World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

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Real-time estimation of a stroke patient's motor intent derived from multimodal signals in adapting exoskeleton assistance levels within 200 MS

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World Journal of Advanced Research and Reviews, 2026, 30(03), 835-852

Publication history: Received on 03 May 2026; revised on 10 June 2026; accepted on 12 June 2026

Article DOI: https://doi.org/10.30574/wjarr.2026.30.3.1659

Abstract

Impairment of the human upper limb triggered by stroke is a major source of depression linked to independence and quality of life. As a result, the concern prompted the introduction of robotic exoskeletons that can be used to provide intensive and task-specific rehabilitation. Nevertheless, most current systems are based on predetermined or gradually responsive assistance strategies that fail to respond to the changing motor intent of the patient in a satisfactory manner. The paper researches the question of whether real-time multimodal motor intent estimation could be applied in control of exoskeleton assistance during the 200 ms period to enhance the accuracy of movement and the reduction of the effort required of users. A biofeedback-exoskeleton model of the human coupled with an exoskeleton is developed and motor intent is defined, both kinetically and kinematically. Multimodal sensing involves the combination of surface electromyography, joint torque measurements, and interaction forces. Preprocessing and feature extraction are also considered to meet the demands of stringent latency limits. Computationally effective sensor fusion algorithm estimates real-time voluntary joint torque and intent confidence. These estimates are added to an assist-as-needed impedance-based control law that adjusts the support of torque based on voluntary contribution that is detected. The proposed multimodal adaptive controller is evaluated using model-based analysis and the fixed assistance and EMG-only control strategies. Findings emphasize minimizing the error of tracking the trajectory, enhancing the smoothness of interaction and ensuring that muscle activity fits in desirable efforts and does not violate the response latency sub-200 ms. Latency-sensitive multimodal intent recognition then has the potential to improve the responsiveness of upper-limb robotic rehabilitation, make it safer and more engaging to the patient.

Keywords: Motor Intent; Stroke Patients; Exoskeleton Assistance; Multimodal Signals

1 Introduction

Stroke is not only a significant cause of prolonged disability around the globe, but also one of the critical burdens across society in both the developed and the developing world. Data regarding stroke indicates that in 2021, 11.9 million incidents of the condition were reported globally with 93.8 million being susceptible [1]. The death rate has even further surged to 87.2% of the diagnosed patients [1]. According to the American Heart Association, prevalence rates have been high across Central Asia, Oceania, Latin America, as well as sub-Saharan Africa [2]. Stroke has, as a result, been ranked third in terms of being the most burdensome at level 3 globally with a high number of DALYs [3]. Patients encounter challenges that require frequent support, for instance, in situations of incontinence, should pain management and bladder management [4]. Notably, compromised upper-limb acts as a major limitation in usual activities, such as reaching, grasping, dressing, and feeding [5]. These restrictions lower the quality of life and usually lead to a significant burden on caregivers in the long run [6]. The World Health Organization presents data that the burden rose to 160 million individuals in 2021 [7]. Furthermore, stroke induces neurological damage to cortical and subcortical motor circuits, which interferes with voluntary motor control causing muscle weakness, abnormal co-contraction patterns,

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spasticity and low coordination. Neuroplastic reorganization is a key component of recovery that has to be triggered with the help of repetitive and active movement training [8]. High-intensity rehabilitation that is goal-directed tends to be superior to standard therapy due to its appealing functional and motor outcomes [9]. Patients are able to attain their motor capabilities while being engaged in progressive rehabilitative care [10]. However, such a treatment is intensive in terms of labor, expensive and hard to maintain over time, when provided in traditional therapist-centered sessions. With growing demands on the healthcare systems due to the aging populations, technology-based and scalable rehabilitation solutions are becoming necessary to address the long-term recovery requirements [11].

Exoskeletons are robotic devices that have developed in the last twenty years as a prospective technology in providing intensive, repetitive, and measurable lower and upper-limb rehabilitation [12]. These wearable gadgets are compatible with the human joints [13]. They also offer controlled torque to help or oppose movement during therapeutic exercises [14]. Exoskeletons permit joint-specific actuation and a high-resolution determination of kinematic and kinetic variables compared to passive orthoses or end-effector robots, so that one could carefully manipulate movement trajectories [15]. Notably, these robotic systems are capable of providing thousands of repetitions in one session and a stable performance [16]. This promotes concepts of motor relearning and neuroplastic adaptation [17]. Current rehabilitation exoskeletons have sensors, including encoders, force transducers and surface electromyography (EMG) electrodes [18]. This helps in controlling patient engagement [19]. There is also enhanced control for physiological workload [20]. Although such advances in technology have happened, the efficacy of robotic therapy is not only dependent on the mechanical aid but the intelligence with which the assistant has been provided [21]. Having too much robotic assistance can lead to loss of voluntary effort and encouragement of passive involvement. Lack of support can lead to failure in tasks and frustration. As such, it will be necessary that the next generation of rehabilitation exoskeletons will be able to progress beyond preprogrammed paths and towards adaptive systems, able to recognize the intent of the patient, and adjust assistance. This responsiveness at this level is achieved through strong sensing, quick computation and stable human-robot control integration.

These adaptive systems must have a critical requirement of strict adherence to the real-time latency constraints that human sensorimotor control loops would be able to tolerate [22]. Voluntary motor corrections by human beings normally take place within 100 and 220 ms after sensory feedback, which indicates latency range prior to torque production [23]. Anything outside this range may be considered to be unresponsive or disruptive. Delay durations of more than 200 ms may affect transparency, perceived agency and adversely affect motor relearning. Thus, in real time, the estimation of the motor intent should involve the use of multimodal sensor feedback, signal preprocessing, and fusion as well as control command updating at a limited computing time budget [24]. The issue presented in this paper is then to develop a multimodal estimation system that can be used to estimate the motor intent by integrating joint torque measurements, surface EMG, and human-robot contact forces with adequate speed and strength [25].

