

STANDARDIZED FRAMEWORKS FOR MYOELECTRIC RESEARCH: SENIAM AND ISEK GUIDELINES, APPLICATIONS, AND ETHICAL PERSPECTIVES

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ABSTRACT

Surface electromyography (sEMG) serves as a versatile tool for assessing muscle activity, relying on standardized acquisition and analysis protocols to reduce variability caused by equipment differences, electrode positioning, and signal processing methods. This work examines the contributions of SENIAM and ISEK standards in establishing consistent methodologies for electrode placement, signal acquisition, and reporting, highlighting their complementary roles in enhancing data comparability and transparency. The historical evolution of electromyography standards is reviewed, emphasizing the transition from heterogeneous local practices to internationally recognized frameworks that support reproducible research and computational modeling. Principles distinguishing surface and fine-wire EMG techniques are discussed, including their operational characteristics, advantages, and limitations in capturing neuromuscular signals. Applications in clinical rehabilitation and prosthetics are explored, demonstrating how adherence to these standards improves diagnostic accuracy, therapeutic monitoring, and control of assistive devices. Ethical considerations related to participant consent, data privacy, and methodological rigor are addressed, underscoring the importance of transparent documentation and responsible data stewardship. Overall, integrating standardized acquisition protocols with comprehensive reporting facilitates reliable neuromuscular analysis across diverse research and clinical settings, supporting advancements in rehabilitation robotics and human-computer interfaces.

1 INTRODUCTION

Surface electromyography (sEMG) has long been recognized as a versatile tool for assessing muscle activity. Its utility relies heavily on standardized acquisition and analysis protocols, which aim to mitigate variability in data resulting from differences in equipment, electrode positioning, and signal processing strategies. According to Hermens et al., (1999), Surface EMG for Noninvasive Assessment of Muscles (SENIAM) guidelines represent one of the most influential frameworks in this domain. They suggest specific procedures for signal collection, amplitude estimation, and spectral analysis, tailored to non-invasive sampling of superficial muscles. These recommendations have provided researchers with a consistent foundation for experimental setup, yet they inherently omit deeper musculature due to the limitations of surface electrodes (Stegeman and Hermens, 2007). Consequently, certain applications, especially those involving smaller or deeper motor units, may suffer from reduced accuracy or fail to capture critical physiological details (Garikayi et al., 2018). The ISEK standards expand this approach by prescribing how sEMG data should be reported. This includes details about sensor type, whether surface, intramuscular, or needle electrodes are employed, alongside specifications for filter ranges used during acquisition. Notably, ISEK refrains from dictating precise sensor placements or signal-processing workflows. Such openness can be advantageous insofar as it allows laboratories to adapt measurements to their unique contexts. At the same time, however, the absence of universal placement requirements can create obstacles when comparing results across studies. This lack of spatial standardization makes it challenging to establish universally normative EMG profiles over movement cycles such as gait. Figure 1 illustrates sEMG signals recorded from three different muscle sites.

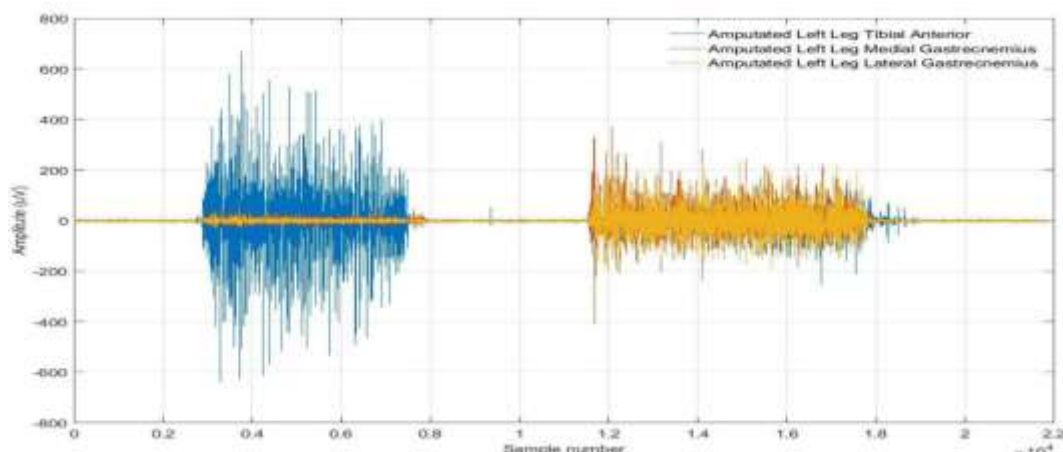


Figure 1: Surface EMG signals recorded from the different muscles (Garikayi et al., 2018)

Hermens et al (2000) argued that beyond technical guidelines themselves, many factors influence the recorded sEMG signals and must be considered in designing research methodologies. As earlier stated by Onmace (2016) and supported by Garikayi et al, (2018) who buttressed the point that technical aspects include electrode position relative to muscle fibers, susceptibility to crosstalk between adjacent muscles, ambient electrical noise, and nuances of data acquisition hardware. Physiological influences range from tissue conductivity variations caused by subcutaneous fat layers to the morphological differences between deep and superficial muscles. The interplay among these variables can introduce biases that propagate through subsequent analytical stages if not properly controlled. In parallel with developments in sEMG acquisition standards, advancements in computational modeling have highlighted the need for highly reliable input signals. For example, machine learning approaches used for classifying neuromuscular activity depend on clear delineations of feature boundaries. According to Putra et al (2019), Learning Vector Quantization (LVQ) methods have been shown to enhance classification accuracy by refining class borders beyond what is achievable with more generic algorithms like backpropagation or Genetic-Based Machine Learning (GBML). Similarly, Radial Basis Function Networks (RBNs), while often requiring more neurons than feed-forward neural networks (FFNNs) for identical classification problems, can offer faster performance when trained on smaller datasets, a property that becomes valuable in clinical settings with limited patient data availability. Figure 2 illustrates the sEMG modeling from skin anatomy to generalized model of electrode-skin interference.

