of joints manipulated, exoskeletons are divided into unilateral and bilateral robots [19]. The exoskeleton controller and the human brain, which consists of the spinal cord and cerebrum, are the two types of controllers that function in conjunction with power assist robots. The most prevalent aspect of exoskeleton robot control methods, particularly in power assist exoskeleton robots, is that they strive to replicate human motion intention. However, a thorough investigation of human mechanics is currently being conducted [20]. As a result, determining the appropriate control mechanism is challenging, and optimizing such a control system is much more complex. In previous investigations, several control systems for controlling the upper-limb exoskeleton robot were developed. Based on the input signal to the motion controller, the human motion intention of upper-limb exoskeleton robots may be categorized into three types [21]:

1) Control techniques based on bioelectrical signal measurements
2) Control methods based on biomechanical measures
3) Platform independent approaches.

Control strategies based on bioelectrical signal measurements entail properly running the system under a variety of externally produced disruptions. In the case of power assist robots, the typical control concept's goal has been extended to include human motion intention. In this group of procedures, control techniques based on bioelectrical signal measurements, electroencephalography (EEG) [22], electrooculography (EOG), electromyography (EMG) [23], and other bioelectrical signals can be used [24]. Among these, the EMG signal is the most often used bioelectrical signal measurement [25]. EMG data are related to muscular activity levels and represent the firing rate of motor neurons. As a result, EMG signals directly represent the human's motion intention. EMG signals are measured in two ways: using surface EMG electrodes or with intramuscular EMG electrodes. Due to the variable circumstances of the skin and body size, EMG-related metrics are subject-dependent and might alter from day to day [26].

Power assist robots that use various strategies to extract the human motion intention are among the control methods based on biomechanical metrics. In the current state of the art, human motion intention is determined using alternative sensing instruments such as force/torque sensors or a dynamic model of the human limb. EMG signals are not employed in these procedures. Control techniques that operate either a human bioelectrical signal or a biomechanical signal are included platform-independent approach. With numerous exoskeleton improvements, several control techniques are given and utilized to improve the characteristics of the power assist robot's control system [27].

The rehabilitation robotics system is mainly divided into active and passive types. A passive type rehabilitation robotic system fully assists the patient in the rehabilitation exercise [28]. However, the power assist robot is an example of a passive type rehabilitation system that assists the patients instead of the therapists and has been developed for fully automatic robotic rehabilitation therapy.

Physically challenged persons can use power assist devices to help them with self-rehabilitation and everyday chores. Even though the main study purpose for power-assist exoskeleton robots was largely for industrial usage, several studies on upper-limb mobility, lower-limb motion, and/or other motions of physically weak persons have been done [29]. The application of fully robotic rehabilitation therapy may induce a higher risk of patient injury and may be uncomfortable for the patients since there is no direct therapist invention in training. There may also be errors in the robot actuation while conducting the therapy [30].

To fulfill the requirement for repeated therapy in stroke rehabilitation, power assist rehabilitation is an important field of study [6]. Technological advancements and the rising need for mobility aid are propelling society toward a future where this desire may be supplied by power assist devices. During the last several decades, the potential for assistive upper-limb devices to improve human quality of life has expanded the number of research activities in this field [31]. As a result of the high number of devices that have joined the scientific community, many assessments have been produced [32]. Human motion intention, lifting things, and other factors can all be used to segment power aid systems.

Brahimi et al. [33] presented a gadget that can construct the intended trajectory based on the designer's estimate of the human's motion intention. Motion Intention was proposed as a solution since it takes a lot of energy for a human to move the exoskeleton arm. This is especially true if the distance between the robot's real position and the human's motion intention is significant. This study only looked at the positions of the human hand; attitude adjustment isn't taken into account.

For active power-assist lower limb exoskeleton robots, Li et al. [34] investigated a new method for analyzing human body motion intention. The inverse dynamics method (IDA) was utilized to calculate the human joint torque online using a dynamic model of the human body and a sensor system included within an exoskeleton robot that was built to monitor the human body's motion data and foot contact force. Kiguchi et al. [35] presented research on estimating interaction motion intention for perception-assist using a wearable power-assist robot. This procedure entails that the user of the power-assist wearable robot engage in utilizing visual information obtained from the worn came to determine the other person's motion intention. To curb these difficulties, wearable power-assist robots have been proposed to assist the motion of physically weak persons [36], such as elderly persons or disabled persons, in their daily life [37]. Chathuramali et al. [38] tackle the difficulty of detecting the user's motion intentions while engaging in desired interactions with others while wearing an upper-limb power-assist wearable robot.

The research contribution is the review papers on power assist rehabilitation robots, control laws, and estimation of power assist upper limb rehabilitation based on human motion intention in recent years and the suggestion of efficient estimation methods and control laws for power assist rehabilitation robots based on motion intention.