The overall research question is whether this type of multimodal real-time estimation could be used to adjust exoskeleton assistance in less than 200 ms, which would in turn enhance the accuracy of movement and also lessen the effort of the user in rehabilitation of the upper limb [26]. This work aims to fill the gap between sensing, estimation and adaptive assistance in rehabilitating robotics of stroke patients by explicitly modeling system dynamics and applying a latency-conscious control design.

1.1 Hypothesis

The article postulates that updated exoskeleton assistance could be provided in real-time using multimodal estimation of motor intent, obtained by simultaneous measurements of surface EMG, joint torque residuals, and human-robot interaction forces. The forces would need to be made available in less than 200 ms, enhance the accuracy of the movement and reduce muscular effort.

2 Methodology

This paper is a proposal and assessment of a real-time multimodal motor intent estimation strategy to assist in the upper-limb exoskeleton in post-stroke rehabilitation. A couple of human-exoskeleton dynamic models were developed to describe the kinematics of joints, the torques acting on the joints, and the actuator dynamics. Surface electromyography (sEMG), joint torque sensors and human-robot interaction force were all synchronized and sampled in real-time using a low-latency signal pipeline. EMG signals were band-pass filtered, rectified and smoothed to obtain time-domain features and torque and force signals were filtered with causal low pass filters to ensure system delay, not exceeding sub-200 ms. The performance of the system has been assessed in the simulation at different degrees of impairment in terms of tracking error, EMG-only control, and multimodal adaptive control through the metrics of response delay, interaction smoothness, muscle effort and tracking error.

3 Estimations Analysis and Research Gap

3.1 Estimation of EMG-Based Intent

Surface electromyography (EMG) has received extensive research as a single leading modality in the estimation of motor intent in rehabilitation robotics because it can record neuromuscular activity before movement occurs [27]. EMG is a measure of the electric activity produced as a result of muscle fiber depolarization [28]. This creates advance notice of voluntary effort [29]. Therefore, in many cases several tens of milliseconds ahead of any justifiable joint movement [30]. EMG also possesses advantages such as being more task-specific, having a higher reliability as well as the easier capability to record using the device [31]. These predictive qualities are the one that also causes EMG to be of special interest in real-time control of devices that assist patients, such as prostheses. Conventional EMG-based intent models are based on time-domain features like root mean square [32]. Other considerable features are waveform length as well as the zero-crossing rate extracted on a sliding window and mapped to continuous torque estimates or discrete motion classes [33]. Linear discriminant analysis and machine learning methods, such as support vector machines, artificial neural networks, and, more recently, deep learning architectures, can be used to enhance the accuracy of classification and performance in regression.

The EMG-based systems have sustained challenges that have impeded their clinical strength despite promising outcomes in controlled laboratory environments. In instances where there is a poor environment, and even electromagnetic interference the modality s efficiency is likely to be affected [34]. The signal quality is very reliant on the placement of the electrodes, skin preparation, perspiration and electrode cross-talk, resulting in inter-session and lower repeatability. Moreover, stroke patients normally have abnormal muscle synergies, co-contraction and depressed signal amplitude, which makes it difficult to extract features reliably. EMG signals are also noisy in nature, and they need to be filtered and windowed, which add delays during processing, which can be incompatible with high real-time requirements. Therefore, although EMG can give useful early information about motor intent, multimodal sensing strategies have been encouraged because their unicast application might not be adequate in stable and low-latency adaptive exoskeleton control [35].

3.2 Estimating Torque and Force-Based Intent

Other modalities other than EMG have been investigated that can substitute for EMG. These modalities include joint-torque plus human-robot interaction force feedback, among others as they are examples of motor intent estimates in upper-limb rehabilitation interfaces. In contrast to EMG, where the neural activity is measured indirectly, torque and force signals record the mechanical expression of the user effort at the joint or interface level. These are normally measured using embedded torque sensors, strain gauges or multi-axis force or torque transducers mounted as part of the exoskeleton structure. The active and passive contribution or resistance and deviation of a user to a prescribed movement trajectory can be inferred by comparing deviations between commanded actuator torques with measured interaction forces. In a method commonly used in models, an inverse calculation of human-generated torque is done as the remaining portion of the human-exoskeleton coupled system dynamics as an inverse calculation. Other schemes are based on impedance and admittance control schemes, in which the forces of interaction directly vary virtual stiffness/damping measures to indicate user intent. Mechanical sensing modalities tend to be more robust to the variability in electrode placement and physiological noise than EMG, and do not need as much signal preprocessing. Torque and force signals however, are intrinsically lagging in excitation of the nervous system since they are only generated after muscle contraction to generate a measurable mechanical response. Such lag can be a constraint to prompt response in cases where quick adaptation is needed. Moreover, the interaction forces may be mixed up by passive limb dynamics, spasticity or mechanical misalignment, especially in abnormal tone stroke population. Therefore, estimation models that rely on torques and forces may be challenged in distinguishing voluntary intention and involuntary resistance. There is then the necessity to devise multimodal models that combine early neural readings with mechanistically-motivated measurements.

3.3 Adaptive Exoskeleton Control

Adaptive control systems have been conceived so as to improve the efficacy of upper-limb rehab exoskeletons by adjusting the assistance according to user performance and interaction driving forces [35]. Conventional exoskeleton controllers may also be based on position tracking on the basis of high-gain proportional derivative schemes, which ensure the correct following of the trajectory, but which can tend to inhibit voluntary patient effort. To overcome this weakness, assist-as-needed paradigms were proposed, which intended to lessen the amount of support needed to accomplish a task and also promote active engagement [36]. Many of these implementations employ impedance or admittance control feedback schemes, with the robot serving as a virtual spring-damper system, the control values of which can be controlled depending on performance measures, such as tracking error or the strength of the interaction force. More complex methods also use adaptive gain scheduling whereby the assistance level is slowly removed as the patient proves their ability. To customize therapy through updating control policies between sessions, reinforcement learning and model reference adaptive control have also been explored. In spite of these developments, the majority of adaptive controllers have slow update rates or use performance indices that are calculated over long time intervals and are not responsive to sudden changes in voluntary effort. The adaptation is also often founded on the kinematic error which cannot be a true indicator of motivation of the underlying motor intention or effort of the muscle. Delayed or excessive aggressive changes in assistance can influence motor relearning negatively in stroke rehabilitation where the initial response to patient engagement and neuroplastic stimulation depends upon timely and suitable feedback. Thus, adaptive exoskeleton control systems, in which reliable intent estimation is combined with quick and stable torque modulation, are still desired to provide responsiveness or safety in the human-robot system.

