Assist-as-Needed Control Strategies for Upper Limb Rehabilitation Therapy: A Review

Shawgi Younis Mounis and Norsinnira Zainul Azlan*

Department of Mechatronics Engineering, Kulliyyah of Engineering
International Islamic University Malaysia
53100 Gombak, Selangor
Malaysia

ABSTRACT

Stroke is one of the leading causes for disabilities that can damage the functional capabilities of survivors and significantly affects their ability to perform activities of daily living. In recent years, assist-as-needed (AAN) strategy has received significant attention because it can encourage the stroke subjects to achieve functional recovery for the loss of motor function. However, the implementation of AAN strategy only becomes possible when the subjects' functional ability is known. Thus, inaccurate and inconsistent estimation of subjects' functional movement or motor ability is crucial and has been a major limitation for the current implementation of AAN. The existing gap in literature between the current robotic approach and clinical practices is also another important concern that can lead to conflict in the near future. This paper aims to provide an overview of the AAN control strategies and estimation techniques found in the research literature. Hence, an overview of specific clinical practices in functional motor assessment and estimation procedure that runs parallel to the robotic system counterpart is also designed to provide the significance and challenges in bridging the gap between robotic and clinical practices. This review concludes with major findings in the state-of-the-art in AAN robotic therapy and outlines the procedures for clinical adoption. This study finds the necessity of further research required to determine the effectiveness of clinical assessment procedure alongside with the robotic therapy that can address this need by providing a consistent and accurate estimation of subjects' functional ability.

Keywords: *Assist-As-Needed (AAN), control strategies, functional ability (FA), Clinical assessment, upper limb rehabilitation*

1.0 INTRODUCTION

In recent years, the number of subjects with upper limb disability has been dramatically increased due to stroke, spinal cord injuries, and accidents [1]. The weakness and loss of the control of the upper limb can cause the subject difficulties in movement, and significantly reduce the subjects' functional ability and performance of activities of daily living (ADL) [2]. In order to restore the subjects' upper limb function ability and reduce the costs of treatment and health care, current research has converged towards more effective treatment methods, such as robotic therapy in lieu of the traditional rehabilitation therapy [3-5].

*Corresponding email: sinnira@iium.edu.my

Robotic therapy has been demonstrated to encourage the subject involvement in a rehabilitation therapy [6]. It has potential to allow multiple training sessions and to evaluate the performance of subject throughout a rehabilitation session [5, 7]. There is a strong evidence that training on the intensive movement, with many repetitions can improve the results of rehabilitation, whether in the each stage of the recovery or for the long term treatment [8]. Several strategies for offering robotic assistance have been developed in the recent past [9].

However, more focus is currently directed to the assist-as-needed (AAN) strategy which has become the most employed contemporary strategy in handling and supporting the robot-aided rehabilitation [10]. The AAN strategy has the potential to help the users in raising their own effort while minimizing the robot function to provide only the amount of assistance necessary to complete the required movements to avoid "slacking" behavior [11, 12]. Also, recently the AAN paradigm has been clinically demonstrated to provoke motor recovery in neurologically impaired subjects [13]. In order to prevent the subjects from relying too much on robotic assistance, some studies proposed a strategy that adjusts its assistance torque according to the subject's performance [12, 14-16]. Krebs *et al*. proposed a method based on subjects' performance progressive robot treatment, which uses parameters namely (speed and time) to initiate the assistance of the robotic device [14]. Papaleo *et al*. introduced a subject tailored adaptive treatment for an upper limb robotic training that involves a module for estimation of subjects' performance based on biomechanical data [15]. The subjects' movement data were recorded through sensors (i.e., from encoders in the device and accelerometer attached on the subjects' upper limb). Wolbrecht *et al*. proposed robotic assistance strategy based on robotic model [16]. Under an adaptive framework, the strategy enables a robot to learn the subjects' functional capability in order to adjust the required assistance to complete targeted movements. Pehlivan *et al*. also proposed a model based strategy, which depend on *Kalman* filter and based on sensor-less force estimation of subjects' function ability [12]. The aim of this technique is to vary the robotic assistance according to the subjects' effort as administrated from the model-based sensorless force estimation. A major limitation of these approaches was the dependency on the robot-model (model errors) for the estimation of subject's ability, and also the inconsistency of the functional ability estimation over time. Moreover, there is another salient factor not explicitly accounted for in these approaches, which is the actual clinical procedure [12, 13].