The rest of this paper is organized as follows: Section 2 presents a power assist system that is developed for the application of power assist robot and power assist rehabilitation robot. Human motion intention and modes of estimation of motion intention are explained in section 3. Control laws used with motion intention estimation in power assist rehabilitation are described in section 4. Section 5 summarized all the discussions and reviews made in this paper. Finally, the conclusion is drawn in section 6.

2. Power Assist System

A power assist system is a human-robot cooperation technology that increases a person's task-doing ability. Currently, power assist devices are mostly used in the rehabilitation and healthcare of the sick, crippled, and elderly [39]. Other applications for power assist devices include; lifting baby carriages [40], supporting agricultural work, hydraulic power-assist for automobiles, skill-assist in manufacturing, power-assisted slide doors for automobiles, power-assisted control for bicycles, and power assistance for sports, and power assistance for horse training [41]. Power assist systems are developed for the following applications: Power assist robot, Power assist rehabilitation robot.

2.1. Power Assist Robot

A power assist robot is a human-robot collaboration that enhances a person's ability and expertise in executing tasks. Power-assist robots are valuable not just for physically disabled people but also for people who work in physically demanding jobs like care or farming [42]. Power assist robots are presently being developed primarily for rehabilitation assistance, lifting objects, and skill-assist for manufacturing, among others, according to the literature [43]. Handling huge objects, which is frequent and important in businesses, might be another area where power assist robots could be useful. It is vital to move massive items in industries like manufacturing and assembly, logistics and transportation, building, mining, disaster and rescue operations, forestry, and agriculture. Handling large objects requires a lot of effort and might lead to work-related diseases and disorders including issues of increasing concern. However, in many circumstances, autonomous devices may not provide the essential flexibility in object handling and positioning [44]. As a result, in the aforementioned industries, the use of appropriate power assist systems is appropriate for handling huge objects.

In the industrial world, manipulating heavy objects is a fairly common and familiar operation. Manual manipulation, on the other hand, is inconvenient [45]. In many real applications, autonomous devices may not give the requisite amount of freedom in object handling [46]. As a result, adequate power-assist devices are regarded to be useful for this function. On the other hand, such gadgets are uncommon in practice. The human operator cannot accurately assess the gravity of the object before handling it with the assist system, resulting in incorrect interactions between the system and the user, such as rapid acceleration, user dread, lack of maneuverability and stability, deadly accident, and so on. Although a few power assist robots have been developed for transporting things [47], they are not as safe, natural, or human-friendly for lifting heavy objects in industries.

With conventional power assist robotics, the operator applies excessive load force (LF- vertical lifting force) because the operator cannot precisely judge the weight of the object before elevating it with the robot. Excessive lifting force, among other things, produces a quick increase in acceleration, operator fear, a lack of agility and stability, and an accident. On the other hand, conventional power assist systems for object handling do not consider this. Other drawbacks of conventional power assist systems for object manipulation include the lack of human characteristics in control, the system's weight, the quantity of power aid being unclear, and the system's safety, mobility, and efficiency not being properly analyzed, among others. Conventional power assist devices, on the other hand, do not take a holistic approach to tackle these problems/issues to make systems more human-friendly [48].

Given these issues, Rahman et al. [49] suggested using a ball screw system to lift goods. When an object is lifted using the power assist robot, a psychophysical link is created between the real weights (weight of an object felt by a person if the object is lifted manually) and the power-assisted weights of an object perceived by a human (operator). The surplus in lifting force is calculated so that the subjects can use the robot system to lift objects. Workers in industrial settings choose whether to move goods with one or two hands based on physical characteristics such as form, size, and mass. As a result, psychophysical correlations are developed, and excess lifting force is computed separately for three protocols: unimanual lift, bimanual lift, and cooperative lift. A unique control technique based on weight perception and lifting force characteristics are used to modify the control. The updated control minimized the excessive lifting power in each lifting protocol, considerably improving the robot system's mobility, operability, naturalness, ease of use, stability, and safety. As a result of the aforesaid method, human-friendly power assists robots in lifting heavy things in industries that can be developed.

2.2. Power Assist Rehabilitation robot

Power assist rehabilitation robots are designed and developed to assist physically disabled people with self-rehabilitation and daily activities. Power assist rehabilitation robots are divided into two categories. The first is an assistive robot that takes over for missing limb movement. A wheelchair-mounted robotic arm controlled by a chin switch or other input device is the Manus ARM (assistive robotic manipulator). Telemanipulation is a technique that operates similarly to an astronaut controlling a spacecraft's robot arm from the cockpit. Powered wheelchairs are another type of teleoperated helpful robot. The second form of rehabilitation robot is a therapy robot, sometimes known as a rehabilitator. According to neuroscientific study, the brain and spinal cord retain a remarkable ability to adapt, even after damage, by using rehearsed motions. Therapy robots are devices or equipment that rehabilitation therapists use to assist patients in practicing motions with the assistance of the robot. MIT-Manus, the first robot employed in this fashion, assisted stroke patients in reaching across a tabletop if they were unable to do it on their own. Patients who got additional therapy from the robot had a faster return of arm mobility [50].