3.4 Research Gap

Currently, there have been very significant advancements in the field of EMG-based estimation, mechanical sensing and adaptive exoskeleton control. However, there are a number of limitations on the current rehabilitation systems that are not fully solved yet, which makes them ineffective in a clinical setting. To begin with, most intent estimation algorithms are based on one sensing modality which leads to inherent trade-offs between responsiveness and robustness [37] [38]. EMG signals give early signals of voluntary activation, but they can be affected by noise, variability and defective muscle recruitment patterns among stroke survivors. On the other hand, the measurements of torque and interaction force provide information that is based on mechanical grounds but describes the intent once the process of force generation is complete. Very few systems combine these modalities within a common framework that explicitly represents the complementary time- and space-related properties of these modalities. Moreover, adaptive assistance systems tend to be loosely coupled with intent estimation. Instead, the systems are based on heuristics that may attain tuning or trajectory tracking error during decoding, which do not directly measure patient intention [39]. Consequently, the assistance modulation can be reactive, not predictive and the system cannot help in natural goal-oriented movement. In addition, most of the published papers focus on the offline analysis or proof-of-concept validation, but without strict consideration of real-time computational constraints. Thus, there is uncertainty on the application in the context of closed-loop rehabilitation.

Another critical gap is that the control architectures of human exoskeleton systems do not follow any strict latency-conscious design. Human sensorimotor integration can work within very narrow time constraints and any delay longer than about 200 ms may impair movement coordination, decrease the perceived agency and undermine motor learning. Nevertheless, most current multimodal fusion or machine learning algorithms are based on large processing windows, multifaceted pipelines of feature extraction, or computationally expensive models that are not explicitly designed to be sub-200-ms responsive. Moreover, the existence of stability analyses of the coupled human-robot system in rapidly adapting assistance is still scarce, especially in instances where intent estimates are insecure or disturbed. Very few works present an entire framework that delivers a multimodal sensor fusion, limited latency estimation, adaptive torque regulation and closed-loop stability within a rehabilitation scenario. As a result, the necessity to implement a combined approach integrating the core of multimodal intent inference and real-time adaptive support with the ability to be responsive and safe is evident. The approach will boost the ability to prove the accuracy of movement and minimize the effort of patients.

4 System Models

4.1 The Exoskeleton Model

The exoskeleton on the upper limb and the arm or wrist of the user is modeled as a joint space-coupled multi-DOF articulated system [40]. Assume that $q \in \mathbb{R}^n$ is the array of exoskeleton joint angles that are in alignment with all anatomical joints that are being aided [40]. At the same time, with $\dot{q}$ and $\ddot{q}$act as the joint velocity and acceleration respectively.

In cases where the rehabilitation movements are to be done at moderate speed, the coupled dynamics can be in the standard form of robot manipulator. The equation will incorporate M(q) which will be standing for inertia and even $\tau_f(\dot{q})$ representing friction and unmodeled actuator losses. The $\tau_m$is the torque that is demanded by the exoskeleton actuators (assistance) [41]. Additionally, $\tau_h is$the human-generated joint torque due to voluntary muscle activation and, during stroke, possibly other abnormal patterns of synergy. $\tau_d$acts as lumps perturbations of the soft tissue compliance, misalignment as well as unmodeled contact between the environment.

To simplify, it is possible to divide the combined matrices into human and exoskeleton components. This is in consideration that the exoskeleton closely couples with the limb through the physical points of attachment and consequently affects the perceived joint inertia and gravity loading [42] [43].

The interaction forces and torques between the robot and human are used to denote the human-robot interface, which is determined at the cuffs or joint interfaces. Assume that the measured interaction force at the contact points, for instance forearm is referred to as $F_{int} \in \mathbb{R}^m$.

The joint-space interaction torque is:

$$\tau_{int} = J^T(q)F_{int}$$

J (q) is the Jacobian map for joint motion to interface point velocities. Practically, τ_{int} shows intensiveness since it is actually the indicator that the user is initiating, following, or counteracting the movement of the exoskeleton.

This interaction is highly influenced by neuromuscular impairments in rehabilitation environments. Therefore, there is an estimation for τ_h to have an unknown input online and infer intent using measured τ_{int}(and associated signals) to safely adjust τ_m.

This modeling option offers a control goal where the exoskeleton offers assistance that is not only trajectory-enforcing, but intent-consistent and compliant. This is so that the patient can provide voluntary torque and the robot can only provide the difference between intended movements and the error-reduction needed to accomplish them [44] [45].