In this paper, a review on the AAN strategies is presented. In order to review the development of the AAN strategy in further detail, the paper is organized as follows: Section 1 is the review methodology while Section 2 gives a short survey of control strategies for upper limb rehabilitation and reviews the recent techniques for estimation of subjects' functional capability. This is followed by the Section 3 that reports the clinical assessment of measurement. Section 4 discusses the multi joints and single joint of exoskeleton. Meanwhile, Section 5 provides a brief discussion and finally, the conclusion is given in Section 6 highlighting the important recommendations for future work as well.

2.0 REVIEW METHODOLOGY

This review aims to figure out the required research for a range of publications within the review scope of this work. It was executed based on various platforms by conducting search operation of related general papers or works published in major scientific databases. A number of published research papers were acquired and reviewed through these databases. The analysis focuses on the AAN control strategy for the upper limb and clinical assessment for subjects' functional ability. Thus, works related to other fields apart from the general strategy, will not be reviewed.

3.0 CONTROL STRATEGIES

3.1 Assist-as-Needed Strategy

The AAN control strategies have been shown to be the most promising techniques for promoting recovery after neurological injuries as well spinal cord injury (SCI) [9]. Assistance towards task completion is supplied only when the subject is unable to perform actively [17]. With no such remedial assistance, the subject may possibly be unable to produce a movement which is at first or perhaps to complete the movements appropriately which is inside the later levels, leading to a small recovery as a result of limited responses [18]. The question on the required amount of assistance to be supplied, has been a subject of interest to many researchers leading to several proposed methods [19]. In the following section some methods and strategies of assistance control for the rehabilitation robotic therapy will be reviewed. Particular focus will be given to the robot-assisted strategies within the paradigm of AAN which is still, however, a subject of major hurdle [20].

3.1.1 Estimation of subjects' functional ability to direct the robotic assistance

To gain the maximum benefit from robot assisted rehabilitation therapy, subjects should be actively engaged in the training session and this can be done through an AAN strategy [6]. The strategy encourages subjects' active participation during physical exercise systematically by modulating the robotic assistance in accordance to subjects' movement ability while at the same time discourage the slacking behavior in motor control. With the implementation of AAN paradigm, the functional ability must be known. So as to be more faithfully accurate and consistence, the subjects' functional ability is needed to complete the targeted treatment exercises as follows:

(1) The consistency of the estimated subject's functional ability with clinical setting and the repeatability across a variety of subjects are desirable. A frequent accurate estimation of the subject's functional ability while using the clinical procedures can give a realistic basis for implementing robotic assistance since it supplies a measure of the subject's actual disability level or recovery improvement, or active participation [21].
(2) The consistency of the functional capability over time [22].
(3) The free functional ability estimation (i.e., not based-model) which may not depend on particular robotic dynamic model to be more standardized and unaffected by the adaptation law. A study by Wolbrecht *et al.* on the development an AAN control strategy, basically consists of the feed forward assistance in addition to the position controller [16]. The AAN strategy aims in inducing the neural plasticity and targets a wide range of severely to mildly impaired subjects as illustrated in Figure 1 that is important for maximizing the therapeutic benefit of robot-assisted movement training [23]. An adaptive seamless AAN control scheme was developed by Frullo *et al.* for the robotic evaluation and training sessions [5]. The AAN control scheme is shown in Figure 2, which uses a standard model-based adaptive technique and the feedback gain is changed on a task by task basis. This can help subjects' capability to adapt to the required assistance and to provide only needed assistance in completing the desired tasks motions [5].