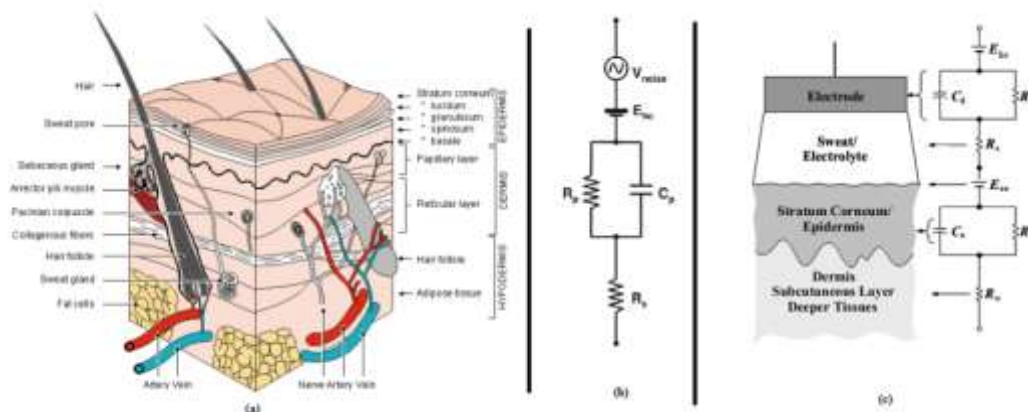


Figure 2: (a) Skin anatomy, (b) electrical model of the charge transfer and (c) generalised model of electrode-skin interface

Wang and Buchanan (2002) stated that Weighted Neural Networks (WNNs) illustrate another computational strategy that integrates speed with high accuracy for waveform processing tasks. Such models reportedly deliver accuracies exceeding 90 %, making them suitable for extracting clinically relevant patterns from EMG signals despite fluctuations in waveform morphology across trials. Their robustness against waveform variability allows them to handle inconsistencies stemming from patient movement irregularities, a frequent occurrence in prosthetics control experiments. Although these algorithmic tools promise enhanced interpretation of sEMG readings collected under established standards like SENIAM and ISEK, certain methodological gaps persist (Choi, 2023). For instance, while WNNs can manage waveform variability well, research into their application within neuromuscular pathology remains insufficient for forming generalizable conclusions. Integrative approaches involving fuzzy logic have been proposed; these improve interpretability by mapping high-dimensional feature spaces into rule-based systems built upon human domain expertise (Yousefi and Hamilton-Wright, 2014). Unfortunately, developing comprehensive fuzzy-rule sets is complex when dealing with multidimensional datasets typical of EMG recordings. These technological perspectives intersect directly with modern prosthetic development efforts that increasingly rely on benchmark datasets gathered under standardized measurement protocols. Trans-radial amputees, a majority among upper limb amputations, currently benefit from myoelectric prostheses capable of basic movements like opening and closing grips. While more sophisticated commercial devices now offer programmable motions controlled through nuanced EMG pattern recognition algorithms, their success depends critically upon consistent and precise input signals grounded in SENIAM-compliant collection practices. From a broader standpoint, these developments suggest an ongoing tension between maintaining strict methodological uniformity and allowing flexibility for case-specific adaptations. Increased portability of sensors and improved mechatronic interfaces enable testing across diverse environments outside conventional laboratories (Atzori *et al.*, 2014), but they also exacerbate potential inconsistencies unless firmly couched within agreed-upon standards. Consequently, any initiative toward improving intuitive control systems, whether in rehabilitation robotics or human-computer interface research, will likely require harmonizing SENIAM's detailed acquisition recommendations with ISEK's comprehensive reporting requirements while enhancing computational models' tolerance for inevitable real-world variability (Merletti, 2000). This introductory perspective establishes why harmonized standards are essential: without them cross-study comparability erodes and algorithmic performance becomes unreliable due to inconsistent input quality. More critically still, user-oriented applications such as prosthetics demand both fine-grained control precision and reproducibility across sessions. The scientific community thus appears poised between upholding rigorous adherence to established frameworks and pushing boundaries with adaptive approaches that acknowledge practical constraints encountered during actual device use cases (Onmance, 2016).

2 Foundations of Myoelectric Research

2.1 Historical development of electromyography standards

Early developments in electromyography (EMG) lacked the consistency and rigor that are now considered fundamental. In its formative years, EMG practice was shaped largely by local laboratory conventions rather than internationally accepted norms (Zielinski and Gawda, 2024). Recording techniques, electrode sizes, filter settings, and placement strategies varied widely, often making cross-study comparisons precarious. The eventual standardization of electroencephalography (EEG) through the implementation of the 10–20 montage system illustrates what EMG lacked at the time: a consistent spatial framework and strict control over sensor geometry. EEG's early adoption of these principles provided long-term benefits for automated seizure detection algorithms and quantitative analyses, underscoring the importance of reproducible acquisition conditions for computational advancements.