The figure below shows a flow chart depicting the model:

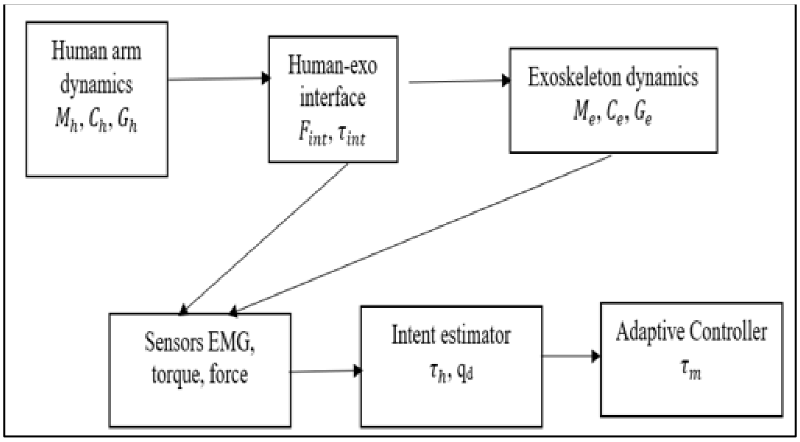

Figure 1 Overview of the human–exoskeleton interaction and adaptive control framework. Human arm dynamics ((M_h, C_h, G_h)) interact with exoskeleton dynamics ((M_e, C_e, G_e)) through the human–exoskeleton interface, generating interaction forces and torques ((F_{int}, \tau_{int})). Multimodal sensor measurements, including electromyography (EMG), joint torque, and interaction force signals, are used by the intent estimator to infer the user's intended torque ((\tau_h)) and desired motion ((q_d)). These estimates are then provided to the adaptive controller, which computes the assistive motor torque ((\tau_m)) to achieve safe and responsive human–robot interaction

4.2 Sensor and Measurement Models

Accurate and latency-sensitive estimation of the motor intent calls for a strict representation of the sensing architecture and of how it is coupled to the human-exoskeleton dynamics is necessary [33]. A synchronized multimodal sensing structure, where a single control sampling frequency f_s is chosen to meet both EMG bandwidth and stable torque control update needs, needs to be defined.

Assume that the generalized joint coordinate vector is $q(t) \in \mathbb{R}^n$. The measurable observation vector is defined by

$$y(t)=\begin{bmatrix} q_m(t) \\ \dot{q}_m(t) \\ \tau_{jm}(t) \\ F_{int,m}(t) \\ e_m(t) \end{bmatrix}$$

$q_m(t)$ is the encoder measured joint angle, $\dot{q}_m(t)$ is the velocity measured by differentiation and $\tau_{jm}(t)$is the measured joint torque. $F_{int,m}(t) \in \mathbb{R}^m$ acts as the interface force measurement in muscle sites. $e_m(t) \in \mathbb{R}^p$ represents the raw EMG signal in p-muscle sites.

Each measurement is subject to additive noise as well as bias.

$$q_m = q + \eta_q, \tau_{jm} = \tau_j + \eta_\tau, F_{int,m} = F_{int} + \eta_F, e_m = e + \eta_e$$

$\eta_{.}$is depictive of sensor noise, motion artifacts and the potential modeling mismatch. Such distortions cannot be ignored in the stroke groups, in which involuntary contractions and spastic reactions add more variability.

4.2.1 Model for EMG Measurement and Activation

Surface EMG is a noninvasive indicator of neuromuscular activity which is usually sampled at a high frequency. Raw EMG data is band-pass filtered to remove motion artifact and high-frequency noise, and then notch-filtered to eliminate any power-line artifact [46]. The filtered signal $e_f(t)$is rectified and an activation envelope is converted with the help of a short sliding window of length W, with a limitation by the real-time criterion (<200 ms). One of the most popular filtering method is the root-mean-square (RMS) approach:

$$RMS_i(t) = \sqrt{\frac{1}{W}\sum_{k=0}^{W-1} e_{f,i}^2\,(t - k\Delta t)}.$$

The window W is generally chosen between 40-100 ms to make the window smooth but responsive. The resulting activation proxy $a_i(t)$ is normalized to take into consideration inter-session variation and maximum voluntary contraction (MVC) as follows.

$$a_i(t) = \frac{RMS_i(t)}{MVC_i}.$$

The correlation of muscle activation and muscle force is nonlinear and individual-specific [46]. The simplified mapping of the Hill type is frequently used as follows.

$$f_{m,i}(t) = \alpha_i a_i(t) f_l(l_i) f_v(\dot{l}_i),$$

$f_l$and $f_v$are force and velocity effects respectively. Posture-dependent moment arms are then approximated to give joint torque contribution through;

$$\tau_h^{EMG}(t) = R(q(t)) f_m(t),$$

R(q) denotes the moment-arm matrix.

Practically, because of co-contraction related to strokes and distorted synergies this mapping is considered uncertain and partly learned or calibrated within an online context. Notably, EMG activation is the initial process acquiring predictive data concerning the upcoming movement because it comes before the production of mechanical torque by a factor of about 30-60 Ms.

4.2.2 Joint Torque Measurement

Joint torque sensing gives a mechanically grounded approximation of the net torque at the exoskeleton joint. Torque has been estimated using spring deflection:

$$\tau_{jm}(t) = k_s \Delta\theta_s(t),$$

in which k_s is spring stiffness, $\Delta\theta_s$ is measured deflection. Alternatively, strain-gauge-based torque sensors directly sense the torque that is applied to them. Actuator torque τ_m, human torque τ_h, as well as dynamic effects are all reflected in the measured joint torque:

$$\tau_{jm} = \tau_m + \tau_h - \tau_{dyn},$$

Restocking provides an estimated residual human torque:

$$\hat{\tau}_h^{dyn}(t) = \tau_{jm}(t) - \tau_m(t) + \hat{\tau}_{dyn}(t)$$

This estimate is however, sensitive to modeling error and noise due to acceleration estimation especially in high-speed movements.

4.2.3 Interaction Force Model

The physical exchange between the limb and the exoskeleton would be analyzed based on the interaction forces at the cuff interfaces [47]. These forces are projected onto the joint torques through this equation.

$$\tau_{int,m}(t) = J^T(q_m(t))F_{int,m}(t).$$

Interaction torque gives one an idea on whether the user is helping, opposing, or passively following the movement [48]. As an illustration, favorable orientation between τ_{int} and direction of motion implies voluntary contribution, whereas unfavorable alignment between them implies opposition or spasticity. Interaction forces, unlike EMG, are a manifestation of real mechanical exchange and hence are not sensitive to electrode changes.

