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Surface Electromyography and Multisensor Fusion for Safe Adaptive Impedance Control of Upper-Limb Rehabilitation Exoskeletons: A State-of-the-Art Review

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Abstract: *Upper-limb rehabilitation exoskeletons are evolving from trajectory-replay devices toward human-in-the-loop systems that estimate voluntary contribution and adapt assistance while maintaining physical safety. This state-of-the-art review synthesizes 61 peer-reviewed studies and two safety standards across robot architecture, surface electromyography (sEMG) acquisition and representation, continuous intention and participation estimation, multisensor fusion, compliant interaction control, safety assurance, and staged validation. The reviewed evidence indicates that high offline gesture-classification accuracy alone is insufficient for rehabilitation control. A control-relevant user state should be continuous, direction-sensitive, individualized, and confidence-aware, and its interpretation should be verified against interaction force and kinematic consistency. Adaptive impedance, admittance, and assist-as-needed strategies provide a promising basis for personalized assistance; however, online parameter adaptation must remain subject to explicit bounds, rate limits, fault detection, and an independent safety supervisor. The principal research gap is the lack of an experimentally validated end-to-end framework that converts synchronized sEMG, interaction-force, and kinematic measurements into a reliable participation state and uses that state to regulate assistance safely. Accordingly, this review formulates a research pathway for a two- or three-degree-of-freedom shoulder–elbow platform, including subject- and session-independent estimation, disturbance and sensor-fault testing, comparisons with PID, fixed-impedance, and single-modality adaptive controllers, and staged progression from bench experiments to ethically approved user studies.*

Keywords: *upper-limb rehabilitation exoskeleton; surface electromyography; multisensor fusion; voluntary participation; adaptive impedance control; assist-as-needed; safety supervision.*

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NOMENCLATURE

Symbol / acronym	Description	Unit or range
q, q_d	Measured and desired joint coordinates	rad
τ_a	Assistive joint torque	N·m
τ_{int}	Human-robot interaction torque	N·m
M_d, B_d, K_d	Desired inertia, damping, and stiffness	kg·m^2, N·m·s/rad, N·m/rad
A(t), c(t)	Estimated participation and confidence	[0,1]
AAN	Assist-as-needed	-
IMU	Inertial measurement unit	-
sEMG	Surface electromyography	mV

I. INTRODUCTION

Upper-limb impairment after stroke, spinal cord injury, traumatic brain injury, or neuromuscular disease restricts reaching, lifting, grasp preparation, and object manipulation. Robotic devices can deliver intensive and repeatable practice while recording joint motion, interaction force, and task performance. Clinical reviews nevertheless show that therapeutic benefit depends not only on repetition but also on training mode, patient engagement, impairment severity, and the relation between robotic assistance and voluntary effort [1]-[6].

Upper-limb systems range from end-effector mechanisms that guide the hand to exoskeletons aligned with the shoulder, elbow, forearm, wrist, or fingers. Hardware reviews identify persistent trade-offs among anatomical alignment, workspace, backdrivability, actuator placement, mass, wearability, and control bandwidth [7]-[10]. These constraints are not secondary to control design: a poor mechanical interface can generate interaction forces that no estimator or adaptive law can interpret reliably.

The control objective has consequently shifted from rigid trajectory reproduction toward patient-cooperative and assist-as-needed behavior. Excessive assistance may suppress voluntary contribution and promote learned dependence; insufficient assistance may prevent task completion or amplify fatigue. A useful controller should infer what the user is trying to do, how much the user is contributing, and whether the resulting interaction remains safe.

sEMG is attractive because muscle activation precedes visible movement and provides access to neural drive. It can support movement classification, continuous activation or torque estimation, fatigue monitoring, and adaptation. However, sEMG is not a direct measurement of joint torque. Its mapping to effort varies with electrode position, skin impedance, muscle length, contraction type, co-contraction, posture, fatigue, and session-to-session re-donning. Interaction force and kinematics provide complementary mechanical evidence but are also affected by bias, robot dynamics, misalignment, and task context.

This review therefore examines the complete sensing-to-control pathway for upper-limb rehabilitation robots. The main evidence base concerns arm, elbow, wrist, and hand rehabilitation or assistance. Prosthetic-control studies are used only when they establish transferable principles of proportional sEMG decoding, domain adaptation, or multimodal estimation; the lower-limb study [48] is retained solely as explicitly labeled transfer evidence for continuous decoding and bounded adaptation. The review is structured around a central question: how can synchronized sEMG, interaction force, and movement state be converted into a reliable participation variable for safe adaptive impedance control?

II. REVIEW METHOD, EVIDENCE BASE, AND SYSTEM REQUIREMENTS

A. LITERATURE SCOPE AND SELECTION

A structured narrative state-of-the-art search was conducted using combinations of upper limb, arm, elbow, hand, rehabilitation robot, exoskeleton, sEMG, electromyography, multisensor fusion, interaction force, assist-as-needed, impedance, admittance, adaptive control, and safety. Priority was assigned to peer-reviewed work from 2016-2026 and to official standards. Earlier studies were retained when they introduced a foundational platform, a widely used myoelectric method, or a control principle that remains necessary for interpretation.

The analytic corpus comprises 61 peer-reviewed publications and two standards. Inclusion required a clear connection to upper-limb rehabilitation or assistance, sEMG processing, continuous intention estimation, human-robot interaction control, or risk control. Studies centered on prostheses, hands, or another limb were included only when their transferable role was stated explicitly. Purely simulation-based control claims without a relevant human-robot or hardware interpretation were not treated as direct upper-limb rehabilitation evidence.

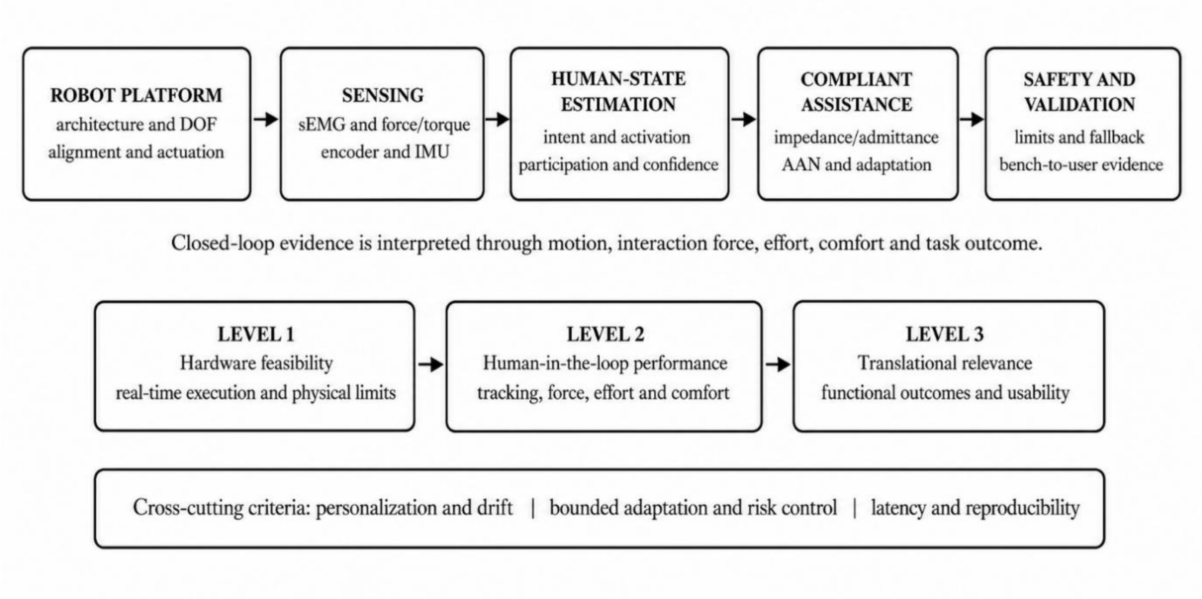

Fig. 1. Evidence map used to organize the state-of-the-art review (authors' synthesis based on [8]-[10], [26]-[29], [49]-[63]).

The evidence map in Fig. 1 separates hardware feasibility, human-in-the-loop performance, and translational relevance. This separation prevents a common category error: high offline decoding accuracy cannot establish stable assistance, and good tracking cannot establish safe or therapeutically appropriate interaction. Across all three evidence levels, the review considers personalization, signal drift, latency, bounded adaptation, risk control, and reproducibility.

B. EVIDENCE FRAMEWORK AND UPPER-LIMB REQUIREMENTS

The comparison addresses five questions: (1) which robot architectures and sensing arrangements are compatible with participation-aware control; (2) which sEMG acquisition, preprocessing, representation, and validation choices support real-time use; (3) how continuous contribution and confidence should be estimated from sEMG, force, and kinematics; (4) how impedance, admittance, and assistance should be adapted without abrupt or unsafe behavior; and (5) which verification stages and outcome measures are required before conclusions can extend beyond a laboratory demonstration. Table 1 summarizes the corresponding evidence dimensions, variables, and recurrent weaknesses.