In contrast to EEG's relatively stable hardware configuration over decades, EMG has remained susceptible to continual technological changes in electrodes, amplifiers, and processing software (Ladegaard, 2002). This adaptability has allowed methodological improvements but has also delayed the establishment of universal electrode positioning rules (Pitta and Jabreb, 2018). The sensitivity of EMG to variables such as inter-electrode distance, orientation relative to muscle fibers, and housing design, factors emphasized in SENIAM's recommendations, means early research often suffered from unquantified measurement variability. A bipolar montage, now common in surface EMG acquisition, emerged as a pragmatic choice because it reduces crosstalk and enhances signal-to-noise ratio (Gentil and Moore, 1997). However, codifying its parameters took decades of dispersed trial-and-error adoption. As sEMG applications expanded into areas such as prosthetic control and movement rehabilitation, the absence of harmonized protocols became more apparent. This spurred coordinated initiatives like SENIAM in Europe during the 1990s, which aimed to unify methodologies for non-invasive measurements by prescribing detailed procedures for electrode placement based on muscle anatomy and biomechanical function (Stegeman *et al.*, 1999). SENIAM differed from earlier ad-hoc practices by not only describing positions but also stressing repeatability across sessions and operators (Merletti, 2000). Over time, these guidelines have been integrated into experimental designs worldwide, forming a *de facto* benchmark for musculoskeletal modeling input data. In parallel, professional societies developed broader reporting norms.

The International Society of Electrophysiology and Kinesiology (ISEK) contributed to this trajectory by codifying what technical details should accompany published EMG work (Armijo-Olivo *et al.*, 2004). While ISEK refrained from declaring exact sensor coordinates or specific processing pipelines, possibly to accommodate regional differences in technology access, it did outline minimum reporting standards covering sensor types (surface vs. intramuscular), filtering ranges, sampling rates, and preprocessing methods (Pullman *et al.*, 2000). Such transparency measures addressed one root difficulty in EMG comparability: even if data were collected differently between labs, clear documentation allowed other researchers to interpret results within their methodological context. These developments also intersect with classification algorithm performance in clinical applications.

Structured datasets built under precise acquisition standards provide cleaner input signals for machine learning models like decision trees or probabilistic neural networks (PNNs). Historical trials without such structure often encountered reduced accuracy due to noise or misaligned feature extractions (Yousefi and Hamilton-Wright, 2014). Invasive approaches have at times achieved performance levels above 90 % classification accuracy for movement intent detection; non-invasive studies more consistently reach 80 – 90 % when collected under standardized protocols like SENIAM (Atzori *et al.*, 2014b). This difference highlights how standardization can act as an enabler for algorithmic refinement rather than a mere procedural formality. Interestingly, while SENIAM pushed toward anatomical rigor in sensor placement, subsequent advances have shown that flexible adaptation may be necessary when moving experiments out of controlled laboratory environments into daily-use scenarios. Portable devices have broadened recording contexts but may compromise positional accuracy; here ISEK's emphasis on detailed technical reporting acts as a safeguard against losing interpretive transparency (Atzori *et al.*, 2014a). Historically, then, EMG standardization has always balanced between two pulls: anchoring methods tightly enough to ensure replicability while leaving enough procedural freedom to integrate emerging technologies.

The classification of evidence quality in medical diagnostics offers another historical lens on standardization's role. Structured frameworks distinguishing Class I evidence, blinded clinical studies using gold-standard references, from lower tiers like Class III expert opinion emphasize reproducibility and robust comparative evaluation (Pullman *et al.*, 2000). Translating this mindset into EMG methodology means preferring experimental designs backed by comprehensive procedural adherence over anecdotal validation or non-blinded observational work. Over several decades these layered contributions, from technical montages akin to EEG's to anatomically rationalized placement grids via SENIAM and transparent reporting through ISEK, have reshaped how researchers view validity in EMG data collection. The progression shows an arc from heterogeneous local practices toward globally recognized protocols that interlock with advances both in instrumentation and computational modeling. Current research operates within this framework while acknowledging its legacy: each improvement in device portability or signal analysis implicitly rests on decades of gradual consensus-building about where and how electrodes are applied and what must be disclosed for others to replicate findings accurately.

2.2 Principles of surface and fine-wire EMG

Surface and fine-wire electromyography (EMG) represent complementary methodologies for capturing muscle electrical activity, each with distinctive operational principles and practical implications (Garikayi *et al.*, 2018). Surface EMG (sEMG) operates by detecting the composite voltage fluctuations generated by active motor units through electrodes placed on the skin above the target muscle (Yousefi and Hamilton-Wright, 2014). According to Garikayi *et al.*, (2015), these voltages emerge from the summation of multiple motor unit potentials (MUPs) as the action potential propagates along fibers, making sEMG inherently a global measure of superficial muscle activity rather than a precise mapping of individual fibers. Fine-wire EMG (FWEMG), in contrast, uses intramuscular electrodes, often inserted via hypodermic

needles, to directly sample localized activity within the muscle belly. This approach allows access to deeper muscle tissues and facilitates discrimination between adjacent anatomical structures that surface electrodes cannot resolve effectively (Onmanee, 2016).

De Luca et al., (2006) stated that the defining aspect of sEMG data quality lies in electrode orientation and inter-electrode distance (IED). When bipolar electrodes are aligned parallel to the muscle fibers, signal amplitude is optimized due to coherent alignment with the propagation path of action potentials. As illustrated in Figure 3 below, SENIAM guidelines recommend an IED of 20mm for most muscles, as this configuration maximizes recorded amplitude in model simulations; for smaller muscles, IEDs exceeding one-quarter of fiber length risk unstable signals due to tendon proximity or motor endplate interference. Although electrode shape has not been shown to exert strong influence on signal morphology, whether circular or rectangular, the electrode surface area does affect measurement resolution. Increasing electrode size perpendicular to fibers integrates a broader potential field but can dilute spatial specificity (Stegeman and Hermens, 1999). Decisions about these parameters become more critical in studies employing high-resolution musculoskeletal models where fine spatial accuracy is necessary.