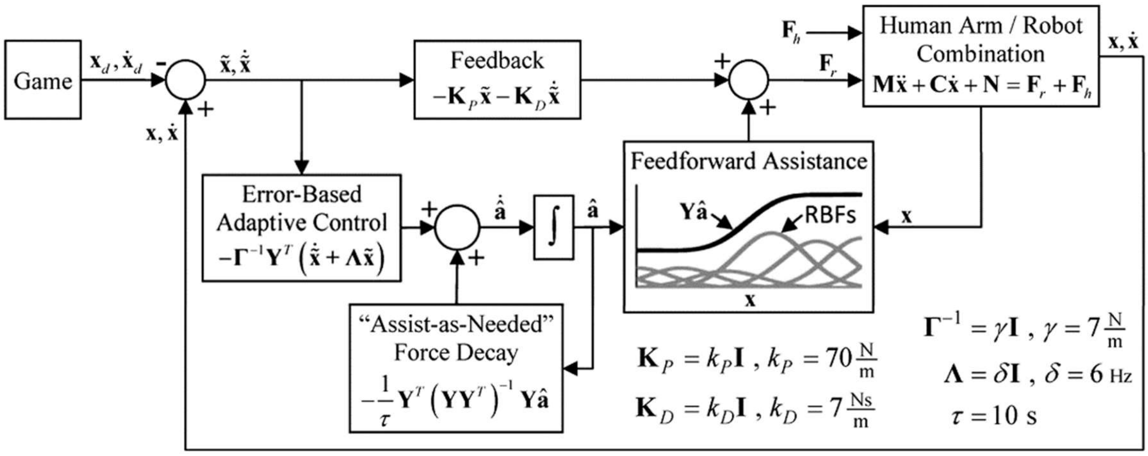

Figure 1: An AAN controller diagram showing the force decay term continuously reducing the feed-forward assistance when errors are small [16]

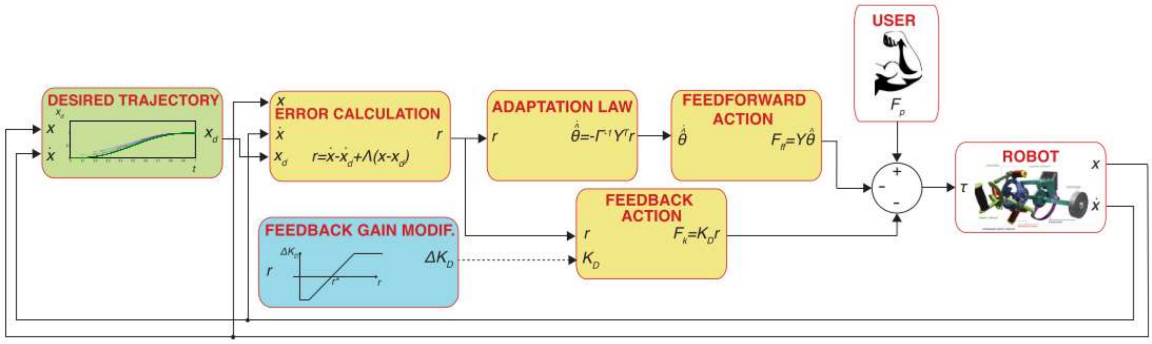

Figure 2: A block diagram of the AAN controller with the dashed line referring to a discontinuous update of the signal variables, i.e., the feedback gain is changed on a task-by-task basis [5]

In addition, the main considerations when designing an exoskeleton control is how to achieve the best control performance, best user interaction, high stability safe operation and the control strategies for subject's rehabilitation [24, 25]. For inducing motor learning, studies have shown that training is only effective if it is associated with the task-oriented movements involving effort by the subject [26].

This method is a vital requirement to obtain an effective cortical reorganization [27]. Wolbrecht *et al*. developed the model-based robotic assistance technique which permits a robot to learn the subjects' capability under an adaptive control framework to direct the robotic assistance with complete specified movements [16]. An important contribution with this work is definitely the derivation and implementation of a Radial-Basis Function (RBF) network which actualizes the training of the subject's movement capacity also known as useful ability [28] and a 'forgetting term' is included in the control mechanism to adjust the robotic assistance in accordance with the subjects' ability, thus, providing the AAN therapy. Pehlivan *et al*. introduced a minimal assist-as-needed (mAAN) approach which counts on a *Kalman* filter based sensor-less force estimation of the subjects' inputs or functional capability instead of the RBF [12]. Under this scheme, the authors attained the AAN strategy by:

(1) Primary updating the derivative responses gain which usually modifies the bounds of the allowable error on the required trajectory.
(2) Secondary bringing out decays a feed-forward disturbance rejection term which reduces the constraint on allowable quick movements. These methods successfully fluctuate the robotic assistance in line with the subjects' capability determined from the model-based sensor-less force estimation.

3.1.2 mAAN and AAN strategies based on tracking error feedback

A. mAAN Strategies

The most utilized contemporary strategy in handling and supporting the robotic devices structures is the one based on the minimum assistance [29]. This encourages users' input or active involvement while minimizing robotic assistance [30]. This strategy is supported by studies which suggest that minimizing the robotic intervention while encouraging subjects' active participation can help induce neural plasticity while significantly promoting motor function recovery [9, 31]. Wolbrecht *et al*. developed an AAN robotic algorithm by assuming the AAN therapeutic goal as an optimization problem [16]. The algorithm was capable of bounding the tracking errors while still allowing learning.