Power assist rehabilitation of upper and lower limb technologies grows quickly due to the increase of the aged population. In the upper limb rehabilitation system, power assist robot training seems to improve arm function for daily life activities. Upper limb rehabilitation robots perform the specified motion to the human upper limbs, which include the shoulder, elbow, arm, and hand. However, lower limb rehabilitation robots help to improve functions of the human lower limbs which include the hip, knee, leg, ankle, and toe. Recently, many researchers in the field of power assist rehabilitation have been in search of the appropriate design that helps humans perform their desired motions.

Hayashi and Kiguchi [51] proposed a perception-assist for a lower-limb power assist rehabilitation robot to help the elderly or physically challenged walk. The proposed perception assist involves the power assist robot observing the surroundings in front of the user and modifying the user's mobility as needed to avoid the user from falling, all while doing the standard power assist. Furthermore, the suggested technique conducts perception-assist while keeping steady walking by taking into consideration Zero Moment Point (ZMP).

Mansour [52] suggested a concept design for an upper limb power assist rehabilitation robot based on electromyogram (EMG) for patients who have problems moving their arms but whose muscle signals are still intact. The recommended design was created and designed using a CAD model. The device has one degree of freedom (DOF) and two basic dimensions: flexion and extension, and it is controlled using electromyogram (EMG) signals acquired from human muscles. The proposed approach may be applied anywhere with only one person's assistance.

Kiguchi et al. [53] presented a task-oriented perception-assist with an upper-limb power-assist rehabilitation robot to aid physically weak people with daily tasks. A method of perception-assist was presented to aid not only the user's mobility but also the interaction with an environment by applying the modification force to the user's motion if necessary. The gripping tool was utilized to evaluate the performing task utilizing contour and color histograms in the perception-assist approach.

Kadota et al. [54] published a report on the development of a power assist rehabilitation robot arm that uses pneumatic artificial rubber muscles (PARMs) and a balloon sensor to help upper-limb and back movements. A single PARM moves the elbow and wrist joints, and the arm components' activity is similar to that of bi-articular muscles. Three PARMs are attached to a waist belt on the costume's back. To provide precise power-assist motion and regulate pressure, PI control (Proportional Integral control) is used, which is based on pressure data collected from a newly designed balloon sensor. One robot arm uses a single PARM to assist the user's wrist and elbow joints. This robot arm is connected to a waist belt by three PARMs that form a suspender-like structure. The output voltage of the servo valves is determined by the control system, and the generated power assist is matched to the pressure in the PARM.

According to the literature reviews, not only the user's motion should be considered for an efficient power assist rehabilitation robot. A method perception-assist was proposed to assist not only the user's motion but also the user's interaction with an environment by applying the modification force to the user's motion if necessary. Furthermore, the most effective technique to assess the effectiveness of a power assist rehabilitation robot is to use an electromyogram (EMG)-based control signal.

3. Human Motion Intention

The predicted acceleration, velocity, and location of a person are defined as human intention [2]. In a human limb model, human intention is represented by the intended velocity, which is estimated in real-time using interaction force and contact point movement parameters such as the robot's current location and velocity [55]. The military, space technology, industry, medical treatment, healing, aiding the elderly and disabled, and entertainment are all examples of human-robot partnership [33]. Synchronization, high contact force, and inadequate motion compliance are among the disadvantages of human-robot collaboration. Impedance control, which allows the robot to follow a preset path, is a potential option for interaction control. The techniques of altering the assistance lever of the impedance parameters are often utilized in many applications of human-robot shared control systems [56]. From visual image acquisition to human behavior forecasting, there are various approaches based on behavioral features, such as facial recognition and outline recognition. These approaches, on the other hand, do not apply to physical human-robot interactions in which just the interaction force information is supplied [57].

To address the aforementioned issues, a machine learning technique (radial-based function neural network model) for identifying collaborators' intentions is required to assess the cooperation intention in touch human-robot collaboration. To begin, sample data is collected using the adaptive impedance control technique to provide training and test data for a neural network. A rudimentary neural network model is generated after mapping sample data. Finally, the collaborator's purpose is determined via online prediction [58]. To confirm that the RBFNN technique is valid, the robot's contact point speed and interaction forces are measured and compared to the suitable experimental parameter values from the adaptive impedance control algorithm. In a contact human-robot interaction, the RBFNN approach can precisely determine the collaborator's purpose, which not only improves motion synchronization but also efficiently reduces the interaction force.

The human-robot collaboration whole architecture is primarily made up of three parts: data collection, offline learning, and online real-time estimate. Human motion intention can be estimated in various ways, which include: Artificial intelligence-based motion intention estimation and Model-based motion intention estimation.