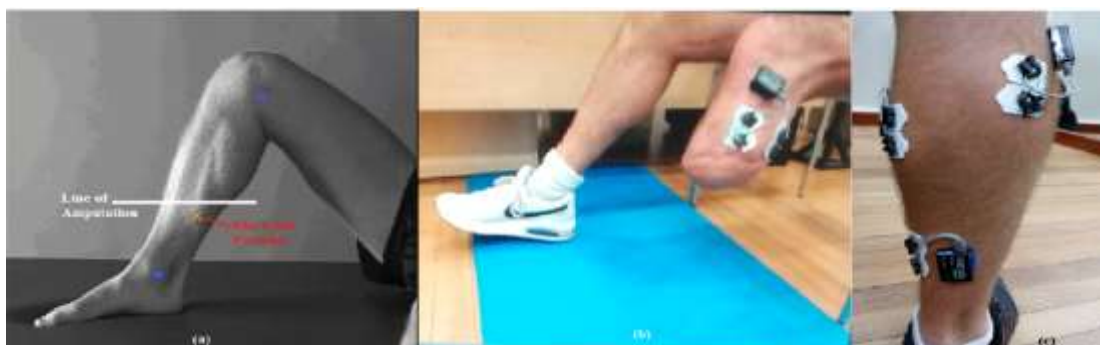


Figure 3: Illustration of (a) SENIAM electrode position on a normal leg, (b) the residual limb and (c) the electrode positioning on the functional leg.

According to Semciw et al., (2014), in practical acquisition setups, fine wire EMG (FWEMG) can achieve a more isolated signal by minimizing crosstalk from adjacent muscles as illustrated in Figure 4. The insertion site relative to anatomical landmarks influences which motor units are sampled; for example, positioning two fine-wire sensors proximally and distally within the tibialis anterior enables assessment of intra-muscular variability while correlating readings with concurrent surface measurements (Onmanee, 2016). This dual-sensor placement strategy provides insight into whether localized recordings reflect overall muscle activation patterns, a question relevant when validating FWEMG data against global sEMG signals. For selected muscles like the tibialis posterior, anatomical constraints present a choice between anterior and posterior insertion approaches, each carrying distinct mechanical risks and access advantages. From an interpretive standpoint, sEMG primarily reflects compound neural drive to superficial motor units under conditions free from significant impedance distortions.

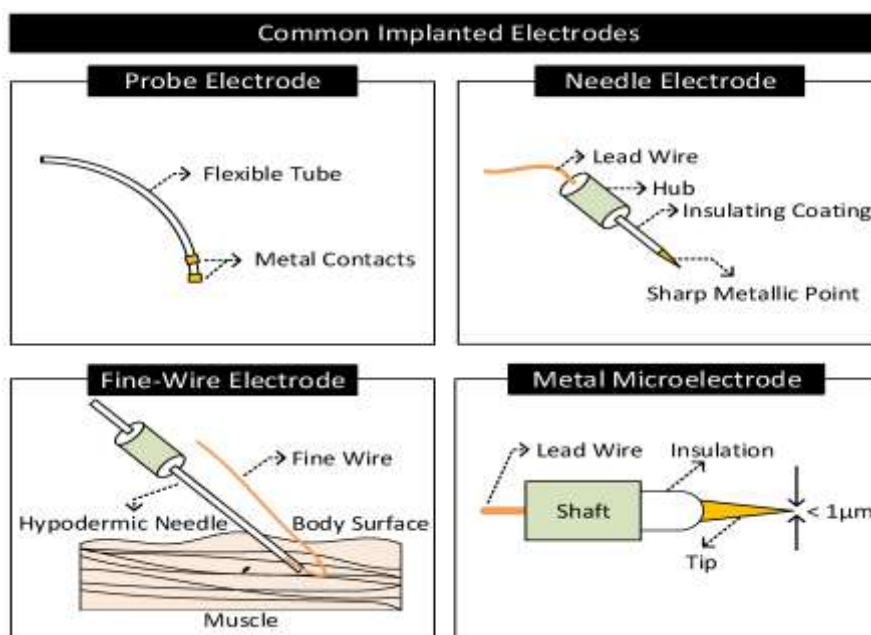


Figure 4: Commonly used implanted electrodes (Polacha et al., 2021)

Variability in subcutaneous fat thickness introduces nontrivial attenuation and filtering effects that can obscure waveform features important for certain diagnostic or classification tasks (Pullman *et al.*, 2000). FWEMG is less susceptible to such superficial impedance issues yet may display localized heterogeneities if electrode placement varies between trials or

operators. This sensitivity means that while FWEMG offers higher spatial fidelity for deep muscle recordings, it demands rigorous procedural reproducibility to support cross-trial comparability, particularly in machine learning contexts where classifier performance depends on consistent feature extraction from training data (Yousefi and Hamilton-Wright, 2014). Non-invasive methods such as sEMG, hold obvious advantages for repeated measures in clinical and experimental designs due to their reduced discomfort and lower infection risk. They also enable multi-channel recordings across several muscles simultaneously, assisting in broader biomechanical analyses such as rehabilitation monitoring or prosthetic control feedback loops (Polachan et al., 2021). However, comparative studies show relatively few direct evaluations against invasive gold standards such as imaging or biopsy techniques; thus, definitive validation of sEMG accuracy for certain diagnostic endpoints remains incomplete (Pullman *et al.*, 2000). In fields where patient tolerance must be prioritized, like longitudinal rehabilitation trials, thus, trade-off often leans toward accepting sEMG's lower depth resolution in exchange for its ease of application across sessions.