It will require the form of an error-based learning controller using a forgetting factor, similar to the human motor controller itself. Such a controller works for the case in which the primary dynamics of recovery are that of learning or strengthening a novel sensory motor transformation [32]. The controller could be distinguished right from previous robot therapy controllers that provide a fixed amount of assistance with impedance, force, or position controllers because it carries a "forgetting" procedure that minimizes the used robotic assistance as subjects' actively. Pehlivan *et al*. also developed an AAN strategy called minimal Assist-as-Needed (mAAN) strategy based on sensor-less force estimation to encourage subjects' active participation by allowing a minimum amount of robotic assistance [12]. Robotic intervention is reduced to a minimum and offered to the subject only when it is needed, with the ultimate goal of motivating neuroplasticity and increasing the expected likelihood of recovery in motor coordination [33]. The mAAN controller determines independently the capability of a subject without assuming the underlying pattern prior to the provision of the respective assistance. The mAAN strategy has been validated for the estimation of the healthy subjects' capability using the *RiceWrist-S* exoskeleton. The results have indicated the potential use of the strategy. However, the drawback of the strategy is in the inconsistencies of the error-prone model-based estimation of subject's movement capability. Wang *et al*. developed an AAN strategy with visual error augmentation training methods [34]. The developed assistive controller is able to provide minimal robotic assistance to the participant as when needed based on the position errors which might be visually fed back to the participant. These kinds of errors happen to be amplified to heighten the participant's motivation to further improve the tracking reliability. However, the challenge is the fact that different error amplification gains would have to be tested to be able to obtain a comprehensive understanding of the visual error enhancement training approach [35].

B. AAN strategies based on tracking error feedback

The various body motion assisting systems operate to meet the desired outcomes based on the trajectory movement [36]. The robotic systems concentrate on the following focal idea which is when subject's motion is within the stipulated trajectory, there should be no intervention from the robot [37]. Otherwise, if there is a deviation by the subject from the intended trajectory, then there must be a restoring force produced by the robot [38, 39]. Thus, the foundation of this approach lies in the prediction of the necessary movement which is required by the underlying system in deciding on whether there is a need to provide the restoring force assistance or otherwise [40]. Rodríguez *et al*. introduced the anticipatory AAN control algorithm that is capable of ensuring that the deviation from the subjects' desired trajectory is restored by giving them the anticipated force assistance [39]. In this way, robotic assistance is always given as a restoring force to maintain the subject on the reference trajectory. However, there is no experimental studies have been done to validate the strategy experimentally. Dao and Yamamoto proposed tracking controller based on the torque trajectory which utilizes a fractional derivative for the tracking purpose [41]. However, the method is unable to adapt the robotic assistance based AAN strategy, due to the fact that the subjects' functional capability is essential. Peng *et al*. developed a CPG-inspired AAN technique based on impedance control that provides assistance according to errors between the robot reference and actual trajectories [42]. However, this becomes challenging to implement the AAN technique when the subjects' function ability is unknown.

C. Subject adaptive controller for AAN

The subject adaptive controller for AAN was introduced simply by Pehlivan *et al*. with feedback a gain modification and on-line trajectory recalculation [6]. The designed controller is capable of changing the amount of error allowed during the movement execution, while concurrently estimating the forces offered by the participant that lead to the movement execution. The feedback gain modification and trajectory generation methods were authenticated using the *RiceWrist* system and the experimental research involves five healthy subjects. The controller input decreases feedback control action each time a subject changes his behavior, i.e. from riding passively on the robot during movement to actively initiating movements [6].

3.1.3 Estimation techniques for the subjects' functional capability

In this section, the existing techniques for estimation of the subjects' movement ability or functional capability with reference to the AAN paradigm are discussed. Two main techniques are found in the literature namely, the Radial Basis Function (RBF) [43] and model-based estimation method [44].