Table 1. Review dimensions and evidence questions

Dimension	Main variables	Evidence question	Common weakness
Mechanical architecture	DOF, alignment, transmission, mass, backdrivability	Can the device generate the required workspace without harmful joint loading?	Performance reported without alignment or wearability data
Biosignal acquisition	muscles, channels, bandwidth, sampling, normalization	Is sEMG quality sufficient and repeatable across sessions?	Electrode placement and calibration incompletely reported
State estimation	class, activation, torque, fatigue, participation, confidence	Is the estimated state physically meaningful for control?	High accuracy on random window splits but weak subject/session generalization
Sensor fusion	sEMG, force, encoder, IMU, context	Does fusion resolve ambiguity or merely add inputs?	No ablation study and no fault handling
Interaction control	impedance, admittance, AAN, adaptive/learning law	Does assistance decrease when voluntary contribution improves?	Parameter adaptation is unbounded or lacks stability discussion
Safety and validation	ROM, force, torque, energy, latency, faults, user study	Can the system fail predictably and conservatively?	Emergency-stop hardware is reported, but algorithmic fallback is not

Upper-limb architectures and representative platforms. The ARMin family demonstrated the feasibility of multi-joint exoskeleton therapy with patient-cooperative modes, gravity compensation, and anatomical alignment [11]. Subsequent clinical and experimental systems showed that intensive reaching practice can be delivered through powered exoskeletons, although gains depend on training design and the user's residual ability [12], [13]. More recent platforms expand this space. U-Rob combines rehabilitation and assistance functions [14]. A 4-DOF exoskeleton by Gull et al. integrates modeling, control, and performance evaluation [15], while EXOTIC emphasizes compact multi-DOF assistance and shared user control for tetraplegia [16]. End-effector work based on dual-quaternion kinematics illustrates an alternative route in which workspace tracking is simplified at the expense of direct joint-level actuation [17]. Patient-oriented control, inverse-kinematic optimization, and capstan-driven wrist impedance systems further show that mechanical and control co-design remains active [18]-[20].

Wearable hand devices extend rehabilitation toward grasping and ADL. The MANO exoskeleton targets everyday assistance and neurorehabilitation [21]. Soft or cable-driven gloves improve wearability and reduce rigid alignment constraints [22]-[25]. Their compliant structures are attractive for safety, but force transmission, hysteresis, sensing, and repeatable donning become harder to model. For proximal arm rehabilitation, rigid exoskeletons provide clearer joint torque authority, whereas end-effector devices simplify fitting. No architecture is uniformly superior; the appropriate choice depends on whether the research question concerns joint-level assistance, endpoint task practice, or portable daily support. Representative platforms and the limitations most relevant to adaptive assistance are compared in Table 2.

Table 2. Representative upper-limb rehabilitation and assistive robot platforms

Study	Architecture / DOF	Sensing and control	Validation	Principal strength	Limitation relevant to adaptive assistance
Nef et al. [11]	Rigid arm exoskeleton, multi-DOF	Encoders, force/torque, patient-cooperative modes	Stroke-oriented platform studies	Established joint-level cooperative therapy	Large fixed installation; biosignal intent not central
Frisoli et al. [12]	Arm exoskeleton for reaching	Position/force feedback and task training	Post-stroke participants	Demonstrated positive reaching-training effects	Limited evidence on biosignal-driven assistance
Proietti et al. [13]	Upper-limb exoskeleton	Coordination-modifying robotic training	Healthy participants	Shows robot can shape inter-joint coordination	Transfer to impaired neuromotor control uncertain
Islam et al. [14]	Dual-function upper-limb robot	Position/force sensing; rehabilitation and assistance	Prototype experiments	Combines training and assistive functions	Participation estimation not fully integrated
Gull et al. [15]	4-DOF rigid exoskeleton	Model-based control, joint sensing	Bench and user performance tests	Detailed design-to-control evaluation	Weight/alignment and user-specific dynamics remain
Thøgersen et al. [16]	Compact 5-DOF EXOTIC	Semi-automated shared tongue control	Users with tetraplegia	User-centered development and shared control	Different input modality; rehabilitation adaptation not primary
Li et al. [17]	End-effector robot	Dual-quaternion kinematics; low-speed spiral tracking	Experimental prototype	Compact task-space modeling	Individual joint assistance is indirect
Tran and Tran [18]	Upper exoskeleton	Patient-oriented control	Prototype evaluation	Explicit patient-centered controller design	Limited multi-session and clinical evidence
Nguyen et al. [19]	Human upper-limb model for rehabilitation robot	Optimization-based inverse kinematics	Numerical / model evaluation	Handles kinematic complexity	Does not resolve interaction-force uncertainty
Phan et al. [20]	Capstan-driven wrist exoskeleton	Impedance control	Prototype experiments	Low-backlash transmission and compliant interaction	Distal-joint scope; no multisensor participation estimate

Study	Architecture / DOF	Sensing and control	Validation	Principal strength	Limitation relevant to adaptive assistance
Randazzo et al. [21]	Wearable hand exoskeleton	User commands and grasp assistance	ADL-oriented tests	Portable functional assistance	Limited proximal-arm applicability
Bützer et al. [22]	Fully wearable soft hand exoskeleton	Soft actuation and task assistance	Everyday activities	High wearability and compliance	Accurate force and state estimation are difficult
Park et al. [23]	Wearable hand robot	User-driven movement training	People after stroke	Links voluntary use to functional task practice	Small study and hand-specific control
Polygerinos et al. [25]	Soft robotic glove	Pneumatic assistance	Assistance / home-rehabilitation concept	Safe, compliant form factor	Pneumatic delay and hysteresis complicate fast adaptation

Human-robot coupling. A rehabilitation exoskeleton is not controlling a known load. Human joint stiffness, reflex response, pain tolerance, co-contraction, and willingness to contribute vary within a movement and across a session. Misalignment between biological and robotic axes generates parasitic forces even when the commanded trajectory is correct. A low tracking error can therefore mask poor interaction. At minimum, evaluation should include interaction force or torque, motion smoothness, voluntary effort, completion rate, and the frequency of safety interventions.

Let $e = q - q_d$ denote the joint-coordinate error and let τ_int follow the sign convention of human torque acting on the robot. Following the classical impedance-control framework [59], a desired interaction behavior can be expressed as

$$M_d(\ddot{q} - \ddot{q}_d) + B_d(\dot{q} - \dot{q}_d) + K_d(q - q_d) = \tau_{int}. \quad (1)$$

In (1), M_d, B_d, and K_d are symmetric positive-definite desired inertia, damping, and stiffness matrices. Higher stiffness improves geometric tracking but may make the device coercive; lower stiffness permits user deviation but may reduce task completion. The equation defines the desired error-interaction relation rather than the full robot dynamics, which must still account for gravity, friction, actuator limits, and model uncertainty.

Six requirements recur across the literature. The device must remain within joint, speed, torque, and force limits under both nominal operation and sensor faults. Interaction should be compliant and parameter changes should be smooth. Assistance should respond to remaining capability and task phase rather than to tracking error alone. Estimation and control latency should be bounded and reported end to end. Calibration should be short enough for clinical use and robust across sessions. Finally, the complete sensor-estimator-controller chain must be reproducible and testable with clearly defined comparators.

These requirements are coupled. A complex estimator may improve average decoding accuracy while increasing latency and uncertainty. Aggressive adaptation may reduce effort in one condition yet create parameter jumps after electrode displacement. A credible system must therefore treat the participation estimate as uncertain, constrain how it changes the robot, and maintain a fallback mode that is independent of the biosignal estimator.

III. SEMG AND MULTISENSOR ESTIMATION OF VOLUNTARY PARTICIPATION

A. ACQUISITION, PREPROCESSING, AND REPRESENTATION

Reliable sEMG amplitude estimation begins with skin preparation, electrode placement, inter-electrode distance, analog front-end quality, sampling rate, and transparent reporting [26], [27]. Reviews of robot control identify band-pass filtering, line-noise rejection, normalization, and consistent windowing as recurring requirements [28], [29]. A practical wearable chain typically preserves the useful myoelectric band, removes DC and mains interference, prevents saturation, and time-aligns all sensing channels before feature extraction.

The filtered signal is segmented into overlapping windows. Window lengths near 100-250 ms are frequently used because they stabilize amplitude features while keeping delay moderate; overlap allows updates every 25-100 ms. The relevant quantity is the end-to-end closed-loop delay, including acquisition, filtering, window accumulation, feature extraction, inference, communication, scheduling, and actuator response. Reporting only neural-network inference time understates the delay seen by the user. The complete real-time processing and mitigation workflow is summarized in Fig. 2.