The integration of these methodologies into musculoskeletal modeling heavily relies on how well their underlying principles align with model requirements. Multichannel sEMG datasets conforming to anatomical placement rules provide input variables capturing aggregate activation timing and amplitude; FWEMG complements these datasets by offering fine-grained insight into differential recruitment patterns within deeper compartments. Hybrid acquisition strategies combine surface arrays and fine-wire channels to construct a layered depiction of neuromuscular dynamics suitable for advanced applications like high-definition prosthetic control interfaces. These configurations enable algorithms to reconcile broad-scale activation cues with localized motor unit behavior during complex movements (Stegeman et al., 1999; Onmanee, 2016). An additional consideration lies in real-world deployment outside laboratory confines, something that has grown more relevant as portable acquisition systems proliferate (Atzori *et al.*, 2014a).

Muscle movement artifacts, variable environmental conditions, and repositioning errors realistically affect both modalities but tend to challenge sEMG more severely due to its reliance on stable skin-electrode contact over time. FWEMG resists such motion-induced impedance changes yet is rarely suited for prolonged wear given its invasive nature. Whether inside rehabilitation centers or out in ambulatory monitoring contexts, adapting protocols from controlled settings demands careful calibration to sustain adherence to principles laid out in established standards like SENIAM while balancing patient comfort and procedural feasibility (Garikayi et al., 2017).

In summary, surface EMG prioritizes non-invasive global sampling at the cost of depth resolution whereas fine-wire EMG targets precise intramuscular activity profiles with greater invasiveness but improved specificity against crosstalk effects. Each method's principles frame its role within musculoskeletal research: sEMG excels at capturing broad patterns suitable for large-scale trend analysis or user-interface control inputs; FWEMG serves specialized inquiries requiring detailed motor unit mapping beyond reach of superficial sensors. Jointly applied under harmonized protocols, they expand analytical possibilities, from verifying model predictions against diverse physiological contexts to informing classifier architectures that depend upon both coarse ensemble features and pinpoint excitation timing for optimal operation across varied neuromuscular applications (Yousefi and Hamilton-Wright, 2014; Onmanee, 2016).

3 SENIAM and ISEK Standards

3.1 Objectives and scope

The primary objective of both SENIAM and ISEK frameworks is to establish a consistent methodological basis for the acquisition, processing, and reporting of electromyographic data so that results can be compared meaningfully across studies and applications (Merletti, 2000). For SENIAM, this centers on the spatial and procedural standardization of electrode placement in surface EMG acquisition, with particular emphasis on anatomical landmarks, inter-electrode distances, and alignment relative to muscle fibers. By prescribing these procedures in detail, SENIAM aims to reduce variability introduced by operator-dependent factors such as inconsistent orientation or placement drift between sessions (Onmanee, 2016). The intent is not merely improved reproducibility within a single laboratory trial but also interoperability between datasets generated at different research sites. This becomes particularly valuable when aggregating results for meta-analyses or multi-center clinical trials that assess neuromuscular performance or rehabilitation interventions.

The scope of SENIAM is focused on non-invasive recordings from superficial muscles, making it directly applicable to a wide range of musculoskeletal modeling efforts where large-scale mapping of muscle activation patterns is needed. While deep muscle activity remains outside its intended coverage due to the limitations of surface electrodes, the guidelines indirectly facilitate comparative work with intramuscular techniques by defining reference positions that can be co-registered with fine-wire placements. In practical terms, this means SENIAM protocols serve as the coordinate grid against which more invasive measurements can be anchored during validation exercises.

ISEK takes a broader stance by not confining itself exclusively to surface methods but instead providing reporting requirements covering various sensor types, surface, fine-wire, or needle, and associated acquisition parameters. Its objective is to guarantee methodological transparency so that recorded signals can be evaluated in full context (Pullman *et al.*, 2000). This includes specifying filter characteristics and sampling rates so that the influence of acquisition hardware and preprocessing can be assessed quantitatively. From a computational perspective, these details afford analysts the opportunity to apply corrections or compensatory models when integrating heterogeneous datasets into a unified analysis pipeline (Merletti, 1999). Although less prescriptive about exact electrode placement than SENIAM, ISEK's flexibility accommodates diverse research environments and technological constraints while still retaining enough structure to prevent ambiguity in interpretation. Beyond technical configuration alone, the combined objectives implicitly target downstream analytical integrity.

In applications like prosthetic control systems or functional electrical stimulation (FES) optimization for clinical gait improvement (Prenton *et al.*, 2018), small differences in feature extraction, caused by inconsistent placement or unreported filter settings, can have outsized effects on classifier decision boundaries (Yousefi and Hamilton-Wright, 2014). Therefore, both standards position themselves as safeguards: SENIAM minimizes physical setup variability at the data collection stage; ISEK ensures sufficient metadata is captured so analytical reproducibility is preserved even when collection conditions differ. Their scope extends further into enabling high-quality databases (Hermens *et al.*, 2000; Stegeman and Hermans, 2007). Large-scale repositories of sEMG recordings benefit from homogeneity in data acquisition protocols because it simplifies subsequent annotation and comparison tasks. For instance, datasets curated under strict SENIAM adherence facilitate machine learning efforts aimed at hand movement recognition in trans-radial amputees with minimal confounding from electrode misplacement artifacts (Merletti, 2000). Conversely, ISEK's detailed reporting requirements become indispensable when integrating less controlled real-world recordings into these models by allowing proper stratification based on acquisition conditions. Ethical considerations also fall within their practical scope.