A. Gaussian Radial Basis estimation technique

The *Gaussian Radial Basis* network was originally proposed for both real-time robot control [45] and arm motion modeling functions [46]. It has been applied subsequently in many researches due to its universal approximation property [46-48]. The RBF approach fundamentally assumes the subject's input to be position dependent and estimates the input via *Gaussian* RBFs distributed throughout the workspace [48, 49]. Wolbrecht *et al*. first implemented an adaptive controller with *Gaussian* RBFs for robot-assisted rehabilitation [16]. The authors integrated a forgetting factor with the RBF to decay the robotic assistance based on the subject's effort. Pehlivan *et al*. also used the RBFs, but decoupled the input estimation and engagement problems by directly manipulating the subject's positional error bounds [6]. Both Bower *et al*. and Guidali *et al*. improve the estimation ability of subject mentioned in [16] through directionally dependent RBFs [50, 51]. For a RBF to adequately estimate a subject's functional capability, the subject's ability to complete a given task must be strictly a function of their position in the workspace [52]. While healthy individuals can consistently comply with this requirement, it is difficult for neurologically impaired subjects due to movement disorders as in [53] and varying velocities on both torque production and reaching capabilities [54, 55]. Furthermore, the parameter adaptation law contained within the RBF based control technique do not guarantee that the parameters will converge to the true values, except under special conditions [12]. Thus, it is difficult to ensure accurate estimation of the subject input at all times. Luo *et al*. proposed a *Gaussian* AAN (GAAN) technique involving a RBF network which was used to model the subjects' functional ability to provide the required assistance [56]. However, this approach is problematic because the estimates of subjects' input are necessarily and RBF perturbed throughout the workspace [12].

B. Model-based sensor-less force estimation method

Model based sensor-less force estimation method involves the use of the exoskeleton dynamic model to estimate the subject's input force or torque without the need of a force or torque sensor [57]. This provides a basis for quantifying subject's functional capability [58]. Model-based methods are attractive because they:

(1) provide theoretical guarantees of estimated disturbance accuracy, unlike the measured motor torques.

(2) do not mandate design modifications, in contrast with the compliant elements. In the model-based estimation methods, subject input can be dynamically determined in time without any assumption of such as position or time dependency [59]. However, one drawback of the model-based disturbance estimation is that the robot's inertial matrix inverse must typically be calculated [12]. Another flaw is the assumption that disturbances are constant unless a prediction of future disturbances is available. This might be the case when performing iterative tasks in which the resultant estimation trails the fluctuating disturbances [12, 60].

Finally, if the plant model is inaccurate, this technique cannot effectively distinguish between the reactions caused by known and unknown inputs [44].

4.0 CLINICAL ASSESSMENT PRACTICES IN FUNCTIONAL MOTOR ASSESSMENT

The upper limb impaired function is actually a consequence of stroke that may be regularly assessed and cured by rehabilitation therapists throughout the acute and rehabilitation practical recovery [61]. The injuries of upper limb function restrict a subject's ability to perform an actions of everyday living [62] and subjects with disability possess identified the return of upper limb function as an essential rehabilitation objective [63].The aim of the therapy for subjects with an upper limb difficulty is always to improve the motor function in the affected part and to boost the ability with the subject to interact successfully in activities of daily living [64]. Therefore, therapists must use standard assessment tools for the measurement of subject improvement, communication regarding subject status between varied treatment sites within the procession of treatment, and study investigating the efficacy of selected interventions.

In the effort to develop an effective control strategy for the rehabilitation system, it is important to know the functional motor assessment for the subjects in clinical practices [65]. There are several developed approaches of upper limb assessments in order to assess subject's recovery following a stroke. The application that is employed for an assessment requires it to be appropriate and applicable to a broad variety of capabilities pursuing stroke [62, 66] and be insightful to the improved level of functioning aspect of the subjects [67].

This study focuses on the upper limb assessments functional ability to measure the recovery and progress level. For this purpose, these assessments are defined as measuring the ability of the upper limb to perform (ADL) activities of daily living [68].

A total of nine assessments have been selected to meet the functional ability technique benchmarks for this work and adopted clinical measures are summarized as follows:

i. Wolf Motor Function Test (WMFT)
ii. Motor Assessment Scale (MAS)
iii. Arm Motor Ability Test (AMAT)
iv. Action Research Arm Test (ARAT)
v. Upper Extremity Function Test (UEFT)
vi. Chedoke Arm and Hand Activity Inventory (CAHAI)
vii. Fugl-Meyer Assessment of sensorimotor recovery after stroke (FMA)
viii. Motor Evaluation Scale for Upper Extremity in Stroke subjects (MESUPES)
ix. Functional Independence Measure (FIM)

This study focuses on the upper limb assessments functional ability to measure the level of disabilities and recovery progress based on two variables which are time and quality movement.

The psychometric assets of all the assessments were rated as adequate to excellent, demonstrating that they can be considered as suitable and consistent procedures for the upper limb functional ability. WMFT, AMAT, ARAT and MAS are all objective methods of the subject's ability to finish the tasks.