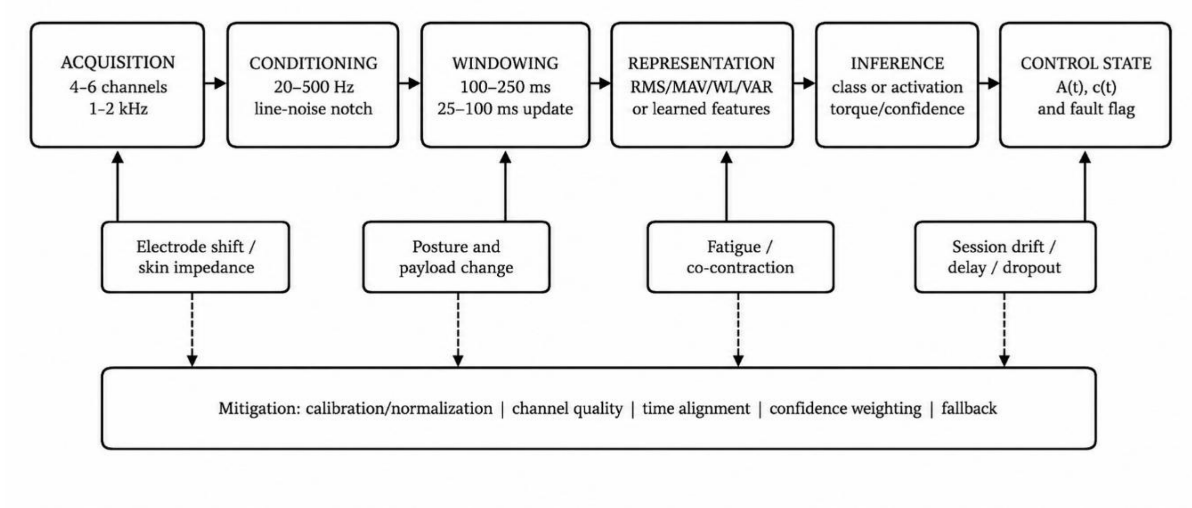

Fig. 2. Real-time sEMG processing chain, nonstationarity sources, and mitigation layer (authors' synthesis based on [26]-[44])

Consistent with amplitude-estimation practice in [26], a bounded, session-normalized activation estimate for muscle channel m may be written as

$$a_m(t) = \text{clip}\left(\frac{\text{RMS}_m(t) - b_m}{r_m - b_m}, 0{,}1\right), \qquad (2)$$

In (2), b_m is the resting baseline and r_m is a subject- and session-specific reference with $r_m > b_m$. The clipping operation prevents extrapolation outside [0,1], but it does not remove nonstationarity. Fatigue, electrode shift, posture, and re-donning can change both baseline and gain; channel-quality monitoring and conservative recalibration are therefore necessary.

Feature engineering and learned representations. Classical myoelectric control established a broad family of time-, frequency-, and time-frequency-domain features [30], [31]. MAV and RMS summarize amplitude; waveform length reflects amplitude and complexity; zero crossings and slope-sign changes approximate spectral content; and mean or median frequency can indicate fatigue. Time-domain features remain attractive for embedded control because they are inexpensive, interpretable, and compatible with the low-cost real-time results reported in [41], [42].

Deep learning can reduce manual feature design. Convolutional models exploit multichannel spatial structure [32], [33], transfer learning reduces recalibration requirements [35], and recent transformer, CNN-BiLSTM-attention, transient HD-sEMG, and in-sensor approaches target temporal structure or low latency [37]-[39], [43], [44]. Their principal limitation is not representation capacity but domain dependence: performance can degrade with a new user, session, posture, electrode placement, or device.

For rehabilitation control, output semantics matter as much as model architecture. A class label selects a movement mode; a continuous output estimates activation, intended velocity, torque, or participation. A fatigue indicator may change training intensity, while a confidence output should govern whether adaptation is permitted. The estimator should therefore be selected according to its role in the control loop, not by accuracy alone. Table 3 compares representative sEMG representations and their implications for real-time closed-loop use.

Table 3. sEMG processing approaches and implications for real-time control

Study	Input representation	Learning / inference	Reported contribution	Control relevance	Remaining concern
Scheme and Englehart [30]	Classical multichannel features	Pattern-recognition review	Established clinical challenges of myoelectric classification	Defines robustness requirements	Prosthetic focus; classification-centric
Farina et al. [31]	Neural information in surface EMG	Decomposition and decoding review	Connects sEMG to motor-neural information	Motivates physiologically grounded estimators	Hardware and computation can be demanding

Study	Input representation	Learning / inference	Reported contribution	Control relevance	Remaining concern
Atzori et al. [32]	Raw/windowed sEMG	CNN	Demonstrated deep representation learning	Reduces manual feature engineering	Dataset and domain dependence
Geng et al. [33]	Instantaneous HD-sEMG images	CNN	Exploits spatial activation patterns	Useful for dense wearable arrays	Electrode-grid shift remains critical
Phinyomark et al. [34]	Wearable EMG feature sets	Feature extraction/selection	Comparative feature guidance	Supports low-cost embedded control	Optimal set is task- and subject-dependent
Côté-Allard et al. [35]	Multichannel windows	Transfer learning	Reduces recalibration data for new sessions/users	Relevant to deployable interfaces	Transfer can fail under large domain shifts
Hellara et al. [36]	Handcrafted feature families	Gesture classifiers	Recent feature-performance comparison	Helps choose compact feature sets	Gesture accuracy does not prove safe control
Secciani et al. [40]	Hand sEMG features	Point-in-polygon classifier	Lightweight classifier for hand exoskeletons	Embedded feasibility	Limited continuous effort information
Chen et al. [38]	Frequency-domain fixed bandwidth	Embedded real-time classifier	Real-time robotic-hand interface	Explicit deployment orientation	Fixed bandwidth may not handle all users
Mahboob et al. [39]	Multichannel sEMG sequence	Transformer encoder	3-D hand-gesture prediction	Captures temporal dependencies	Model size and calibration burden
Qiu et al. [37]	Transient HD-sEMG	In-sensor computing	Low-latency hand-gesture recognition	Reduces data-transfer delay	Dense sensing and hardware complexity
Dao et al. [41]	RMS, WL, VAR from low-cost hardware	Real-time feature extraction	1-kHz acquisition and sliding-window interface	Reproducible embedded baseline	Initial validation on limited subjects
Nguyen et al. [42]	sEMG features	Fuzzy logic	Feasible sEMG-driven robotic-arm control	Interpretable nonlinear mapping	No force-fusion or rigorous safety layer
Zhao et al. [43]	Multichannel sEMG sequence	CNN-BiLSTM-attention	Upper-limb human-exoskeleton state classification	Rich spatial-temporal decoding	Generalization and latency need independent testing
Moin et al. [44]	Wearable biosignal channels	In-sensor adaptive machine learning	Adaptive on-device gesture recognition	Promising for low-power personalization	Rehabilitation interaction not directly evaluated

Generalization and control-facing evaluation. Randomly splitting highly overlapped windows from the same recording into training and test sets can leak temporal and session-specific information. Stronger evaluation separates repetitions, sessions, and subjects. Leave-one-subject-out and cross-session tests expose calibration burden and domain shift; deliberate electrode displacement, posture changes, added payloads, and sensor dropout reveal failure modes. Accuracy should be accompanied by confusion patterns, calibration error for continuous outputs, latency distribution, and failure-detection performance.

The acceptable error depends on consequence. A mistaken interface selection can be immediately reversed; a falsely high participation estimate can remove needed support, while a falsely low estimate can cause over-assistance. Control-facing estimates should therefore be smoothed only within an explicit delay budget, limited in magnitude and rate, and rejected when confidence or channel quality is insufficient.

B. CONTINUOUS ESTIMATION, FUSION, AND CONFIDENCE

From movement class to continuous contribution. Simultaneous and proportional myoelectric control established that multiple degrees of freedom can be estimated continuously rather than selected one at a time [45], [46]. Although these studies arose largely from prosthetics, the transferable principle is important for rehabilitation: an estimator should supply a continuously varying state rather than only a movement class. Multimodal sEMG-IMU evidence further shows that complementary sensing can improve robustness [47].

For an upper-limb robot, the sEMG-derived state a_e represents neural activation, the force-derived state a_f represents task-directed mechanical contribution after compensation for robot dynamics and gravity, and the kinematic state a_k represents motion progress or consistency. Each modality is assigned a confidence $c_j(t)$ that decreases under saturation, drift, disagreement, packet loss, or implausible dynamics.