3.1. Artificial Intelligence Based Motion Intention Estimation

Surface electromyography (SEMG) based control, EMG based control, EMG-based admittance control (EAC), and Extreme Learning Machine (ELM) based methods have all been proposed in the literature for predicting, detecting, and assessing motion intention. Recognition of the wearer's movement intention is critical in the examination of power-assist robots [59]. Accurate and real-time recognition of human motion intention is necessary for flawless human-machine synchronization and wearing comfort [60]. Surface electromyography (SEMG) is a bioelectrical signal produced when a neuron transmits human motion intention information directly to connected muscles [61]. As a consequence, the motion intention may be fully inferred without any information delay or loss [62]. A better human-machine interface might be created using SEMG-based motion intention recognition. Human motion intention recognition based on SEMG is going to become widespread because of its abundant information, sophisticated acquisition technology, and noninvasiveness [63].

The two techniques of SEMG-based motion intention recognition are SEMG-driven musculoskeletal (MS) model-based motion and machine learning (ML) based motion. A biomechanics model of muscles for the SEMG-driven musculoskeletal (MS) model can be used to build a relationship between SEMG and joint moment, angular velocity, or angular acceleration. This technique has the advantage of detailing the motion generation process. Machine learning uses the SEMG feature or processed SEMG as an input. To achieve discrete-motion classification or continuous-motion estimation, a mapping between input and human motion intention is used. Support vector machines (SVMs), linear discriminant analysis (LDAs), back-propagation neural networks (BPNNs), and deep learning (DL) are some of the most often utilized machine learning techniques for motion intention identification [64]. The ML model has reduced computing complexity, shorter operation time, and real-time performance than the SEMG-driven musculoskeletal model. Deep learning (DL) is increasingly being utilized for human motion intention identification as deep learning research has progressed in recent years. DL outperforms the competition in terms of model nonlinearity, capacity to solve complicated problems, and recognition accuracy [65]. Three DL models are often used for motion intention recognition: deep belief network (DBN), convolutional neural network (CNN), and stacked auto-encoder (SAE) [66]. SEMG is an excellent alternative for estimating motion intention [67]. EMG-driven MS model and ML model are two techniques to implement the SEMG-based human-machine interaction method. The identification of human motion intentions is the most crucial part of the entire operation [68].

The capacity to foresee future motion is required for motion interaction. Motion prediction is a branch of study with applications in many different fields, ranging from video surveillance to robot navigation. Motion intention prediction is used to determine the human-robot collaboration goals. A power-assist rehabilitation robot, which is directly attached to the user's body and supports movement in line with the user's goal [69], is one of the most effective assistance robots for physically weak persons. Although EMG signals from the user's muscles directly reflect the user's motion intention, EMG-based control (control based on the user's skin surface EMG signals) is one of the most effective control methods for many types of assisting robotic systems, particularly power-assist exoskeleton robots. However, even with the same person, EMG-based control is challenging to implement since obtaining the same EMG signals for the same movement is difficult. Furthermore, because a joint motion involves numerous muscles, real-time motion prediction is difficult because each muscle's activity level and how each muscle is used for a specific motion varies from person to person. The participation of each muscle in a certain motion changes depending on joint angles [70], and the activity level of some muscles, such as biarticular muscles, is influenced by the motion of the other joint.

Kiguchi [71] suggested a Neuro-fuzzy approach for accurately estimating the motion intention of the user of the power-assist rehabilitation robot, which could be utilized to compensate for the effect of the posture difference. The neuro-fuzzy controller is a cross between a fuzzy controller that can handle ambiguous input and employ human expertise and an artificial neural network controller that can adapt and learn. Combining several neuro-fuzzy controllers can alleviate the above-mentioned issues with EMG-based control. The mapping ability of an artificial neural network may also be employed to tackle the problems. Changing the weight values (i.e., the consequence component of the fuzzy IF-THEN control rules) as functions of EMG data of the linked muscles can also solve the problems. If the degree of freedom of the assist motion is limited, another method based on EMG signals to assess the user's motion intention might be used. Although those neuro-fuzzy controllers are excellent at controlling the power-support robot using EMG data, the controller becomes more difficult as the degree of freedom of the power help rehabilitation robot increases.

The suggested neuro-fuzzy modifier has a topology similar to a neural network, and the signal flow method is akin to fuzzy reasoning. The five steps of a neuro-fuzzy modifier's architecture are the input layer, fuzzifier layer, rule layer, defuzzifier layer, and output layer. The neuro-fuzzy modifier takes into account the shoulder flexion/extension angle, shoulder adduction/abduction angle, shoulder internal/external rotational angle, elbow flexion/extension angle, and forearm pronation/supination angle. Each joint angle is divided into three halves. (FL: flexed region, IM: intermediate region, and EX: extended region for shoulder flexion/extension and adduction/abduction angles, and IN: internal region, CE: center region, and EX: external region for shoulder internal/external rotational angle and forearm pronation/supination angle). The output of the neuro-fuzzy modifier is the coefficient for each weight [71].