The WMFT is utilized frequently in the field of rehabilitation to measure outcomes of constraint-induced movement therapy [69]. WMFT has the aptitude to easily distinguish between the subject's disability levels and functioning ability movements [70, 71]. The revised version of the test expands can be applied to moderately impaired clients [72]. WMFT is considered an outstanding motor measurement scoring technique with 19 functional assessment tests. The functional capability scale is from 0 to 5 (6 points scale), with the understanding that 0 is equal to no attempt and 5 is equal to normal functional movement. The functional ability overall rating scores is to deliberate the item scores [71].

The AMAT is very similar to WMFT. It truly is originally built to supplement the WMFT and assess the upper limb function in higher functioning stroke subjects [73]. Chae *et al*. described the fact that AMAT provides the capacity to identify the changing scale of motor recovery status for individuals with mild to moderate motor impairment and also to present constructive insight into a subject's capacity to use the paretic arm or leg just for useful actions [74]. On the other hand, it was also pointed out that the tendency for the AMAT to misjudge the limb motor status of those with more severe motor impairments because several tasks in the AMAT can also be challenging with respect to subjects with very little recovery [71].

The ARAT is based on observation and mainly focuses on evaluating the upper limb function [75]. It includes 19 tasks that are grouped into several categories to include the grasp, pinch, grip, and gross arm movements. These activities involve making use of the objects of numerous sizes and shapes, e.g., washers [76]. Every single task is specifically graded between 0-3 points scale with 3 points given for a task completed normally, while 2 points given for tasks completed with difficulty, 1 point given for a partially completed task and 0 points awarded for an uncompleted task. The grading in this analysis was performed depending on the well-informed findings associated with an occupational specialist [77].

The MAS is a simple test of a subject's functional capability [78]. An Occupational Therapy (OT) or Physical Therapy (PT) performs the MAS selected sets of muscles by flexing or extending the corresponding joint over a count of one second. The muscle set is then scored on a scale from 0 to 4, where 0 is no increase in muscle tone, 2 is a more marked increase in muscle tone though most of the range of motion, but the affected part is easily moved, and 4 is the affected part or parts are rigid in flexion or extension [79].

The UEFT can be a superb evaluative strategy to determine the upper extremity functional impairment and the severity of disability in subjects exhibiting dysfunction in the upper extremity [72]. The test determines function based upon the supposition that intricate upper extremity actions employed in ordinary activities will be made up of specific movement patterns (e.g., supination/pronation, grasp/release, pinch grasp, etc.) so that analysis of these movements patterns can easily predict the subject's capability to perform functional activities [80]. CAHAI is certainly a useful assessment tool examination of this regaining their hand strength after following stroke. The CAHAI compliments the *Chedoke-McMaster* Stroke Assessment [81].

The FMA is definitely a stroke-specific, performance-based disability index. Actually, it is designed to assess motor functioning, balance, sensation and joint performing found in subjects with post-stroke hemiplegia [82, 83]. It is applied clinically and utilized in many research to determine the disease severity, describe motor improvement and assess the therapy [84].

The MESUPES quantify the quality of movement functionality of the hemiparetic upper limb in stroke subjects. This method of the assessment was introduced by Van de Winckel *et al*. [85] as the original version of the scale and later improved in the final version of the scale [86]. The novel publication of the final version of the scale is presented in [85].

The FIM was also initially produced to present a consistent program of description for disability based on the international classification of impairment, disabilities and handicaps for use in the medical system in the United States [87]. The level of a subject's disability indicates the amount of support necessary to care for them and items are scored on the basis of how much assistance is certainly required for the subjects to handle actions of daily living [88]. In short, these robotic assessment methods involve a performance of motion data recorded during the evaluation portion of each therapy session and the assessments were quantitatively analyzed in order to evaluate the improvement in the movement capability of the subjects during the training engagement therapy. All of the above-mentioned assessments methods are engaged with functional ability and their evaluation were based on either quality of movement or time or both of them.

5.0 MULTIPLE JOINTS AND SINGLE JOINT OF EXOSKELETON

The mechanical devices are considered for their ability to change the positions of all joints of the arm, not only the effector or hand [89]. As shown in Table 1, the importance of these fully actuated exoskeleton over a manipulator lead to significant advance of the rehabilitation practice [90]. A simpler process can be used with some auxiliary inputs such as the one proposed by Zhou *et al*. and Proietti *et al*., [91, 92]. What is significant about these devices is that, most of them possess the ability to quantify the chosen kinematic parameters as well as repetitive training sessions with a cost compared to the traditional methods [9].