For an auditable late-fusion baseline, a confidence-weighted participation estimate can be defined as

$$A(t) = \frac{\sum_{j\in\{e,f,k\}} w_j\, c_j(t) a_j(t)}{\sum_{j\in\{e,f,k\}} w_j\, c_j(t) + \varepsilon}, \tag{3}$$

In (3), w_j are nominal modality weights, $c_j(t) \in [0,1]$ are online confidence values, and $\varepsilon > 0$ avoids division by zero. The expression is an auditable baseline rather than a claim that linear fusion is universally optimal. When total confidence falls below a defined threshold, A(t) should not drive adaptation; the controller should return smoothly to a conservative nominal mode.

Fusion architecture and failure handling. Fusion can occur at signal, feature, decision, or control-state level. Early fusion can learn cross-modal interactions but is vulnerable to scale mismatch and missing channels. Late fusion is easier to audit and isolate during faults but may discard useful dependencies. State-space, Bayesian, neural, or attention-based fusion can represent temporal uncertainty, although they require synchronized data, explicit treatment of missing observations, and independent calibration of confidence.

Upper-limb studies connect EMG to compliant or cooperative control through hybrid impedance-admittance behavior, motion compensation, and soft-elbow assistance [49]-[51]. The studies demonstrate feasibility but rarely unify sEMG, interaction force, movement state, confidence, bounded impedance adaptation, and independent safety supervision. The transferable lower-limb study [48] illustrates continuous decoding and adaptive control, but its biomechanics and contact conditions cannot be assumed to generalize to the upper limb.

The most informative experiment is a disturbance-aware ablation. The same participants and tasks should be tested with sEMG only; sEMG plus force; sEMG plus force and kinematics; and the full confidence/fallback architecture. Electrode displacement, channel dropout, force bias, packet delay, and payload change should then be introduced. Without these comparisons, an apparent improvement may reflect model capacity rather than improved observability or safety. Table 4 relates representative multimodal estimators and adaptive controllers to the safety mechanisms actually reported.

IV. ADAPTIVE COMPLIANT CONTROL, SAFETY, AND VALIDATION

A. IMPEDANCE, ADMITTANCE, AND ASSIST-AS-NEEDED CONTROL

Impedance control specifies the force response to motion error, whereas admittance control converts measured force into a motion reference. Impedance is natural for torque-controlled and backdrivable devices; admittance is common when a stiff inner position loop is already available. Hybrid structures can allocate different directions or frequency ranges to each behavior. Fixed compliance is a necessary baseline, but it cannot respond to changing effort, fatigue, recovery, or task phase.

Adaptive iterative-learning impedance, disturbance-observer-based impedance, predicted impedance parameters, sensorless interaction-torque estimation, sEMG motion compensation, and neural cooperative control have all been demonstrated in upper-limb rehabilitation or assistance [50]-[55]. These studies establish feasibility but also reveal a recurring limitation: adaptation is often judged mainly by tracking error even though rehabilitation additionally requires voluntary effort, low interaction force, comfort, and predictable fault behavior.

Physiologically informed assist-as-needed behavior. EMG-feedback minimization, EMG-scaled upper-limb power assistance, and compliant model-based assistance support the assist-as-needed principle [56]-[58]. The robot should provide sufficient support to enable a successful movement while preserving a measurable opportunity for the user to contribute. This principle does not imply that lower sEMG is always better; a reduction can represent beneficial unloading, fatigue, or disengagement and must be interpreted with force and task performance.

Motivated by assist-as-needed adaptation in [56]-[58], an illustrative bounded mapping from participation to impedance and assistance for a scalar or decoupled diagonal implementation is

$$K_d(t) = \mathrm{sat}_{[K_{\min},K_{\max}]}\big(K_{\max} - (K_{\max} - K_{\min})A(t)\big), \tag{4}$$

$$B_d(t) = 2\zeta\sqrt{M_d K_d(t)}, \tag{5}$$

$$\tau_a(t) = \mathrm{sat}_{[\tau_{\min},\tau_{\max}]}\Big(\big(1 - A(t)\big)\tau_{req}(t)\Big). \tag{6}$$

In (4)-(6), A(t) is the fused participation state. Higher participation reduces stiffness and assistance within predefined bounds. The damping expression is valid componentwise for diagonal M_d and K_d and maintains the selected damping ratio ζ; a coupled multijoint design requires an appropriate matrix construction. The implemented K_d, B_d, and τ_a must also be rate-limited. If confidence is low, parameters should converge smoothly to a conservative nominal set rather than jump to an extreme.

Hogan's impedance framework provides the mechanical-interaction foundation [59], while broader human-robot collaboration and safety research emphasizes that physical safety, intention communication, ergonomics, and adaptation must be considered jointly [60], [61]. A representative evaluation objective may combine tracking error, interaction force, assistive torque, and parameter variation as in (7). This expression is a comparison framework, not a universal clinical cost, and every term must be normalized and weighted according to the task.

$$J = \sum_{k=1}^{N} \left(\alpha_q \parallel e_q(k) \parallel^2 + \alpha_f \parallel f_{int}(k) \parallel^2 + \alpha_a \tau_a^2(k) + \alpha_\Delta \parallel \Delta\theta_c(k) \parallel^2 \right), \qquad (7)$$

Here $\theta_c = [K_d, B_d, \tau_a]^T$. Minimizing (7) cannot establish safety; independent state, force, torque, energy, and fault constraints must be enforced regardless of objective value. The resulting confidence-aware control and safety architecture is shown in Fig. 3.

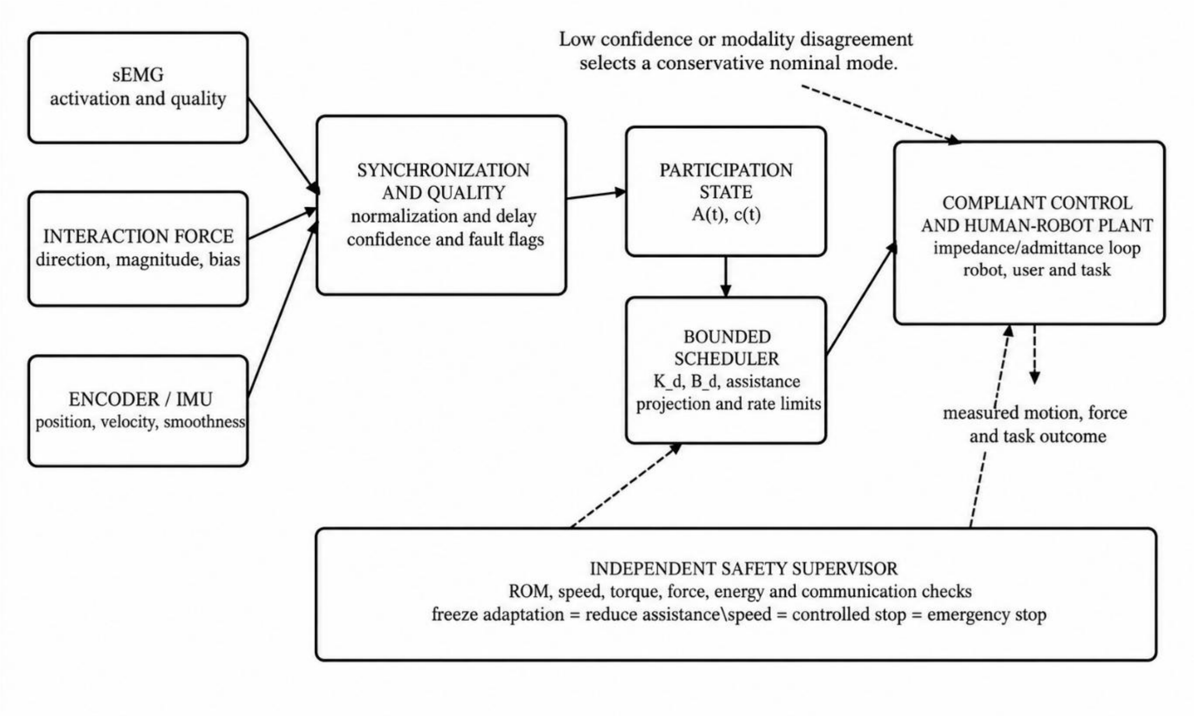

Fig. 3. Confidence-aware architecture for bounded adaptive assistance and independent safety supervision (authors' synthesis based on [49]-[63]).

Stability of online adaptation. A stable inner impedance loop does not guarantee stable behavior after its parameters are changed online. The user is time-varying, delays are present, and a participation estimate can be confidently wrong. Projection and saturation, parameter-rate limits, passivity observers or energy tanks, robust or adaptive Lyapunov arguments, barrier functions, and a supervisory state machine are complementary mechanisms. The analysis must include estimator uncertainty and switching to fallback, not only nominal robot dynamics.