The detection of motion intention is difficult, especially when it comes to upper-limb motions, which are predominantly used for dexterous manipulation activities. Myoelectric signals can provide useful information about a person's movement's purpose and the amount of effort they put in. As a result, electromyography (EMG) data may be used to construct natural human-machine interfaces for prosthetics, orthotics, telemanipulation, and functional electrical stimulation. Although the EMG control showed promise in improving the quality of life of patients with limb impairments, its clinical and commercial uses are still limited. Given the challenges of providing reliable control just by EMG, it appears that many sensor modalities are necessary for sophisticated device control [72]. An EMG-based admittance controller (EAC) was created to overcome the concerns. However, deciphering human intent for effective use and efficient functioning of a multifunctional device involves several challenges. The fundamental explanation is that the EMG signals are time-varying and noisy [73]. Furthermore, there is a complicated non-linear connection between the various muscles and the output forces they provide.

Antuvan [74] proposed a novel method called Extreme Learning Machine (ELM) to overcome these challenges. ELM is a new learning paradigm that combines single and multi-hidden layer neural networks, radial basis function networks, and kernel learning to provide an efficient unified method for generalizing feed-forward neural networks. ELM is a Single-hidden Layer Feed-forward Neural Network (SLFNN) [75], which is a relatively recent supervised learning technique. ELM has many advantages, including quick learning, simplicity of deployment, and little human interaction [76]. Thus holds a lot of promise as a feasible alternative approach for large-scale computing in a variety of applications, such as image [77], text [78], voice [79], multimodal processing [80], cognitive learning [81], and reasoning [82].

Huang et al. [83] also suggested ELM as a new algorithm to solve the above issues. Hidden layer (biased) weights are determined at random in the ELM method. After selecting a random weight, the network's output weights (which connect the hidden and output layers) are calculated analytically using a simple generalized inverse operation on the hidden layer output matrices. The learning pace of this technique is hundreds of times quicker than that of typical feedforward networks that employ the back-propagation algorithm. The ELM method is straightforward to implement and free of the over-fitting concerns that afflict RBFNN-based algorithms. Feedforward neural networks, such as RBFNN, have long been used in a variety of fields due to features like a direct approximation of complex nonlinear functions using input and output samples and the provision of models for a wide range of natural phenomena that are difficult to model using traditional parametric methods.

These methods, however, are inadequate for applications such as determining human purpose since they are slow when approximating a large class of natural events. It's hardly unexpected that training such neural networks can take many hours. The main cause of this delayed learning is that all of the network's parameters must be fine-tuned. Based on inputs from force sensors, current joint location, and current moving speed, ELM may smoothly assess intended intentions, learn human motion patterns, and anticipate future movement [84]. In rehabilitation and assistive robotics, this desired motion can be used to increase performance and robot compliance.

Using filtering technology, a quantitative model may be utilized to infer human motion intention. The user's inferred intent can be utilized as a control input for robot mobility. The human-robot interface has a basic design and is easy to put on and take off. An exoskeleton-type rehabilitation or assistive robot might be better handled by employing the recommended interface, intention estimation, and intention-based control algorithms to make the user feel natural and comfortable [21]. The power-assisted rehabilitation robot must be able to increase power in proportion to the required mobility. To do so, the robot has to figure out which components of the encounter are dependent on human intent [85].

3.2. Model-Based Motion Intention Estimation

Impedance and admittance control interaction is presented for estimating the Motion intention equation. The synchronization of output torque is crucial during human-robot interaction. When a torque sensor is used to detect motion intention, a delay between the human's voluntary torque and the robot's supportive torque might obstruct human-robot synchronization. When compared to earlier equations such as a torque sensing-based equation, an admittance and impedance interaction equation is devised to improve human-robot synchronization.

When the exoskeleton's endpoint is too far away from the blue ball on the prescript trajectory, Xing et al. [86] developed an interaction control strategy derived from impedance control to allow the individual to actively execute the training activity while being driven by the power assist robot. The relationship between the interaction torque τ_h of each joint, and the motion state of the endpoint is known as the impedance interaction.

$$\tau_h + J^T F_g = J^T \left[K_1 (X_0 - X) + K_2 \dot{X}\right] \quad (1)$$

where J is the Jacobian matrix of the exoskeleton robot, J^T is the transposed form, F_g is the extra gravity compensated force. X and X_0 represent the position of the endpoint from the exoskeleton and the nearest position of the endpoint on the prescript trajectory, respectively. K_1 and K_2 are the stiffness and damping coefficient, respectively. F_g is equivalent to that there is a virtual handholding of pulling the endpoint of the exoskeleton.

The Jacobian matrix may be used to translate it into compensated torques for each joint, which can then interact with the observed interaction torques. $\dot{X} = J\dot{q}$ is the velocity of the endpoint. The admittance control may be used to define the connection between the desired speed and the interaction torque of each joint (1).

$$\dot{q} = \frac{\tau_h + J^T F_g = J^T \left[K_1 (X_0 - X) + K_2 \dot{X}\right]}{K_9 J^T J} \quad (2)$$

As demonstrated by the equation, the intended velocity of each joint will change as the interaction torques from the associated joint vary throughout active training sessions (2). The current speed changes are influenced by contact torques, deviation from the end point's reference trajectory, and the damping impedance coefficient K_2. When the position of the endpoint deviates from the prescript trajectory, implying that $X_0 \neq X$, t the desired velocity of each joint changes to bring the subject back to the reference trajectory. The stiffness and damping impedance coefficients K_1 and K_2 determine the adjustment range. To conduct speed tracking of the robot and accomplish control of the active interaction training sessions, the Model-Free Adaptive Sliding Mode Controller (MFASMC) will employ the target velocity of each joint q, which is output by the interaction controller.