There are a number of researchers who have developed robotic devices for rehabilitation of the upper limb. For example, Tsagarakis *et al*. invented a rehabilitation device that supports a full range of motion for the upper limb exercise therapy [93]. This machine uses a seven degree of freedom (7-DOF) actuation, in addition to pneumatically-actuated-muscles (pMAs) for light weight design. The device *RiceWrist-S* proposed by Pehlivan *et al*. was meant for affirming the developed AAN controller algorithm experimentally [12]. It was a 3-DOF and able to freely actuating the user's forearm and wrist exoskeleton, pronation/supination (SP), flexion/extension (FE), and radial/ulnar deviation (RU) can all be supported. Moreover, an electrically actuated 7-DOF robotic device introduced by Rosen *et al* is able to accomplish 99% of the range of motion (ROM) needed for ADL [94]. Mihelj *et al*. came up with a 6-DOF, electrically actuated device, ARMin that focuses on creating a natural movement in the shoulder complex of the user [95]. The X-Arm2, is a machine devised in [96] that utilizes eight actuated and passive 6-DOF to alleviate the ergonomic interactions between the subjects and the machine.

The aim of exoskeleton devices is to replicate as much as possible the human kinematic in the targeted joints [97]. Therefore, the alignment of the rotating axes in these machines with the user's biological axes of the rotations is an importance requirement [98]. But, as the number of the DOFs of the device increases, the challenging and the difficulty of achieving the requirement increase as well, thereby requiring a more highly complex design [99]. This requires applying the system principles that result in more complex design to produce all the desirable outcomes. Studies that show functional training, which is the main reason behind the development of exoskeleton devices with high DOFs, does not actually provide more benefit than a single DOF in terms of motor functional recovery rehabilitation [100].

A recent study by Milot *et al*. suggests that multi-joint functional robotic training is not actually superior to a single joint robotic training [101]. In addition, some research groups tend to develop a more simplified design which focuses on the selected joints of the upper extremity therapy. For instance, the machine, BONES developed by Klein *et al*. is a 4-DOF exoskeleton that could accommodate shoulder horizontal FE, upper arm internal/external rotation, elbow FE and forearm SP [102]. Another device called CAREX is a cable driven upper arm exoskeleton[103] while the L-Exos is a force-feedback arm exoskeleton that focuses on the proximal part of the upper extremity and could correspond to the shoulder rotations and elbow FE [104].

Lastly, the pneumatic and electrical actuators are the two most widely used actuation machines for the exoskeletal rehabilitation training. The biggest advantage of the pneumatic actuators is their high power to weight ratio that enables the design of smaller size/lighter machines. Parts of the pneumatically actuated devices, that uses pneumatic muscle actuators (pMAs) are Pneu-WREX made by Sanchez *et al*. [105], BONES proposed by Klein *et al*. [102] and the 7-DOF exoskeleton by Tsagarakis *et al*.[93] although they provide a higher band-width and allow the implementation of sophisticated controllers. Thus, the electrical actuators are mostly preferred over pneumatic counterpart in the rehabilitation robotics system [106].

Table 1: Summary of the control strategies by previous researches on the AAN control strategies

References	Control Strategy	Name of Devices	DOF	Main Outcome
[6]	AAN	RiceWrist	3-DOF	They present a robotic system that features an AAN controller with a feedback algorithm and a real-time trajectory for subject adaptive control. The outcomes show that the developed system is accurate in estimating the environmental forces applied by the subject during therapy
[5]	Effect of AAN	MAHIExo-II	4-DOF	The evaluation of the effect of two different interactive schemes implemented on the MAHIExo-II robotic upper limb exoskeleton.
[107]	Model-based AAN	Robotic platform	3-DOF	Controller is able to provide the operator with the desired level of assistance as governed by the model-based paradigm.
[108]	AAN	Manipulator's end-effector	6-DOF	Maximize dart throwing score and minimize robotic physical assistance.
[109]	AAN	PASCAL	4-DOF	Deviation of the trajectory was minimized.
[12]	mAAN	RiceWrist	3-DOF	Model-based sensor-less force estimation regulates and determines the subject's capability. The control law using mAAN provides only the required aid.
[110]	Stability-Guaranteed AAN	One-degree-of-freedom forearm orthosis	1-DOF	Stable AAN controller for Powered Orthoses that can simply adopt and assist a subject's voluntary motion.
[39]	AAN	VR simulator	1-DOF	Anticipatory actuation for the subjects, avoiding trajectory deviations and minimizes the degree of actuation.
[111]	AAN	Pneu-WREX	4-DOF	Improvements in *Fugl-Meyer* Assessment (FMA) score. High improvement in functional ability, as measured by the Nottingham Sensory.
[101]	AAN	BONES	6-DOF	Improvements in FMA and functional tests WMFT, with no differences between the multi joint/single joint training.