Accurate documentation as stipulated by ISEK serves an additional role in ensuring informed consent processes capture the kinds of physiological data being collected and how they will be processed. When combined with SENIAM's structured approach, which inherently limits ad-hoc deviations likely to cause inadvertent participant discomfort, the standards align with principles of minimizing harm while maximizing scientific utility. An important nuance lies in balancing comprehensiveness against feasibility outside laboratory contexts. As portable EMG systems extend testing into daily life situations (Atzori *et al.*, 2014a), perfect adherence to fixed electrode maps may prove impractical due to time constraints or user skill levels. Here the scope shifts slightly: rather than enforcing rigid compliance at all costs, adaptations may be documented precisely following ISEK conventions so that any deviation from strict SENIAM layouts does not erase interpretive value. Such flexibility preserves longitudinal comparability without discarding ecologically valid data gathered under suboptimal but realistic conditions. Their objectives are thus complementary across different project scales: small-scale experimental trials aiming for optimal signal-to-noise ratios may fully implement SENIAM's geometric prescriptions; larger multi-site collections with varied hardware setups can lean more heavily on ISEK's exhaustive reporting rules to normalize post hoc analyses or meta-research syntheses. Both contribute toward advancing fields like rehabilitation robotics where integration of accurate sEMG signals into human-computer interface algorithms depends equally on controlling acquisition variables and transparently communicating them across interdisciplinary teams (Yousefi and Hamilton-Wright, 2014).

Overall, by simultaneously addressing procedural uniformity and documentary comprehensiveness, these frameworks create a dual-layer foundation. One layer stabilizes how raw physiological signals are obtained; the other secures interpretive continuity regardless of inevitable contextual variability across studies and applications. This interplay between standardization in practice and transparency in communication defines both their objectives and their functional reach within neuromuscular research ecosystems spanning basic biomechanics to clinical device implementation.

3.2 Electrode placement and signal acquisition

The precision of electrode placement in surface electromyography (sEMG) and its correct integration with acquisition systems plays a central role in the validity of experimental outcomes (Hermens *et al.*, 2000; Garikayi *et al.*, 2018). According to Hermens *et al.*, (2000), SENIAM guidelines provide a spatially explicit framework, recommending that electrodes be positioned at the center of the muscle belly, away from anatomical borders where crosstalk from adjacent muscles can distort measurements. Locating the sensor at a site that maximizes geometrical distance to neighboring muscles increases selectivity by reducing interference effects as illustrated in Figure 5 below. This is particularly relevant when investigating muscles with close anatomical proximity or shared functional roles, as misplacement here can lead to signals dominated by overlapping motor unit activity rather than the intended target muscle.

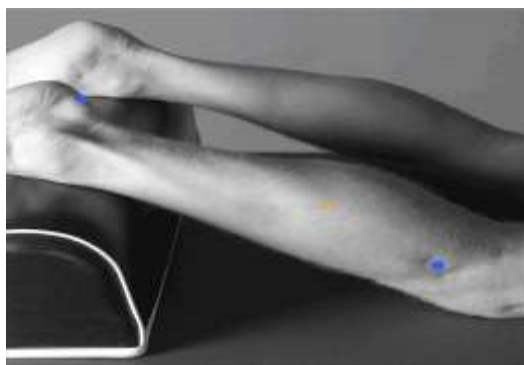


Figure 5: Sensor position for the lower limb based on SENIAM standards

The guidelines also address inter-electrode distance (IED), advising values standardized for typical recording conditions, most commonly around 20mm, to balance amplitude fidelity against susceptibility to noise. Deviation from these norms alters not only amplitude but also frequency content of the recorded signal, which can impede feature extraction for pattern recognition tasks. For more selective recordings targeting superficial motor units, shorter IEDs in the range of 3–5mm may be optimal; these parameters need careful calibration since they influence both spatial resolution and sensitivity to minor anatomical shifts between sessions (Day, 2002). Electrode material selection is equally consequential. Ag/AgCl electrodes remain the most widely used because they provide stable electrolyte interfaces with low impedance and minimal

drift over time, a property essential for repeated measurements across experimental repetitions without reintroducing calibration uncertainty (Stegeman and Hermens, 1999).

While SENIAM outlines where and how to place electrodes, ISEK contributes by stipulating what must be reported about these setups. Recording mode, monopolar or differential, should be documented alongside hardware properties such as input impedance, common mode rejection ratio, gain range, and filtering boundaries. Explicit notation on high-pass and low-pass cut-off frequencies ensures other researchers can reconstruct or reinterpret signal bandwidths accurately (Merletti, 1999). For sEMG, primary information resides within approximately 5–450Hz; amplifier designs outside this bandwidth risk attenuating physiologically relevant components (Rainoldi et al., 2004). Needle or fine-wire EMG signals demand broader cut-offs (at least up to 1500 Hz) due to their higher-frequency content. Signal acquisition protocols intertwine with electrode placement choices and environmental factors. Accurate timestamping, as implemented in systems where multi-sensor streams are synchronized via performance counters, is critical when combining sEMG data with auxiliary kinematic measurements like glove-based motion capture or accelerometer-derived limb dynamics (Atzori et al., 2014b). This timing precision enables alignment between electrical activation patterns and mechanical events as illustrated in Figure 6, making correlation analyses reliable even when datasets stem from heterogeneous acquisition devices.