Zhuang et al. [87] employed a lower-limb neuro musculoskeletal model to calculate human joint torque using EMG data and then applied an admittance control approach to achieve the desired position. An EMG-based admittance controller (EAC) was used to generate a synchronized and stable Human-Robot Interaction (HRI). To create a synchronized and reliable Human-Robot Interaction, an EMG-based admittance controller (EAC) was employed (HRI). The power assist exoskeleton robot was controlled by an admission controller to aid patients in completing the movement. The subject's planned movement position in the admittance controller was decided by the admittance model, into which the subject's voluntary torque was entered. The PD controller was then used to control the power assist robot, which monitored the subject's intended posture.

Li et al. [88] used a human upper-limb model to characterize human motion intention as the intended trajectory, then used neural networks to identify model parameters online before incorporating the desired trajectory into an upper-limb humanoid robot's impedance control. When the human motion intention is uncertain, and the robot dynamics are unknown, adaptive impedance control is employed for a robot working with a human partner. The planned trajectory in the human partner's limb model is characterized as human motion intention, which is extremely difficult to fulfill because of the limb model's nonlinear and time-varying features. Neural networks are employed to tackle this challenge, and an online estimation technique is built around them. The robot follows a specified target impedance model thanks to the created adaptive impedance control, which integrates the anticipated motion intention. Using the described technique, the robot might actively cooperate with its human counterpart.

Impedance and admittance control interaction were proposed for human motion intention estimation. The admittance control strategy is used to attain the required position so as assist the patient in completing its movement. The power assist rehabilitation robot follows a target using an adaptive impedance control method. To enable the robot to actively engage with its human partner, the estimated motion intention is included in the developed adaptive impedance control.

4. Control Laws Used With Motion Intention Estimation in Power Assist Rehabilitation Robot

The primary component driving upper limb power assists robot development is human motion intention. Human motion intention can be obtained if the estimation is right. Estimating the wearer's motion intention is a critical difficulty in rehabilitation or assistive robot since any helpful robot should move in accordance with the wearer's intention. The development of an accurate identification mechanism for determining the wearer's motion intention is especially crucial in wearable power assist systems [89]. A quantitative model describes human intention, which may be determined using filtering technology. The expected intent of the wearer might be used as a control input to guide the robot's movements, making the user feel at peace. Through the analysis of the conduction path and the different stage manifestations of motion intention in the human body, it was confirmed that the joint torque of the human body meets the basic requirements of motion intention estimation for the active power-assist, and it was suggested that: it reflects the direction and intensity of the wearer's efforts, it precedes human limb motion, and it generates real-time and continuous output. As a result, a correct model, assessment of human purpose, and technique of calculating human joint torque are necessary [20].

Conventional control systems based on force/torque sensors have difficulties recognizing human intentions and are prone to misinterpreting or distorting such intentions as a consequence of external contact force disturbances, such as those experienced in everyday activities. As a result, the genuine human force cannot be properly dissected by a power-assist robot controller. The total of the applied force, including unknown external elements and human intention, is detected by force/torque sensors [90]. The power assist robot can also employ motion sensors on the user to assist with the anticipated motion [91].

Tang et al. [92] used the proportional myoelectric control approach to run an upper-limb power-assist exoskeleton controlled by pneumatic muscles in real-time according to the user's motion intention. An electromyogram (EMG)-angle model was created for pattern detection using the feature extraction approach and classification (back-propagation neural network). The elbow angle was assessed using EMG data, and a back-propagation neural network (BPN) was utilized to construct the EMG-angle model to make the exoskeleton configurable to each participant. The network prediction performance was used to measure the control strategy's dependability throughout varied motion durations, with the four-second interval having the best prediction performance. Furthermore, the power-assist performance was evaluated in a variety of circumstances, and a positive effect was proven. The findings revealed that the exoskeleton could be controlled in real-time by the user's motion intention and that it was useful for improving arm performance with neurological signal control, which might be useful for elbow rehabilitation after neurological damage. Zeng et al. [93] utilized the contact force and the EMG data to apply a state-space model to predict the knee joint angle in real-world applications, and the Gaussian process was used to enhance the adaptive method.

A hybrid active control approach with human intention detection was proposed by Yang et al. [94]. To continually analyze the goal location and velocity of the human intention, the human upper-limb model and the minimal jerk model were utilized. The human upper-limb model and the Minimum Jerk model (MJM) were used to compute the proper location and velocity. Also, because the end-effector had such a low mass, the observed cable force was interpreted as the robot-human contact force. The motion intention was then supplied to an upper-limb cable-driven rehabilitation robot's hybrid force and position controller (CDRR). A three-dimensional reaching task with no predetermined trajectory was utilized to assess the efficacy of the suggested control mechanism.