Consistent with the risk-control principles in [62], [63], the fastest reliable control layer should enforce

$$q_{\min} \le q \le q_{\max}, \quad |\dot{q}| \le \dot{q}_{\max}, \quad |\tau| \le \tau_{\max}, \quad \parallel f_{int} \parallel \le f_{\max}. \qquad (8)$$

The inequalities in (8) are componentwise for joint variables, while the interaction-force norm must be selected consistently with the sensor and anatomical contact. Mechanical stops, current limits, thermal protection, and an independent emergency stop remain necessary. A graded fault response is preferable to a binary stop: transient low confidence freezes adaptation; persistent disagreement reduces assistance and speed; force or range-of-motion violations trigger a controlled stop; communication or power-stage faults may require immediate torque removal.

Table 4. Multisensor estimation and adaptive interaction-control approaches

Study	Modalities / state	Controller	Evidence	Safety mechanism reported	Main gap
Muceli and Farina [45]	sEMG to continuous kinematics	Proportional regression	Offline / user data	Output constraints not central	Prosthetic/mirrored-movement context
Jiang et al. [46]	sEMG, simultaneous 2-DOF command	Online proportional myoelectric control	Upper-limb amputees	User-mediated online tests	Not a rehabilitation impedance loop
Krasoulis et al. [47]	sEMG + IMU	Concurrent multimodal estimator	Prosthetic-control experiments	Sensor combination improves robustness	Force and physical interaction absent
Wang et al. [48]	Multichannel sEMG	Continuous decoder + adaptive controller	Lower-limb exoskeleton	Bounded controller parameters	Transfer to upper limb requires validation
da Silva et al. [49]	EMG + interaction variables	Hybrid impedance-admittance	Upper-limb exoskeleton study	Compliant control structure	Limited uncertainty and fault treatment
Meng et al. [50]	sEMG + robot state	Motion-compensation control	Active upper-limb training	Controller-level limits	Participation not explicitly fused with force
Wu et al. [51]	sEMG + elbow state	Adaptive cooperative multi-mode neural control	Soft elbow exoskeleton	Multi-mode logic	Neural compensation complicates verification
Wang and Song [52]	Tracking error across repetitions	Adaptive iterative-learning impedance	Robot-aided passive training	Learning bounded by design	Passive/repetitive emphasis; little sEMG
Brahmi et al. [53]	State + disturbance estimate	Adaptive impedance + time-delay observer	Exoskeleton experiments	Robustness to model uncertainty	Biosignal confidence not considered
Zhang et al. [54]	Motion/interaction features	Predicted adaptive impedance parameters	Upper-limb robot experiments	Parameter ranges	Generalization and patient data limited
Abdullahi et al. [55]	Sensorless interaction-torque estimate	Hybrid adaptive impedance/admittance	Upper-limb case study	Torque estimation and bounded adaptation	Sensorless error under atypical contact
Peternel et al. [56]	EMG feedback	Assistance adaptation minimizing EMG	Exoskeleton human experiments	Iterative adaptation	EMG minimization may conflict with engagement goals
Kiguchi and Hayashi [57]	EMG activation	Upper-limb power-assist control	Human experiments	Torque scaling	Sensitive to calibration and co-contraction
Wolbrecht et al. [58]	Performance error	Compliant model-based optimal assistance	Neurorehabilitation paradigm	Compliant dynamics	Limited multisensor physiological state
Proposed synthesis	sEMG + force + kinematics + confidence	Bounded adaptive impedance/AAN with supervisor	Requires staged validation	ROM/speed/torque/force/energy limits and fallback	Not yet a clinical claim; serves as testable architecture

B. SAFETY ASSURANCE AND STAGED VALIDATION

ISO 14971 frames medical-device safety as a life-cycle process of hazard identification, risk estimation, risk control, and monitoring [62]. ISO 13482 supplies useful concepts for physical assistant robots, although robots regulated as medical devices are outside its scope [63]. Consequently, it should be treated as an adjacent engineering reference rather than a substitute for the applicable medical-device framework. Each identified hazard should be linked to a preventive control, a detectable fault condition, a fallback response, and a verification test.

Relevant hazards include excessive joint excursion, pinch points, high interaction force, unexpected acceleration, runaway assistance after a biosignal artifact, actuator overheating, communication loss, incorrect calibration, and unsafe donning. Layered controls are required. Shoulder overextension, for example, can be addressed by mechanical stops, software range limits, trajectory constraints, and therapist override. An sEMG artifact can be addressed by amplitude and spectral checks, confidence reduction, rate-limited adaptation, and a fallback mode that does not depend on the affected channel.

Staged validation. Offline decoding supports algorithm development but cannot establish physical safety. Real-time bench and hardware-in-the-loop tests reveal timing, saturation, actuator behavior, model uncertainty, and fault response. Healthy-user studies expose fit, discomfort, co-contraction, and unexpected strategies. Target-user studies are required because weakness, spasticity, abnormal synergies, and fatigue are not reproduced by healthy participants. Comparative and longitudinal evidence is necessary before a rehabilitation-effectiveness claim is justified. This cumulative evidence pathway is illustrated in Fig. 4.

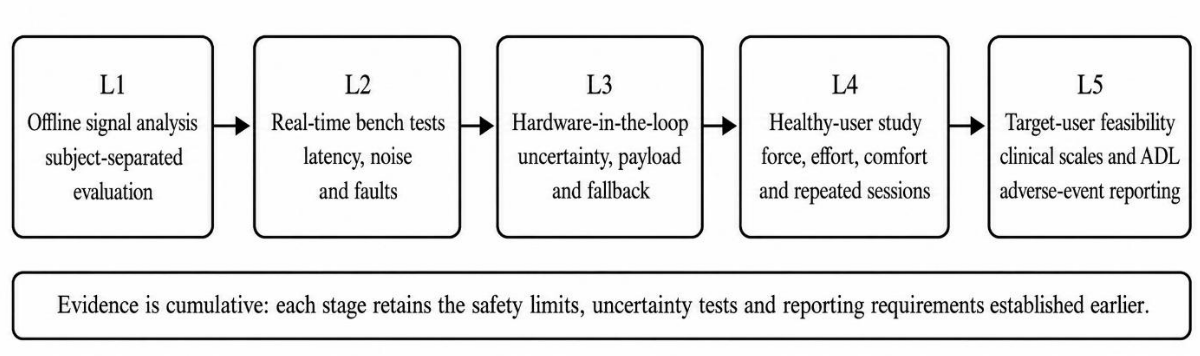

Fig. 4. Cumulative validation pathway for upper-limb rehabilitation exoskeleton research (authors' synthesis based on [1]-[6], [62], [63]).

A minimum bench protocol should include nominal movements, payload changes, friction uncertainty, worst-case sensor noise, encoder dropout, force-sensor bias, delayed packets, communication loss, and emergency-stop response. Healthy-user tests should vary movement direction and assistance, randomize conditions, record discomfort, and report all adverse events. Target-user protocols should specify impairment, inclusion and stopping criteria, therapist involvement, and ethical approval. The complete latency distribution should be reported at every stage.

Outcome measures. Joint tracking remains useful and can be summarized with the standard root-mean-square error

$$\mathrm{RMSE}_q = \sqrt{\frac{1}{N}\sum_{k=1}^{N} \| q(k) - q_d(k) \|^2}. \tag{9}$$

RMSE_q in (9) should be paired with peak and RMS interaction force, assistive and user-generated mechanical work, sEMG activation and co-contraction, movement smoothness, completion time, success rate, and number of safety interventions. Adaptive systems should report parameter ranges, rates, and time spent in fallback. Estimators should report confidence calibration, cross-session drift, failure-detection recall, and the effect of each modality through ablation.

Clinical studies should add validated impairment and activity scales and ADL outcomes, but robot-level measures remain essential for mechanism. Lower trajectory error accompanied by higher interaction force may indicate that the robot is overpowering the user. Lower sEMG can indicate unloading, fatigue, or disengagement. No single metric is therefore sufficient.

Reproducibility. Studies remain difficult to compare when muscle placement, window overlap, normalization, filter phase, controller rate, actuator limits, user instructions, and data exclusions are incompletely documented. A reproducible report should include participant characteristics; robot geometry and transmission; sensor models and placement; synchronization; preprocessing; train/test split; total latency; controller equations, bounds, and rates; calibration duration; task scripts; faults; adverse events; and exclusions. Sharing synchronized anonymized signals and executable code is especially valuable for fusion methods.

V. STATE-OF-THE-ART SYNTHESIS AND RESEARCH AGENDA

A. CONSOLIDATED FINDINGS AND UNRESOLVED GAPS

The central gap is not a shortage of classifiers; it is the absence of a validated control state that quantifies voluntary participation. Muscle activation, voluntary torque, task progress, and engagement are related but not interchangeable. A useful participation state should be continuous, direction-aware, normalized to the individual, accompanied by confidence, and validated against independent measures such as voluntary force in transparent mode, task-directed mechanical work, or therapist rating.