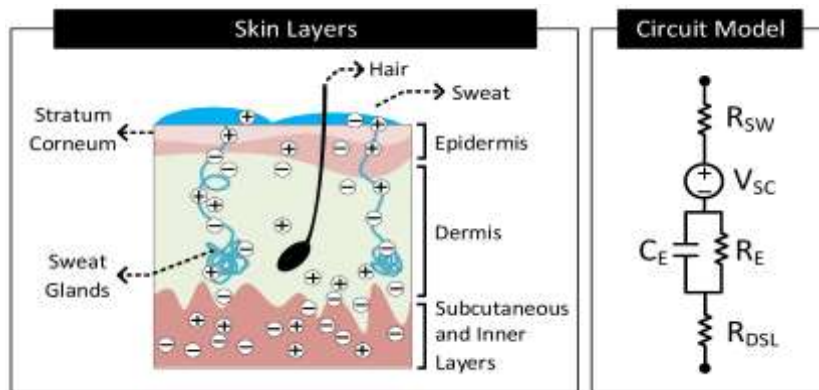


Figure 6: Human skin layer and its equivalent circuit model (Polachan et al., 2021).

Even though the stratum corneum has high electrical resistance, ions from inner bodily fluids still reach the skin surface and mix with the sweat. A part of this ion transport is through the pores in the stratum corneum. However, a significant portion of this ion transport happens through the sweat glands and hair foliage (Polachan et al., 2021).

Maintaining appropriate sampling rates further avoids aliasing artifacts; while raw EMG often requires rates exceeding 1 kHz to capture waveform detail for spectral analysis, rectified and smoothed envelopes may be sampled adequately at lower rates such as 50–100 Hz if preprocessing has reduced bandwidth accordingly (Merletti, 1999). Real-world application introduces complexities absent in controlled laboratory environments. Portable acquisition units expand testing scenarios but impose constraints on absolute adherence to fixed electrode maps; movement artifacts, inconsistent skin preparation, or changes in ambient electromagnetic fields challenge data stability (Merlo and Campanini, 2021). Under such conditions, following ISEK’s documentation standards becomes vital: precise metadata on deviations from canonical SENIAM placement allows post hoc interpretation within proper methodological context (Pullman et al., 2000). This degree of reporting also facilitates meta-analyses that attempt to normalize across studies with varying setup accuracy. Figure 7 shows the filtered 60 Hz signal resulting from the main power supply.

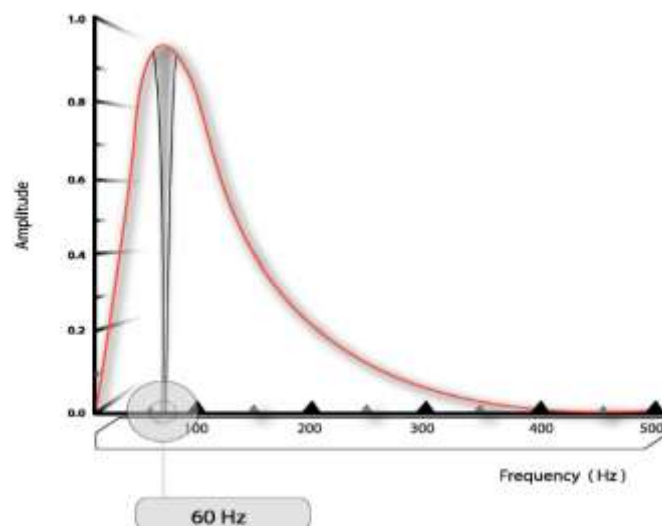


Figure 7: Schematic representation of a typical sEMG power spectrum. The shaded area indicates the signal lost when notch filtering is used, in this case to eliminate 60 Hz power source noise (Day, 2002).

Acquisition quality does not depend solely on design adherence but involves vigilance against physiological confounders (De Luca *et al.*, 2006). Variability in subcutaneous tissue thickness modulates impedance pathways between electrode and muscle fibers, attenuating high-frequency components more strongly; fatigue effects and clinical variables, such as amputation parameters in prosthetic studies, can alter baseline signal amplitude independently of placement precision (Atzori *et al.*, 2014b). Incorporating these considerations into placement strategy improves robustness for machine learning models tasked with classifying neuromuscular activity: clean separation of motor unit potentials allows classifiers to operate on features derived with reduced contamination from irrelevant sources. Concurrent use of multiple muscle recordings intensifies these challenges but also expands analytical potential by providing richer activation maps for complex motion patterns. In such configurations, modified majority voting schemes or weighted voting classifiers benefit from consistent electrode positioning because classifier confidence weights often correlate with channel quality metrics directly linked to placement reliability (Yousefi and Hamilton-Wright, 2014). Without strict conformity in sensor alignment relative to targeted fiber orientation, statistical learning approaches lose some discrimination capability due to increased intra-class variance. Even invasive modalities like fine-wire EMG are affected by analogous concerns: insertion points must be selected based on palpated “hot spots” of activation during functional tasks; optimal positioning augments signal-to-noise characteristics while limiting mechanical disruption during movement cycles (Atzori *et al.*, 2014). Spatial registration techniques integrating both surface and intramuscular readings allow cross-validation between deep localized activity patterns and surface-derived global measures, a methodology enriched when electrode positions comply consistently with SENIAM’s anatomical recommendations. Taken together, optimal electrode placement involves a convergence of geometric accuracy relative to musculature, appropriate choice of inter-electrode spacing suited to research objectives, suitable electrode materials ensuring stable contact over time, and thorough documentation per ISEK standards regarding all technical parameters influencing acquisition fidelity. According to Garikayi *et al.*, (2018), signal acquisition should be approached as an integrative workflow: synchronized multi-device logging, correctly tuned sampling rates aligned with preprocessing stages, environmental noise awareness, and proactive adjustment for individual physiological variability form the operational backbone capable of supporting reliable neuromuscular analysis across contexts ranging from controlled biomechanical experiments to dynamic clinical rehabilitation trials.