Wang et al. [95] proposed a motion intention-based bionic control system for a power assist exoskeleton robot arm. Filtering is used to pre-process the motion signal that has been captured. The motion intention and motion mode of the processed signal are then classified using a hierarchical multi-classification support vector machine. The required parameters are then transmitted, and the oscillator network is reconstructed to produce periodic motion control for rehabilitation training, depending on the user's aim.

For an upper-limb power-assist robot, Huang et al. [96] designed an intention-guided control approach. The wearer's upper-limb motion intention is evaluated in real-time by force-sensing resistors (FSRs), and the Intentional Reaching Direction (IRD) is used to quantify this intention. The motions of three DC motors mounted at the relevant joints of the robotic arm are controlled by the inferred IRD using an admittance control approach.

Yang et al. [97] suggested an upgraded robot skill learning system that took into account motion creation as well as trajectory tracking. Dynamic movement primitives (DMPs) were utilized to simulate robotic motion during robot learning demonstrations. Each DMP is made up of a group of dynamic systems that work together to improve the stability of the produced motion toward the objective. To increase the DMP's learning performance, a Gaussian mixture model and Gaussian mixture regression were combined, allowing more aspects of the skill to be retrieved from repeated demonstrations. In both space and time, the motion created by the learned model was scaled. To monitor the trajectories provided by the motion model, the robot was given a neural network-based controller. A radial basis function neural network is utilized in this controller to adjust for the influence of changing surroundings.

Ravandi et al. [98] suggested an adaptive fuzzy controller that combines hybrid force/position control of robotic manipulators working in unpredictable settings with conventional sliding mode control (SMC). After decomposing the manipulator dynamics into position, force, and redundant joint subspaces, the universal approximation capacity of fuzzy systems is utilized to approximate the corresponding part of the control input produced using the SMC approach. An adaptive PI controller estimates the robust component of the controller to correct variations caused by model uncertainty and disturbances.

Liu et al. [99] developed a hybrid force/position control system for robotic arms based on the stiffness estimation of an unknown environment, resulting in precise control and a stable system. To increase the robot's applicability and dependability in welding, polishing, and assembling, a frequency-division control method is devised.

Predicting human intent necessitates human-robot interaction. As a result, synthesizing a precise model-dependent controller is challenging, and control rules based on a simplified version of the dynamics may fail in real-world applications. Hybrid force/position control has been known as a kind of control method for the contact work of the manipulators [100]. Hybrid force/torque control was designed to avoid force control challenges in which the position, force, and redundant joint subspaces are orthogonal to one other. Hybrid control is also useful when tracking precision and a sufficient range of interface force are required.

The planned trajectory in the human partner's limb model is characterized as human motion intention, which is extremely difficult to fulfill due to the limb model's nonlinear and time-varying features. To solve this problem, neural networks are used, and an online estimating approach is constructed based on them. The created adaptive impedance control incorporates the predicted motion intention, causing the robot to follow a set target impedance model. The power assist robot's intention-guided control can be employed as a useful and pleasant power support device. Furthermore, the usual trajectory control method's flaws are avoided.

5. Results and Discussion

Power assist system, power assist robot, power assist rehabilitation robot, and human motion intention estimation is reviewed in this article. Power assist devices are systems that help a person's capacity to perform a task. Power assist systems can be used for various applications such as; liftings objects, manufacturing processes, healthcare, and rehabilitation exercises. Power assist rehabilitation robots are robots used to help the old, ill, and physically disabled people with self-rehabilitation and daily activities. Power assist rehabilitation can be upper limb rehabilitation or lower limb rehabilitation. For an efficient power assist rehabilitation robot, not only the user's motion should also be considered, but a method perception-assist is proposed to assist not only the user's motion but also the user's interaction with an environment. Human motion intention is the prediction of the velocity, acceleration, and position of a person.

Rahman et al. [49] developed One Degree of Freedom (1DOF) power assist robot that took into account human weight perception in unimanual, bimanual, and cooperative modes. Also, a power assist robot arm using pneumatic rubber muscles with a balloon Sensor was developed by Kadota et al. [54]. Hence, motion intention was not considered in both projects. Zhuang et al. [87] published a paper on admittance control based on an EMG-driven musculoskeletal model that enhances human-robot synchronization. This paper explained how EAC was used to generate a synchronized and stable Human-Robot Interaction (HRI) but did not mention this application on power assist rehabilitation robots using motion intention. This review paper was able to explain the methods, control laws, and motion intention estimation that can be used for power assist rehabilitation robots using motion intention.