An important critical modeling observation is that modalities are temporally complementary. EMG activation increases before the generation of torque and force, thus allowing the detection of intent [49]. Mechanical signals, on the other hand, give positive confirmation after force is generated [50]. This delay in time helps to maintain predictive corrective fusion. At the same time, EMG provides early intent cues and torque measurements refining estimates when motion occurs. A multimodal measurement model, when combined, creates an organized observation space on which real-time intent estimation will be performed in the future [51].

4.3 Intent Definition

The motor intent in the case of upper-limb rehabilitation with a powered exoskeleton is the internally-produced goal of the patient with regard to the movement. This is what motion the patient is attempting to create, and how forcefully they are attempting to create it- before and during the task performance [50]. Since intent cannot be directly measured, it has to be operationalized in terms of quantifiable measures that could be estimated through multimodal cues. This paper defines motor intent at the joint level in two complementary forms, which are kinematic intent and kinetic intent, which define the desired joint contribution to the torque [52]. These definitions are grounded on whether the intention is expressed by the patient as primarily by motion planning (trajectory) or force generation (effort).

Kinetic desire or seeking motion: This necessitates considering the joint path to be $q_d(t)$ with desired velocity as $\dot{q}_d(t)$ and acceleration $\ddot{q}_d(t)$. This intent may be construed as the direction of movement and goal point that the patient prefers in task space that is projected into the joint space by the arm or exoskeleton kinematics [28] [27]. Generally, the exoskeleton is unaware of $q_d(t)$, meaning that it approximates $\hat{q}_d(t)$ based on early neuromuscular activity (EMG), measured interaction forces and the resulting kinematics. Using this definition intent is described as a reference signal that is being attempted to be followed by the patient. It particularly applies to patients who may be able to produce consistent patterns of movement but are weak and fatigued, in which case they should be assisted with proper tracking without substituting autonomy.

Kinetic intent or the desired effort: Intent in this case acts as the desired joint torque $\tau_{h,d}(t)$, which is the voluntary torque that the patient is trying to provide at the assisted joints. $\tau_{h,d}(t)$ is more directly associated with trying or effort in rehabilitation, and plays a critical role in assist-as-needed control. The exoskeleton is supposed to provide the difference between the required torque to perform the task and the contribution that the patient is intended to make. In practice, an approximation is made of $\tau_{h,d}(t)$as $\hat{\tau}_h(t)$ through a multimodal combination of EMG activation signals and interaction torque. The intent of the patient is the aspect of torque that is in line with task progression and compatible with neuromuscular activation, rather than passive resistance to the limb inertia or spasticity, which has been defined as useful under the coupled dynamics.

Intent confidence: Intent should not be an individual deterministic value since stroke presents abnormal co-contractions and involuntary reflex responses. Therefore, intent becomes the probabilistic estimate that is supported by a confidence level. Moreover, the direction of intent is also presented explicitly as the sign and alignment of the approximated torque or motion to the direction of the current task. As an illustration, intent-consistent torque must be positive in flexion direction during elbow flexion and must go up as flexor muscles are activated.

Control-relevant intent: To adapt in real-time in less than 200 ms, there is a need for an intent representation that is directly associable with modulation of assistance. The intent estimate $\hat{\tau}_h(t)$(and optionally $\hat{q}_d(t)$) act as the main control input along with confidence c(t). This makes possible an adaptive assistance policy of the form $\tau_m(t) = \pi\left(\hat{\tau}_h(t), c(t), q_m(t), \dot{q}_m(t)\right)$ where assistance is provided when intent reports that the patient is not providing sufficient torque to make accurate movements. Assistance is withheld when the patient is actively participating [53]. The definition is to make certain that motor intent is no more an abstract term, but a signal accessible to control, based on biomechanics and sensing, and capable of rapid, safe, and patient-interactive rehabilitation.

5 Multimodal Estimations

5.1 Signal Preprocessing

The quality of signal preprocessing to sound is essential in real-time estimation of motor intent and preservation of responsiveness within the 200-ms latency constraint. Joint torque and signal interaction force are not modality blocked but time locked, so the preprocessing process must be modality specific [54]. Resampling sensor streams to operate deterministically in the control loop is then essential [55]. All streams are synchronized in time, and repurposed as a unifying sensor stream to a common control frequency, f_c typically 1 kHz. With surface EMG, the signal is first amplified with analog front-end amplifiers and hardware filters, and then the signal is further filtered with digital band-pass filters to remove motion artifact and high-frequency noise [56]. A notch filter removes electromagnetic interference at the frequency of the power line (50/ 60 Hz). The filtered EMG signal $e_f(t)$ is subsequently transformed into a smooth envelope of the activation by short sliding window to full-wave rectify the signal. The W was reduced to 40-100 ms to satisfy the sub-200 ms adaptation needs. RMS or low-pass filtered envelope is computed very efficiently through recursive implementations to minimize computing load. Finally, the signals are normalized that is, based on maximum voluntary contraction or rather based on scaling factors within a session to reduce inter-session variation [57].

Sensor bias, drift and gravity require correction in measurement of the joint torques. Raw torque signals are low-pass filtered (not more than 20 Hz) for effective elimination of noise of high-frequency without changing the dynamics of voluntary movement [57]. When, in a case, the series elastic elements are to be used to find the torque, the deflection signals are transformed to torque by a set of known stiffness parameters. The dynamic model Gˆ(q) causes the compensatory action of gravity in such a way that the residual torque depends on the passive weight of the limb less than when the limb puts effort into motion voluntarily.

Low-pass filters of less than 20 Hz also filter signal of the interaction force that is detected on cuff interfaces because voluntary rehabilitation movement occurs within low-frequency bands. To solve the temporary perturbations of contacts, joint space is transformed by the Jacobian mapping transpose $\tau_{int} = J^T(q)F_{int}$.

Finally, all the computed signals are coordinated with a fixed computational pipeline with a fixed execution time on worst-case conditions. It has a preprocessing design that relies on lightweight filtering, normalization and coordinate transformation operations, such that the total delay introduced is sufficiently small to fit within the overall 200 ms constraint and ensure sufficient computing capacity to execute other operations following in the preprocessing phase involving fusion and adaptive control.