Fusion as a safety function. Multisensor fusion is often justified by higher mean accuracy, but its more consequential role may be inconsistency detection. High sEMG with opposing force can indicate co-contraction or spastic resistance; forward motion with low sEMG can indicate robot-dominated movement; high force without intended motion can indicate misalignment or pain. These combinations should be encoded explicitly and tested under sensor faults.

Fast and reversible personalization. Long calibration sessions conflict with fatigue and clinical throughput. Adaptive normalization, transfer learning, and embedded learning may reduce data needs, but all online updates must be bounded. A new model or parameter set should be accepted only when a monitored objective improves without reducing safety margin. The previous safe state should be retained for rollback, and cross-session testing is mandatory because re-donning changes both sEMG and mechanical alignment.

Estimator-aware stability. Many analyses assume that the adaptation signal is bounded and otherwise correct. In practice, the dominant hazard may be a confident but incorrect estimate. Stability and safety arguments should include delay, confidence dynamics, parameter-rate limits, and switching between normal and fallback modes. Energy- or passivity-based supervision can constrain the physical interface even when estimation is imperfect; barrier functions are useful only when state estimates are sufficiently reliable and feasible corrective actions exist.

Task-level and longitudinal relevance. Sinusoidal tracking is useful for identification but insufficient for rehabilitation relevance. Evaluation should include ADL-inspired movements, object interaction, variable payload, user choice, and repeated sessions. Assistance should be judged not only by immediate task success but also by whether voluntary contribution is preserved or increases as capability changes. Table 5 consolidates the unresolved gaps, design responses, and minimum verification tests.

Table 5. Research gaps and verification requirements

Gap	Why current evidence is insufficient	Recommended design response	Minimum verification test
Participation is treated as a gesture class	A class does not quantify effort, direction, or reliability	Estimate continuous $A(t)$ with calibrated $c(t)$	Compare with voluntary force/work across assistance levels
sEMG drift is handled by one-time calibration	Re-donning, posture, fatigue, and skin condition change the mapping	Channel-quality monitoring, adaptive normalization, and bounded recalibration	Cross-session and deliberate electrode-shift tests
Fusion is not ablated	Improvement may reflect model capacity rather than observability	Compare sEMG only, sEMG+force, and sEMG+force+kinematics	Same participants and tasks with dropout, bias, delay, and payload change
Adaptive impedance lacks rate constraints	Noisy or delayed estimates can cause abrupt mechanical behavior	Projection, saturation, parameter-rate limits, and conservative fallback	Artifact injection while measuring force, energy, and command rate
Safety is reduced to an emergency stop	Hazards can develop before a stop is triggered	Layered limits for ROM, speed, torque, force, energy, validity, and temperature	Fault-injection matrix with measured detection and response times
Validation is dominated by healthy users	Impairment changes synergy, reflexes, fatigue, and tolerance	Progress from bench and HIL tests to ethics-approved target-user studies	Report impairment, adverse events, usability, and functional task outcomes
Results are difficult to reproduce	Signal, timing, calibration, and controller details are omitted	Publish synchronized data, code, parameter bounds, and task scripts	Independent rerun of preprocessing and controller on shared trials

B. RESEARCH PROGRAM ALIGNED WITH THE DOCTORAL STUDY

A defensible program can proceed in four stages. Stage 1 identifies and verifies a two- or three-DOF shoulder-elbow model under fixed impedance, actuator limits, and an independent stop. Stage 2 collects synchronized four- to six-channel sEMG, interaction force, encoder, and IMU data during active, assisted, resisted, and relaxed movements; estimators use repetition-, session-, and subject-separated evaluation. Stage 3 closes the loop with confidence-weighted fusion, bounded and rate-limited impedance adaptation, and independent supervision. Comparators include PID or rigid position control, fixed impedance, adaptive impedance without multisensor fusion, and sEMG-only adaptation under identical safety limits. Stage 4 introduces controlled disturbances with healthy users before ethically approved feasibility testing in the target population.

The primary hypotheses should be declared before data collection. Representative hypotheses are that multisensor fusion reduces participation-estimation error and unsafe command frequency relative to sEMG alone; bounded adaptive impedance reduces interaction force and assistive work without increasing task failure; confidence-triggered fallback limits peak force during electrode shift, channel loss, bias, or delay; and these benefits persist across sessions and payloads. Evaluation should include RMSE/IAE tracking error, force, assistive torque and work, latency, smoothness, muscle activation, parameter rates, fallback events, and user comfort.

VI. CONCLUSION

Upper-limb rehabilitation exoskeletons are progressing toward intention-aware, compliant, and increasingly personalized interaction. The literature establishes mature foundations in robot architecture, sEMG processing, proportional decoding, impedance/admittance control, and assist-as-needed adaptation. It does not yet establish a generally validated end-to-end link from uncertain biosignals to safe adaptive assistance.

The principal synthesis is that sEMG should not act as an unqualified command. It should contribute to a continuous participation state whose confidence is checked against interaction force and movement consistency. That state may schedule stiffness, damping, and assistance only through bounded, rate-limited laws, while an independent supervisor enforces range, velocity, torque, force, energy, validity, and fallback constraints.

Future evidence should prioritize cross-session robustness, disturbance-aware ablation, complete latency reporting, explicit fault response, and progression from bench and hardware-in-the-loop verification to healthy-user and target-user studies. For the doctoral research program considered here, the most coherent contribution is a two- or three-DOF shoulder-elbow platform that unifies synchronized sEMG-force-kinematic sensing, confidence-aware participation estimation, safe adaptive impedance control, and reproducible comparison with conventional and single-modality baselines.

REFERENCES

[1] P. Maciejasz, J. Eschweiler, K. Gerlach-Hahn, A. Jansen-Troy, and S. Leonhardt, "A survey on robotic devices for upper limb rehabilitation," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, art. 3, 2014. DOI: https://doi.org/10.1186/1743-0003-11-3.

[2] L. Marchal-Crespo and D. J. Reinkensmeyer, "Review of control strategies for robotic movement training after neurologic injury," *Journal of NeuroEngineering and Rehabilitation*, vol. 6, art. 20, 2009. DOI: https://doi.org/10.1186/1743-0003-6-20.

[3] A. Basteris, S. M. Nijenhuis, A. H. A. Stienen, J. H. Buurke, G. B. Prange, and F. Amirabdollahian, "Training modalities in robot-mediated upper limb rehabilitation in stroke: A framework for classification based on a systematic review," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, art. 111, 2014. DOI: https://doi.org/10.1186/1743-0003-11-111.

[4] J. M. Veerbeek, A. C. Langbroek-Amersfoort, E. E. H. van Wegen, C. G. M. Meskers, and G. Kwakkel, "Effects of robot-assisted therapy for the upper limb after stroke: A systematic review and meta-analysis," *Neurorehabilitation and Neural Repair*, vol. 31, no. 2, pp. 107-121, 2017. DOI: https://doi.org/10.1177/1545968316666957.

[5] R. Bertani, C. Melegari, M. C. De Cola, A. Bramanti, P. Bramanti, and R. S. Calabrò, "Effects of robot-assisted upper limb rehabilitation in stroke patients: A systematic review with meta-analysis," *Neurological Sciences*, vol. 38, pp. 1561-1569, 2017. DOI: https://doi.org/10.1007/s10072-017-2995-5.

[6] J. Mehrholz, M. Pohl, T. Platz, J. Kugler, and B. Elsner, "Electromechanical and robot-assisted arm training for improving activities of daily living, arm function, and arm muscle strength after stroke," *Cochrane Database of Systematic Reviews*, no. 9, CD006876, 2018. DOI: https://doi.org/10.1002/14651858.CD006876.pub5.

[7] H. S. Lo and S. Q. Xie, "Exoskeleton robots for upper-limb rehabilitation: State of the art and future prospects," *Medical Engineering & Physics*, vol. 34, no. 3, pp. 261-268, 2012. DOI: https://doi.org/10.1016/j.medengphy.2011.10.004.

[8] R. A. R. C. Gopura, D. S. V. Bandara, K. Kiguchi, and G. K. I. Mann, "Developments in hardware systems of active upper-limb exoskeleton robots: A review," *Robotics and Autonomous Systems*, vol. 75, pp. 203-220, 2016. DOI: https://doi.org/10.1016/j.robot.2015.10.001.

[9] M. A. Gull, S. Bai, and T. Bak, "A review on design of upper limb exoskeletons," *Robotics*, vol. 9, no. 1, art. 16, 2020. DOI: https://doi.org/10.3390/robotics9010016.

[10] M. Tiboni, A. Borboni, F. Vérité, C. Bregoli, and C. Amici, "Sensors and actuation technologies in exoskeletons: A review," *Sensors*, vol. 22, no. 3, art. 884, 2022. DOI: https://doi.org/10.3390/s22030884.