Papers on human motion intention and types of motion intention estimation are reviewed based on artificial intelligence-based motion intention estimation and model-based motion intention estimation. The method of estimating motion intention based on artificial intelligence includes; Electromyography (EMG) based control method, Neuro-fuzzy control method, EMG-based admittance control (EAC) method, and Extreme Learning Machine (ELM) method. For Artificial intelligence-based motion intention, EMG-based control signal is one of the most effective control methods for many types of power assist robotic systems, especially for power assist rehabilitation robots. Hence, EMG-based control is difficult to execute, time-varying, and noisy. To solve these issues, the neuro-fuzzy technique is proposed to properly estimate the motion intention of the user of the power-assist rehabilitation robot. However, neuro-fuzzy controllers are great at directing the power-assist robot, but as the degree of freedom of the robot increases, the controller becomes more complicated.

In light of these problems, an EMG-based Admittance Controller (EAC) was developed to successfully interpret the human motion intention of the robots with more degree of freedom. However, EAC is a complicated non-linear connection between the various muscles and the output forces they provide. Functional usage and efficient operation of a multifunctional gadget present a number of obstacles. Given these issues, a new algorithm called Extreme Learning Machine (ELM) is suggested. The ELM algorithm is simple to construct and effective for multifunctional gadgets.

Having reviewed various papers, for a power assist rehabilitation robot to actively engage with its human partner, an adaptive impedance control method and admittance control method are suggested for estimating motion intention. Hybrid force/ position control and adaptive control are proposed for control laws to be used for motion intention estimation in power assist rehabilitation robots. To obtain an efficient estimation based on artificial intelligence, EAC and ELM are proposed.

Table 1 summarizes the motion intention estimation technique, input signal, controller, and types of rehabilitation robots of the power assist rehabilitation robots.

Table 1. Summary of Review Result

No	Authors, Year	Type of Rehabilitation Robot	Motion Intention Estimation Technique	Input Signal	Controller
1	K. Kiguchi [71], 2007	Upper Limb Rehabilitation (Shoulder, Elbow, and Fore Arm)	Neuro-Fuzzy Technique	EMG Signal	EMG based control
2	C.W. Antuvan [74], 2019	Upper Limb Rehabilitation	Extreme LearningMachine (ELM)	EMG Signal	EMG based control
3	L. Xing, X. Wang, and J. Wang [86], 2017	Upper Limb Rehabilitation (Shoulder, Elbow, and Fore Arm)	Motion Intention-Based Virtual Reality Training System (MIVRTS)	Motion Intention Detector (MID)	Impedance and Admittance Control
4	Y. Zhuang, S. Yao, C. Ma, and R. Song [87], 2019	Upper Limb Rehabilitation	EAC and Torque-sensing-based Admittance Control (TAC) Method	EMG signal	Admittance Control
5	Y. Li and S. S. Ge [88], 2014	Upper Limb Rehabilitation	Radial Basis Function Neural Network (RBFNN) Model	Neural Network Signal	Adaptive Impedance Control
6	Z. Tang, K. Zhang, S. Sun, Z. Gao, L. Zhang, and Z. Yang [92], 2014	Upper Limb Rehabilitation	Back-Propagation Neural Network (RPNN) Model	EMG Signal	EMG based Control
7	Q. Yang, C. Xie, R. Tang, H. Liu, and R. Song [94], 2020	Upper Limb Rehabilitation	Minimum Jerk model (MJM)	EMG Signal	Hybrid position/force control

No	Authors, Year	Type of Rehabilitation Robot	Motion Intention Estimation Technique	Input Signal	Controller
8	W. Wang, L. Qin, X. Yuan, X. Ming, T. Sun, and Y. Liu [95], 2019	Upper Limb Rehabilitation (Shoulder, Elbow, and Arm)	Support Vector Machine (SVM) Model	EMG Signal	Central Pattern Generator (CPG) Based Bionic Control
9	J. Huang, W. Huo, W. Xu, S. Mohammed, and Y. Amirat [96], 2015	Upper Limb Rehabilitation (Shoulder, Elbow, and Arm)	Intention Guided Control technique	EMG Signal	Admittance Control
10	A. Karamali Ravandi, E. Khanmirza, and K. Daneshjou [98], 2018	Upper Limb Rehabilitation (Arm)	Adaptive Fuzzy Sliding Mode Control (AFSMC) Method	Sliding Mode Control (SMC) Signal	Hybrid Position/Force Control
11	G. Liu and L. Fang [99], 2020	Upper Limb Rehabilitation (Arm)	Recursive Least Squares Method Improved With A Variable Memory Factor (RLSVF)	Frequency-Division Signal	Hybrid Position/Force Control

6. Conclusion

Power assist robots are developed to amplify human muscle strength. Patients employ power assist robots for rehabilitation exercises with the help of a therapist. In the subject of robot rehabilitation, the power assist system is the current research focus. Power assist rehabilitation robots are devices designed to help physically weak persons such as elderly persons, ill, and physically challenged persons to live an independent life. This article discusses human motion intention and different types of motion intention estimation, with an emphasis on the estimation, prediction, detection, and control laws issues. However, other models and controls can be used for other varieties of robots, depending on the application. For future research, a power-assist rehabilitation robot can be developed based on the motion intention estimation and controller strategies reviewed in this paper.

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