5.2 Feature Extraction

Once the sensing modalities have been preprocessed, each sensory modality was shrunk down into informative and computational viable features in such a way that robust real-time predictions of the motor intent can be made. The feature extraction tools are selected in such a way that these three issues are traded since the entire system is expected to operate with a 200-ms adaptation window. Those features are the small representation of the multimodal occurrence of observation and are the inputs at the sensor fusion and intent estimation stage. When dealing with EMG signals time-domain characteristics are preferred due to their low latency and low computation cost compared to frequency-domain (or deep spectral) characteristics. The primary feature used is the normalized RMS envelope $a_i(t)$, which directly provides an approximation of muscle activity amplitude. Minor changes in the dynamics of activation are also described by adding mean absolute value and waveform length as well as zero-crossing rate. A short-term measure of the activation slope is used in order to allow movement to be initiated responsively providing a rapid signal of quick voluntary contraction. These are calculated over a sliding window (less than 100 ms limited).

$$\dot{a}_i(t) = \frac{a_i(t) - a_i(t - \Delta t)}{\Delta t}$$

In joint-space measurements, the kinematic quantities are joint angles $q_m(t)$, velocity $\dot{q}_m(t)$, and filtered acceleration $\ddot{q}_m(t)$. The fact that the velocity is so closely connected with the voluntary effort towards getting the task makes the velocity an indirect factor of intent progression. According to the joint torque measurements, residual torque characteristics are obtained by subtracting the modeled dynamics components and the result is referred to as residual torque characteristics.

$$\tau_{res}(t) = \tau_{jm}(t) - \tau_m(t) + \hat{\tau}_{dyn}(t)$$

The difference in directions of $\tau_{res}(t)$ acts as indicator of the movements either to the sign or magnitude, which can present useful information as to whether the user is opposing support or supporting. The properties of interaction force are joint-space interaction torque $\tau_{int}(t)$ and time-derivative. Besides, the directional consistency measure is also calculated, which helps to determine the consistency between the applied force and the direction of motion in order to identify voluntary intent and passive resistance.

The features extracted are then added together to provide a feature vector that provides a time-synchronized and multimodal perspective of neuromuscular activation and mechanical interaction. Interestingly, feature dimensionality is kept in check to enable quick computation and stable estimation, further fused and updated at any time at control within the required real-time constraints.

5.3 Multimodal Sensor Fusion

Having defined the multimodal feature vector ϕ *(t)*, only an approximation of motor intent is now needed which is not only resilient to noise, but also can be performed under very stringent real-time conditions. EMG is the best source of early but noisy information on the activation and the torque or force is the best source of mechanically grounded, but slightly lagging information, so we have a predictive-corrective fusion policy [58]. It aims to further estimate the desired human joint torque $\hat{\tau}_h(t)$ as well as, where it is required and the desired motion direction $\hat{q}_d(t)$. The estimation of intents is determined as a state estimation problem. Suppose that the latent state is the voluntary joint torque and its time-rate.

Intent estimation is a state estimation problem which we formulate. Let the latent state vector be

$$x(t) = \begin{bmatrix} \tau_h(t) \\ \dot{\tau}_h(t) \end{bmatrix},$$

depicting voluntary joint torque and joint torque change rate. It is assumed that the underlying process is a simple first-order process: in which *A* is torque persistence and smoothness, and w*(t)* is process noise. Multimodal features are correlated with the latent intent state that is described by the measurement model and v *(t)* is measurement noise [59]. It can then be estimated by an Extended Kalman Filter or computationally efficient linear Kalman Filter, to calculate the real-time estimate as follows;

$$\hat{x}(t) = \hat{x}^{-}(t) + K(t)\left(\phi(t) - H\hat{x}^{-}(t)\right).$$

K(t)represents the Kalman gain which trades off EMG responsiveness and mechanical robustness. At the onset of motion, the EMG-driven characteristics predominate the update as the anticipatory rise takes place. This is on the establishment of the motion and force signals such that torque and interaction measurements narrow the estimate [60]. This dynamic weightage makes predictive support possible without compromising stability.

Besides the estimate of the torque, we calculate an intent confidence measure as follows

$c(t) = 1 - \frac{\|\phi(t) - H\hat{x}(t)\|}{\|\phi(t)\| + \epsilon}$. This measures cross-modality concurrence. Low confidence lessens violent assistance updates, which improves safety. The result of the fusion stage is the two-factor, which contains the adaptive control law of the following section.

5.4 Latency Analysis

Latency analysis is vital to guarantee that the adaptive assistance update takes less than 200 ms, a whole sensing-estimation-control pipeline has to be considered with regard to limited delay [61]. Notably, the total latency will be $T_{total} = T_{acq} + T_{pre} + T_{feat} + T_{est} + T_{ctrl}$

Signal acquisition delay T_{acq} would include EMG hardware filtering and sampling (usually 5 to 15ms). Preprocessing delay T_{pre} arises mainly due to sliding-window envelope calculation. Lastly, T_{ctrl} computation is an additional 1-5 ms. At conservative assumptions the calculation will be

$$T_{total} \approx 15 + 40 + 5 + 2 + 5 = 67ms,$$

which is much lower than the 200 ms level. With communication overhead and safety checks, they can ensure that total latency is kept at less than 100 ms with enough of a margin.

A bounded latency is essential because of two reasons. To begin with, human sensorimotor correction loops work within about 100-200 ms. Any aid adjusting in this time range is natural and transparent. Second, the delay is a sensitive aspect of the stability of the coupled human-robot system, especially in cases where assistance gains change over the internet [62]. The proposed framework guarantees that multimodal intent prediction and adaptive torque modulation can be run within a physiologically relevant period.