[11] T. Nef, M. Mihelj, G. Colombo, and R. Riener, "ARMin-Robot for rehabilitation of the upper extremities," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 15, no. 3, pp. 333-342, 2007. DOI: https://doi.org/10.1109/TNSRE.2007.903899.

[12] A. Frisoli, C. Procopio, C. Chisari, I. Creatini, L. Bonfiglio, M. Bergamasco, B. Rossi, and M. C. Carboncini, "Positive effects of robotic exoskeleton training of upper limb reaching movements after stroke," *Journal of NeuroEngineering and Rehabilitation*, vol. 9, art. 36, 2012. DOI: https://doi.org/10.1186/1743-0003-9-36.

[13] T. Proietti, E. Guigon, A. Roby-Brami, and N. Jarrassé, "Modifying upper-limb inter-joint coordination in healthy subjects by training with a robotic exoskeleton," *Journal of NeuroEngineering and Rehabilitation*, vol. 14, art. 55, 2017. DOI: https://doi.org/10.1186/s12984-017-0254-1.

[14] M. R. Islam, M. Assad-Uz-Zaman, B. Brahmi, Y. Bouteraa, I. Wang, and M. H. Rahman, "Design and development of an upper limb rehabilitative robot with dual functionality," *Micromachines*, vol. 12, no. 8, art. 870, 2021. DOI: https://doi.org/10.3390/mi12080870.

[15] M. A. Gull, M. Thøgersen, S. H. Bengtson, M. Mohammadi, L. N. S. A. Struijk, T. B. Moeslund, T. Bak, and S. Bai, "A 4-DOF upper limb exoskeleton for physical assistance: Design, modeling, control and performance evaluation," *Applied Sciences*, vol. 11, no. 13, art. 5865, 2021. DOI: https://doi.org/10.3390/app11135865.

[16] M. B. Thøgersen, M. Mohammadi, M. A. Gull, S. H. Bengtson, F. V. Kobbelgaard, B. Bentsen, *et al.*, "User based development and test of the EXOTIC exoskeleton: Empowering individuals with tetraplegia using a compact, versatile, 5-DoF upper limb exoskeleton controlled through intelligent semi-automated shared tongue control," *Sensors*, vol. 22, no. 18, art. 6919, 2022. DOI: https://doi.org/10.3390/s22186919.

[17] L. Li, J. Han, X. Li, B. Guo, X. Wang, and G. Du, "A novel end-effector upper limb rehabilitation robot: Kinematics modeling based on dual quaternion and low-speed spiral motion tracking control," *International Journal of Advanced Robotic Systems*, vol. 19, no. 4, 2022. DOI: https://doi.org/10.1177/17298806221118855.

[18] H.-T. Tran and S. M. Tran, "Design and patient-oriented control of a rehabilitation assistance upper exoskeleton," *Control Engineering and Applied Informatics*, vol. 25, no. 3, pp. 23-34, 2023. DOI: https://doi.org/10.61416/ceai.v25i3.8341.

[19] T. Nguyen, T. Bui, and H. Pham, "Using proposed optimization algorithm for solving inverse kinematics of human upper limb applying in rehabilitation robotic," *Artificial Intelligence Review*, vol. 55, no. 1, pp. 679-705, 2022. DOI: https://doi.org/10.1007/s10462-021-10041-z.

[20] G. H. Phan, M. N. Nguyen, and T. T. Trinh, "Capstan-driven wrist exoskeleton for rehabilitation: Design and impedance control," *Journal of Technical Education Science*, vol. 47, no. 2, pp. 58-68, 2023. URL: https://www.jte.edu.vn/index.php/jte/article/view/1499.

[21] L. Randazzo, I. Iturrate, S. Perdikis, and J. del R. Millán, "MANO: A wearable hand exoskeleton for activities of daily living and neurorehabilitation," *IEEE Robotics and Automation Letters*, vol. 3, no. 1, pp. 500-507, 2018. DOI: https://doi.org/10.1109/LRA.2017.2771329.

[22] T. Bützer, O. Lambercy, J. Arata, and R. Gassert, "Fully wearable actuated soft exoskeleton for grasping assistance in everyday activities," *Soft Robotics*, vol. 8, no. 2, pp. 128-143, 2021. DOI: https://doi.org/10.1089/soro.2019.0135.

[23] S. Park, M. Fraser, L. M. Weber, C. Meeker, L. Bishop, D. Geller, J. Stein, and M. Ciocarlie, "User-driven functional movement training with a wearable hand robot after stroke," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 10, pp. 2265-2275, 2020. DOI: https://doi.org/10.1109/TNSRE.2020.3021691.

[24] R. A. Bos, C. J. W. Haarman, T. Stortelder, K. Nizamis, J. L. Herder, A. H. A. Stienen, and D. H. Plettenburg, "A structured overview of trends and technologies used in dynamic hand orthoses," *Journal of NeuroEngineering and Rehabilitation*, vol. 13, art. 62, 2016. DOI: https://doi.org/10.1186/s12984-016-0168-z.

[25] P. Polygerinos, K. C. Galloway, E. Savage, M. Herman, K. O'Donnell, and C. J. Walsh, "Soft robotic glove for combined assistance and at-home rehabilitation," *Robotics and Autonomous Systems*, vol. 73, pp. 135-143, 2015. DOI: https://doi.org/10.1016/j.robot.2014.08.014.

[26] E. A. Clancy, E. L. Morin, G. Hajian, and R. Merletti, "Tutorial: Surface electromyogram (sEMG) amplitude estimation: Best practices," *Journal of Electromyography and Kinesiology*, vol. 72, art. 102807, 2023. DOI: https://doi.org/10.1016/j.jelekin.2023.102807.

[27] M. Al-Ayyad, H. A. Owida, R. De Fazio, B. Al-Naami, and P. Visconti, "Electromyography monitoring systems in rehabilitation: A review of clinical applications, wearable devices and signal acquisition methodologies," *Electronics*, vol. 12, no. 7, art. 1520, 2023. DOI: https://doi.org/10.3390/electronics12071520.

[28] T. Song, Z. Yan, S. Guo, Y. Li, X. Li, and F. Xi, "Review of sEMG for robot control: Techniques and applications," *Applied Sciences*, vol. 13, no. 17, art. 9546, 2023. DOI: https://doi.org/10.3390/app13179546.

[29] X. Zhang, Y. Qu, G. Zhang, Z. Wang, C. Chen, and X. Xu, "Review of sEMG for exoskeleton robots: Motion intention recognition techniques and applications," *Sensors*, vol. 25, no. 8, art. 2448, 2025. DOI: https://doi.org/10.3390/s25082448.

[30] E. Scheme and K. Englehart, "Electromyogram pattern recognition for control of powered upper-limb prostheses: State of the art and challenges for clinical use," *Journal of Rehabilitation Research and Development*, vol. 48, no. 6, pp. 643-660, 2011. DOI: https://doi.org/10.1682/JRRD.2010.09.0177.

[31] D. Farina, N. Jiang, H. Rehbaum, A. Holobar, B. Graimann, H. Dietl, and O. C. Aszmann, "The extraction of neural information from the surface EMG for the control of upper-limb prostheses: Emerging avenues and challenges," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 4, pp. 797-809, 2014. DOI: https://doi.org/10.1109/TNSRE.2014.2305111.

[32] M. Atzori, M. Cognolato, and H. Müller, "Deep learning with convolutional neural networks applied to electromyography data: A resource for the classification of movements for prosthetic hands," *Biomedical Signal Processing and Control*, vol. 28, pp. 44-54, 2016. DOI: https://doi.org/10.1016/j.bspc.2016.02.003.

[33] W. Geng, Y. Du, W. Jin, W. Wei, Y. Hu, and J. Li, "Gesture recognition by instantaneous surface EMG images," *Scientific Reports*, vol. 6, art. 36571, 2016. DOI: https://doi.org/10.1038/srep36571.

[34] A. Phinyomark, R. N. Khushaba, and E. Scheme, "Feature extraction and selection for myoelectric control based on wearable EMG sensors," *Sensors*, vol. 18, no. 5, art. 1615, 2018. DOI: https://doi.org/10.3390/s18051615.

[35] U. Côté-Allard, C. L. Fall, A. Drouin, A. Campeau-Lecours, C. Gosselin, K. Glette, F. Laviolette, and B. Gosselin, "Deep learning for electromyographic hand gesture signal classification using transfer learning," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 4, pp. 760-771, 2019. DOI: https://doi.org/10.1109/TNSRE.2019.2896269.

[36] H. Hellara, R. Barioul, S. Sahnoun, A. Fakhfakh, and O. Kanoun, "Comparative study of sEMG feature evaluation methods based on the hand gesture classification performance," *Sensors*, vol. 24, no. 11, art. 3638, 2024. DOI: https://doi.org/10.3390/s24113638.