6.0 DISCUSSION

In this research, the analysis and focus were on the AAN and related control strategies for the robotic exoskeletons for neurorehabilitation in which the review includes a number of publications describing its existing devices. Several issues that contributed to the rehabilitative performances of current exoskeleton devices were spotted and highlighted. The analyses focus on the controller that features the implementation of the AAN controller algorithm. It is important to underline how this AAN strategy is a different problem from controlling the exoskeleton, hardware limiting control strategies and input estimation possibilities. In the previous work which discussed above and relatively related to AAN controllers for robotic rehabilitation have used different types of control strategies such as impedance controllers to regulate assisting forces based on deviations from desired trajectories [112]. AAN controllers based on an adaptive control architecture and adaptive control combines Gaussian radial basis functions for estimating interaction forces, as earlier proposed by Tondu *et al*.[106] and later proposed by Wolbrecht *et al*.[16] for rehabilitation applications. Impedance schemes have been frequently employed within the context of AAN control, where their controller properties are modified based on subject performance. However, these approaches are also oblivious to more complicated subject capabilities and may therefore intervene sub-optimally across the robot workspace [12]. Also, adaptive controllers that model the subject's functional capability have been proposed within AAN algorithms. Specifically, *Gaussian* radial basis networks which possess a universal approximation property [47] have been frequently included in adaptive controllers for estimating interaction forces. However, this approach relies on the *Gaussian* radial basis which is not consistent and not accurate over the time. It is task-space position dependent and parameters convergence under an adaptive control framework of this kind is not always guaranteed [13]. Also, this method reliance on the robot model and the model errors always exist and can significantly excite the disturbance term making it difficult to correctly distinguish the contribution of the subject’s input, as different robot structures has different models which can make it hinder to be standardized for clinical setting.

The literature review findings pertaining to the main challenges were in relations to efficiently and consistency in the determination of subjects’ performance in order to regulate robotic assistance. Henceforth, the above objective is essential to determine the amount of assistance needed. The literature depict the two classifications which are likely used: (kinematic and biomechanics) sensor-based and model-based techniques [12, 14, 16, 113]. However, in order to overcome these challenges, the newly proposed AAN strategy can obviously be necessary to serve as a mitigating tool with the current robotic control strategies [114, 115]. Based on the limitations of the previous strategies, there is a real need for a new free-model which is based on subject’s ability or disability levels, consistent and accurate in the desired subject’s movement estimation, safe and clinically approved by regulators. Thus, these advances can have a huge clinical impact in accelerating recovery and improve functional independence and quality of life in these subjects [116].

Experienced rehabilitation therapists advocate AAN control strategy due to the intrinsic potential to improve motor function control. In terms of implementation, however, the concept of AAN is still vague, because different levels of assistance could be applied according to specific applications. Typical AAN schemes determine the amount of assistance based on functional capability. This however presents a major challenge as the existing strategies for functional capability estimation are neither repeatable nor consistent with clinical procedures. The main findings obtained from this study of (AAN) can be reviewed as:

- There is not a single concrete technique for the estimation of subjects’ functional ability that is free from robotic model.

- There is a lack of accuracy and consistency in the estimation of subjects' functional ability over time or range of subject population.
- To date, a number of works are on-going to evaluate the therapeutic efficacy of the AAN control strategy by a clinical trial.
- Most of the papers' main efforts are focused on developing the exoskeleton devices, however, the control of these robotic rehabilitation remains an open-ended research area.

7.0 CONCLUSION

With an increase in subjects with impaired mobility or motor functional disabilities, there is no doubt that Assist-as-Needed (AAN) controller strategy will have significant roles in robot-assisted therapy. Furthermore, the use of AAN strategy is also promising in rehabilitation training therapy, which assist the subject to complete the task only when needed. In this paper, a comprehensive review has been presented which analyze and classify the literature on the AAN controller strategy and functional ability estimation techniques. The existing gap between the current robotic approach and clinical practices was also studied. There is limited work done relating the actual clinical assessment with the AAN control strategy. Thus, it is deemed significant to improve the current AAN strategies for future use, focusing on how to develop a more accurate and consistent estimation technique for subjects' functional ability and following clinical tools to ensure the best motor function recovery of the upper limb.

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