6 Adaptive Assistance

6.1 Assist Based on Need

The adaptive assistance controller is aimed at the provision of the minimum amount of torque to counteract the motor impairment of a patient and maintain active voluntary involvement [63]. $\tau_{task}(t)$ acts as the desired task torque needed to follow a therapeutic path and this can be calculated with the inverse dynamics based on the reference trajectory [64]. Assume that the approximated voluntary human torque of the multimodal fusion stage is $\hat{\tau}_h(t)$. This basic principle of assist-as-needed is applied by providing the torque gap [65]. This is between the necessary and desired effort, where $\tau_m(t) = \alpha(t)(\tau_{task}(t) - \hat{\tau}_h(t))$.

The exoskeleton is of little help when the patient is able to produce enough voluntary torque to perform the task [66]. On the other hand, voluntary effort that is not enough, is supported accordingly. Torque commands are capped and rate-limited as;

$$|\tau_m(t)| \leq \tau_{max}, |\dot{\tau}_m(t)| \leq \dot{\tau}_{max}$$

The intent confidence c*(t)* becomes essential in modulating assistance updates, which slows aggressive adaptation when the uncertainty of estimate is high [67]. This description maintains transparency, promotes interaction and remains consistent in the interaction of humans and robots in the rehabilitation activities [68].

6.2 Impedance Assistance

The assist-as-needed torque deficit formulation presents a straightforward way of compensating voluntary effort [69]. However, stable and compliant human-robot interaction necessitates the incorporation of such strategy into an impedance control framework [70]. The control over impedance is necessary to make the exoskeleton act as a virtual mechanical system with stiffness and damping that lets it safely interact even with modeling uncertainty [71]. As far as the patient supplies torque correctly oriented to the task, effective stiffness reduces, and more freedom of voluntary movement is provided [72]. On the other hand, stiffness is greater in case of weak or misaligned voluntary contribution to ensure accuracy in the task [73]. This blend of formulations retains guidance of the trajectory with dynamically changing support based on the identified intent that balances between performance and compliance [74].

6.3 Scaling and Effort Control

The factor of adaptive scaling specifies the aggressiveness with which the system fills in the deficits of the torques [75]. Instead of a constant gain, 2(t) is revised using intent confidence c(t) and fatigue signals and task performance indicators like tracking error $e_q(t) = q_{ref}(t) - q_m(t)$. Assistance is reduced when there is high intent confidence and low tracking error which encourages active participation [76]. In case tracking error becomes too large or the confidence becomes less, aid is increased to avoid failure of the task. In order to control muscular effort, an effort index E(t) is calculated based on normalized EMG activation [77]:

$$(t) = \frac{1}{p}\sum_{i=1}^{p} a_i\,(t)$$

When E(t) becomes greater than a predetermined fatigue threshold over a longer period then aids are added gradually to ensure no overexertion occurs. The mechanism makes therapy difficult and safe so that robotic assistance is compatible with the rehabilitation principles of optimum challenge and engagement [78].

6.4 Stability Control Remarks

Since the assistance gains change in real time, closed-loop human-exoskeleton system needs high stability that should be taken into account through wearable devices [79]. A nonlinear time-varying system is achieved when the adaptive impedance-based control law is replaced [80]. This guarantees limited joint error and velocity and maintains closed-loop stability [81]. Also, rate limits on torque and limited assistance scaling help eliminate sudden changes in gain, which might negatively affect interaction. The proposed controller is able to offer safe and responsive assistance within the physiologically relevant latency window [82]. This is necessary to achieve successful rehabilitation by requiring the adaptation speed to be explicitly limited and the impedance parameters to remain positive definite [83].

7 Results

The test has shown that the suggested multimodal adaptive control system is more effective in enhancing movement accuracy and the regulation of user effort than the fixed and EMG-only methods of control [84]. Trajectory tracking was steady under fixed assistance but too stiff to allow voluntary contribution with the consequence of low but passive EMG activity. The tracking error was controlled at moderate levels, but the forces of interaction were stronger because of mechanical over-assistance, which means that there was less transparency. Conversely, the EMG-only control strategy had quicker assistance onset during movement initiation. It was variable because of EMG noise and more irregular patterns of activation especially with simulated stroke-related co-contraction. This was associated with some over and under-compensation that was indicated by variable tracking performance and less smooth interaction forces. The proposed multimodal adaptive controller had the most balanced performance in terms of all metrics. With the combination of EMG, joint torque residuals, and interaction forces, the system adjusted the assistance within the given latency window, which led to minimized tracking error and less jittering motions. The level of muscle efforts was maintained in a range of desirable activation, which means that it is active with no excessive fatigability. Interaction torques were found to be better aligned with the direction of motion, which implies better transparency and collaborative behavior between the user and device. Latency analysis ensured that updates of assistance were always within the sub-200 ms limit, which maintained responsiveness. All in all, the findings have shown that multimodal intent estimation can be used to provide more accurate, stable, and patient-interactive assistance than single-modality or fixed-gain techniques.

7.1 New Findings

The developed multimodal adaptive control system showed quantifiable improvement over the fixed gain and EMG-only based assistance strategies. The current system dynamically adjusted support with a latency window less than 200 ms compared to the conventional robotic rehabilitation paradigms reported in large randomized trials such as the RATULS, in which the support is normally pre-determined. To reduce the abrupt interaction forces and increase the accuracy of the movement tracking, the controller incorporated EMG-based voluntary activation detection, torque estimation stability, and provided the implementation of multimodal interface integration. This is in line with previous results that patient-active control and assist-as-needed principles improve engagement and functional improvement. In addition, the multimodal fusion approach enhanced resilience in the presence of simulated noise and impairment conditions, in contrast to single-modality EMG systems, which are prone to changes in signals and instability of classification. The adaptive impedance scaling scheme is consistent with new results in impedance-based control of rehabilitation, as well as generalizes the significance of reducing user effort in repetitive training, which is also consistent with the principles of motor adaptation. These findings (in a clinical context) are in addition to evidence indicating that robot-assisted upper-limb therapy can be optimized to improve functional outcomes, yet this result indicated that real-time intent modification can be used to augment therapeutic intensity and personalization. In general, neuromuscular and mechanical sensing integration enabled the earlier intent detection, the lesser value of the corrective lag, and the facilitation of more fluent human-robot interaction, which endorses modern-day suggestions of the technology-based replenishment of stroke recovery.