[37] Y. Qiu, *et al.*, "A real-time hand gesture recognition system for low-latency HMI via transient HD-sEMG and in-sensor computing," *IEEE Journal of Biomedical and Health Informatics*, 2024. DOI: https://doi.org/10.1109/JBHI.2024.3417236.

[38] B. Chen, *et al.*, "A real-time EMG-based fixed-bandwidth frequency-domain embedded system for robotic hand," *Frontiers in Neurorobotics*, vol. 16, art. 880073, 2022. DOI: https://doi.org/10.3389/fnbot.2022.880073.

[39] T. Mahboob, M. Y. Chung, and K. W. Choi, "EMG-based 3D hand gesture prediction using transformer-encoder classification," *ICT Express*, vol. 9, no. 6, pp. 1047-1052, 2023. DOI: https://doi.org/10.1016/j.icte.2023.04.005.

[40] N. Secciani, A. Topini, A. Ridolfi, E. Meli, and B. Allotta, "A novel point-in-polygon-based sEMG classifier for hand exoskeleton systems," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 28, no. 12, pp. 3158-3166, 2020. DOI: https://doi.org/10.1109/TNSRE.2020.3044113.

[41] T.-M.-P. Dao, V.-K. Nguyen, N.-K. Nguyen, L. Le, T.-D. Nguyen, T. Nguyen, T.-D. Bui, D.-T. Nguyen, and H.-T. Nguyen, "Optimized feature extraction via custom low-cost sEMG hardware for real-time myoelectric interfaces," *Engineering, Technology & Applied Science Research*, vol. 16, no. 1, pp. 32186-32194, 2026. DOI: https://doi.org/10.48084/etasr.16242.

[42] N.-K. Nguyen, T.-M.-P. Dao, T.-D. Nguyen, D.-T. Nguyen, H.-T. Nguyen, and V.-K. Nguyen, "An sEMG signal-based robotic arm for rehabilitation applying fuzzy logic," *Engineering, Technology & Applied Science Research*, vol. 14, no. 3, pp. 14287-14294, 2024. DOI: https://doi.org/10.48084/etasr.7146.

[43] D. Zhao, *et al.*, "Upper limb human-exoskeleton system motion state classification based on sEMG: Application of CNN-BiLSTM-attention model," *Scientific Reports*, vol. 15, art. 18969, 2025. DOI: https://doi.org/10.1038/s41598-025-02864-5.

[44] A. Moin, A. Zhou, A. Rahimi, A. Menon, S. Benatti, G. Alexandrov, S. Tamakloe, J. Ting, N. Yamamoto, Y. Khan, F. L. Burghardt, L. Benini, A. C. Arias, and J. M. Rabaey, "A wearable biosensing system with in-sensor adaptive machine learning for hand gesture recognition," *Nature Electronics*, vol. 4, pp. 54-63, 2021. DOI: https://doi.org/10.1038/s41928-020-00510-8.

[45] S. Muceli and D. Farina, "Simultaneous and proportional estimation of hand kinematics from EMG during mirrored movements at multiple degrees-of-freedom," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 20, no. 3, pp. 371-378, 2012. DOI: https://doi.org/10.1109/TNSRE.2011.2178039.

[46] N. Jiang, I. Vujaklija, H. Rehbaum, B. Graimann, and D. Farina, “Intuitive, online, simultaneous, and proportional myoelectric control over two degrees-of-freedom in upper limb amputees,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 22, no. 3, pp. 501-510, 2014. DOI: https://doi.org/10.1109/TNSRE.2013.2278411.

[47] A. Krasoulis, I. Kyranou, M. S. Erden, K. Nazarpour, and S. Vijayakumar, “Improved prosthetic hand control with concurrent use of myoelectric and inertial measurements,” *Journal of NeuroEngineering and Rehabilitation*, vol. 14, art. 71, 2017. DOI: https://doi.org/10.1186/s12984-017-0284-8.

[48] X. Wang, C. Zhang, Z. Yu, and C. Deng, “Decoding of lower limb continuous movement intention from multi-channel sEMG and design of adaptive exoskeleton controller,” *Biomedical Signal Processing and Control*, vol. 94, art. 106245, 2024. DOI: https://doi.org/10.1016/j.bspc.2024.106245.

[49] L. D. L. da Silva, T. F. Pereira, V. R. Q. Leithardt, L. O. Seman, and C. A. Zeferino, “Hybrid impedance-admittance control for upper limb exoskeleton using electromyography,” *Applied Sciences*, vol. 10, no. 20, art. 7146, 2020. DOI: https://doi.org/10.3390/app10207146.

[50] Q. Meng, Y. Yue, S. Li, and H. Yu, “Electromyogram-based motion compensation control for the upper limb rehabilitation robot in active training,” *Mechanical Sciences*, vol. 13, no. 2, pp. 675-685, 2022. DOI: https://doi.org/10.5194/ms-13-675-2022.

[51] Q. Wu, Z. Wang, and Y. Chen, “sEMG-based adaptive cooperative multi-mode control of a soft elbow exoskeleton using neural network compensation,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 31, pp. 3384-3396, 2023. DOI: https://doi.org/10.1109/TNSRE.2023.3306201.

[52] T. Wang and A. Song, “An adaptive iterative learning based impedance control for robot-aided upper-limb passive rehabilitation,” Frontiers in Robotics and AI, vol. 6, art. 41, 2019. DOI: https://doi.org/10.3389/frobt.2019.00041.

[53] B. Brahmi, M. Driscoll, I. K. El Bojairami, M. Saad, and A. Brahmi, “Novel adaptive impedance control for exoskeleton robot for rehabilitation using a nonlinear time-delay disturbance observer,” *ISA Transactions*, vol. 108, pp. 381-392, 2021. DOI: https://doi.org/10.1016/j.isatra.2020.08.036.

[54] Y. Zhang, T. Li, H. Tao, F. Liu, B. Hu, M. Wu, and H. Yu, “Research on adaptive impedance control technology of upper limb rehabilitation robot based on impedance parameter prediction,” *Frontiers in Bioengineering and Biotechnology*, vol. 11, art. 1332689, 2024. DOI: https://doi.org/10.3389/fbioe.2023.1332689.

[55] A. M. Abdullahi, A. Haruna, and R. Chaichaowarat, “Hybrid adaptive impedance and admittance control based on the sensorless estimation of interaction joint torque for exoskeletons: A case study of an upper limb rehabilitation robot,” *Journal of Sensor and Actuator Networks*, vol. 13, no. 2, art. 24, 2024. DOI: https://doi.org/10.3390/jsan13020024.

[56] L. Peternel, T. Noda, T. Petrič, A. Ude, J. Morimoto, and J. Babič, “Adaptive control of exoskeleton robots for periodic assistive behaviours based on EMG feedback minimisation,” *PLOS ONE*, vol. 11, no. 2, e0148942, 2016. DOI: https://doi.org/10.1371/journal.pone.0148942.

[57] K. Kiguchi and Y. Hayashi, “An EMG-based control for an upper-limb power-assist exoskeleton robot,” *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 42, no. 4, pp. 1064-1071, 2012. DOI: https://doi.org/10.1109/TSMCB.2011.2163783.

[58] E. T. Wolbrecht, V. Chan, D. J. Reinkensmeyer, and J. E. Bobrow, “Optimizing compliant, model-based robotic assistance to promote neurorehabilitation,” *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 16, no. 3, pp. 286-297, 2008. DOI: https://doi.org/10.1109/TNSRE.2008.918389.

[59] N. Hogan, “Impedance control: An approach to manipulation-Part I: Theory,” *Journal of Dynamic Systems, Measurement, and Control*, vol. 107, no. 1, pp. 1-7, 1985. DOI: https://doi.org/10.1115/1.3140702.

[60] A. Ajoudani, A. M. Zanchettin, S. Ivaldi, A. Albu-Schäffer, K. Kosuge, and O. Khatib, “Progress and prospects of the human-robot collaboration,” *Autonomous Robots*, vol. 42, pp. 957-975, 2018. DOI: https://doi.org/10.1007/s10514-017-9677-2.

[61] P. A. Lasota, T. Fong, and J. A. Shah, “A survey of methods for safe human-robot interaction,” *Foundations and Trends in Robotics*, vol. 5, no. 4, pp. 261-349, 2017. DOI: https://doi.org/10.1561/2300000052.

[62] International Organization for Standardization, *ISO 14971:2019-Medical Devices-Application of Risk Management to Medical Devices*, 3rd ed., 2019. URL: https://www.iso.org/standard/72704.html.

[63] International Organization for Standardization, *ISO 13482:2014-Robots and Robotic Devices-Safety Requirements for Personal Care Robots*, 1st ed., 2014. URL: https://www.iso.org/standard/53820.html.