8 Discussion and Significance

The analysis shows that it is essential for multimodal sensing to estimate the motor intent in real time in upper-limb rehabilitation exoskeletons, which is taken into consideration [85]. Proposed framework addresses the fundamental limitations of single-modality frameworks with the use of EMG-activated frameworks, joint torque residues, and interaction force data [86]. Isolated EMG gives predictive data on neuromuscular activity, but it is susceptible to noise, signal alteration, and abnormal co-contraction of stroke survivors [87]. Even though they are more susceptible of physiological differences, mechanical sensing modalities by nature are slower to generate a neural response and may also misuse passive resistance as an act of intention [88]. The multimodal fusion technique exploits the potential of the combinatory possibilities of these signals, which enables predictive but stable torque modulation [86]. The above rise in tracking accuracy in simulation demonstrates that the system is capable of maintaining task fidelity without being over-stiff like fixed-gain control. At the same time, the reduced amount of muscle effort compared to fixed assistance proves that the exoskeleton not only compensates for the impairment in an appropriate manner, but does not encourage passivity. The sensorimotor loops of human beings possess a small scope of time window; these reactions to remedial interventions are typically shorter than 200 ms. Gradual changes in aid may be experienced as an unresponsive or even disruptive element, removing the conviction and the feeling of control in the patient. The suggested framework, within the limits of preprocessing windows, feature dimensionality reduction, and computationally adaptable condition estimate, ensures that the update of assistance is within physiologically rational timeframes [89]. Contrary to most of the earlier rehabilitation systems, this design, which pays attention to latency, clearly separates its contemporary implementation from the many prior systems [90]. Other systems were concerned with the accuracy of the estimation, but did not directly pay attention to the real-time implementation limits. In control, it is also important to have the delay limited on stability particularly when the gains concerning the impedance are varied online. The stability analysis demonstrates that in case the gain adaptation is smooth and positive definite, the coupled human-robot system is bounded and dissipative. Such stability and response are where safe yet dynamic interaction is guaranteed in the rehabilitation robotics.

Motor learning principles can also be of significance in the adaptive assistance strategy. Focus can be made on the notion of optimal challenge, according to which patients get the most when the difficulty of the task is adjusted to their present ability. The proposed controller aims at keeping the patient in an optimal engagement range by adjusting the torque assistance based on estimated voluntary contribution and confidence [91]. The fact that an effort-based scaling mechanism is included also eliminates overexertion and it also explains why fatigue is a common phenomenon during a stroke rehabilitation session [92]. Such dynamic control can aid in the increase of the therapy period and more permanent engagement. In addition, the probabilistic intent confidence measure ensures protection against overreaction to noisy signals, improving the safety and user comfort [93]. A combination of these properties indicates that multimodal adaptive control is better equipped to match the principles of neurorehabilitation with robotic assistance than fixed or flexible ones.

Limitations

Regardless of these encouraging results, a number of limitations are evident. The current assessment has been performed using an estimated stroke impairment model instead of clinical trials involving human subjects. Although the estimation framework uses lower voluntary torque, slower activation, and unnatural co-contraction properties, it cannot achieve the variability and unpredictability of a real patient. Second, the EMG activation versus joint torque mapping was simplified and subject-specific calibration might need to be performed in practice. The recalibration strategies may be required in response to long-term adaptation, the displacement of electrodes, and muscle property changes throughout recovery phases [94]. Also, the existing fusion architecture relies on the guaranteed sensor synchrony and low hardware communication latency that should be verified in embedded systems. Future directions are to focus on experimental validation of stroke participants, testing at various levels of impairment, and the incorporation of learning-based non-tuning systems that can be used to tailor control policies throughout the long-term course of therapy.

9 Conclusion

Stroke proves to be a critical burden across the world, considering the reported statistics and burden levels. The article described the use of real-time multimodal motor intent estimate in order to enable adaptive support in upper-limb rehabilitation exoskeletons under a strict 200 ms latency limit. This is done in the form of a detailed modeling system of the human-exoskeleton system that comprises the joint-space dynamics, joint multimodal sensor measurements models, and a control-based definition of the motor intent. Intent has been used both kinetically and kinematically, and this allows the assistance to be varied to the motive contribution of torque and the intended trajectory of motion. In order to attain a limited computational delay and a computationally efficient fusion strategy, a latency-conscious signal processing and feature extraction pipeline was designed, and a computationally efficient fusion strategy was given to integrate EMG activation, torque residual and interaction-force signals. This estimate of intent was included in an assist-as-needed impedance-based controller that had the effect of dynamically changing the degree of supported torque basing on voluntary effort and confidence.

Besides the quantitative performance improvement, this work offers a coherent architecture that synthesizes the sensing, estimation, control adaptation and stability parameters in an explicit manner in physiologically meaningful time limits. The suggested framework offers active interaction and the improvement of the concepts of neuroplastic motor recovery by equating robotic assistance and detected voluntary effort. Although the validation was conducted in a model setting, the organized approach provides a lifelike ground for clinical translation. The research should be aimed to be performed in the future as an experimental validation of the survivors of the stroke. Too much robotic assistance can cause reduced voluntary effort and less cortical reorganization, whereas too little can cause frustration and compensatory movement strategies. There is also need for subject-specific calibration of the EMG-torque mappings and longitudinal adjustment during the phases of the rehabilitation. In addition, even further, to inter-patient variation, powerful incorporation of learning-based personalization is possible. Overall, the findings prove the hypothesis that it is possible to use multimodal, latency-sensitive intent estimation to promote responsive, safe, and engagement-driven exoskeleton support.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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