4 Applications of Myoelectric Standards

4.1 Clinical and rehabilitation contexts

Clinical applications of standardized sEMG protocols extend deeply into the assessment and rehabilitation of neuromuscular disorders, where the precision of electrode placement and rigor in signal acquisition described earlier directly influence diagnostic confidence and therapeutic outcomes. In contexts such as post-stroke rehabilitation, SENIAM’s spatially defined methodology serves to ensure that targeted muscle groups are consistently monitored across multiple sessions, enabling accurate tracking of recovery trajectories without variability introduced by inconsistent sensor orientation or position (Stegeman and Hermens, 1999). This stability becomes indispensable when evaluating subtle changes in motor output, for instance during progressive gait retraining wherein small improvements in dorsiflexion must be detected amidst noise from compensatory movements. Fine-wire EMG offers an additional layer here by capturing deeper compartmental activity that might remain unseen in surface recordings but plays a critical role in regaining functional strength after neurological injury (Onmanee, 2016).

Rehabilitation scenarios often require continuous monitoring over extended periods, including both clinical settings and home-based interventions. Portable acquisition systems facilitate such longitudinal tracking but impose challenges on strict adherence to SENIAM layouts due to practical limitations during unsupervised use (Atzori *et al.*, 2014a). In these cases, ISEK’s detailed reporting requirements mitigate potential interpretive losses by documenting any deviations from standard placement and noting environmental or procedural conditions that might affect signal characteristics (Pullman *et al.*, 2000). This means that even if electrode arrays were shifted slightly to accommodate patient mobility constraints, downstream analysts can contextualize results appropriately during meta-analysis or algorithmic training phases. Signal quality in these environments directly impacts therapeutic decision-making. For example, interventions aimed at correcting foot drop through functional electrical stimulation depend on precise timing between observed muscle activation patterns and the electrical pulses delivered to assist movement as illustrated in Figure 8.



Figure 8: Amputee walking using a myoelectric rehabilitation device.

The equivalent effects on walking speed reported across devices likely stem from increased practice time enabled by restoring ankle motion rather than purely from neural recovery (Prenton *et al.*, 2018). Without accurate sEMG monitoring

aligned with established standards, it becomes difficult to distinguish whether observed gait improvements represent genuine motor function restitution or compensatory adjustments, an important distinction when planning ongoing therapy. In progressive conditions like multiple sclerosis or muscular dystrophy, maintaining a consistent measurement framework enables longitudinal studies where decline or stabilization trends are quantified over months or years. Here, SENIAM's standardized inter-electrode distances reduce amplitude drift unrelated to pathology, while ISEK ensures all changes in acquisition hardware or filtering strategy are recorded. These combined measures preserve dataset integrity for computational models attempting to predict disease progression rates based on historical signal features (Yousefi and Hamilton-Wright, 2014). Even small undocumented changes in acquisition parameters could confound these models and lead to erroneous forecasts with potential consequences for treatment choices.

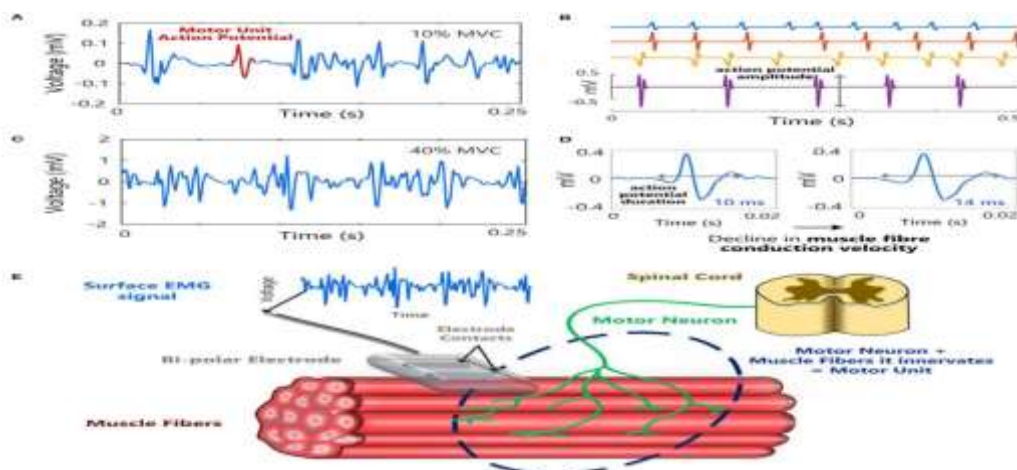


Figure 9: Example of a surface EMG signal utilized for clinical diagnosis at a low force level (10% of maximum voluntary contraction, MVC) (A) and a higher force level, 40% MVC (C), in the first dorsal interosseous muscle. (B) Single motor unit action potential trains with different inter-spike intervals (ISIs), i.e., different motor unit firing rates and (D) an illustration of the increase in action potential duration that can occur with a decline in muscle fiber conduction velocity. (E) A schematic to illustrate a motor unit, and how a surface EMG signal could be recorded from a muscle using a bipolar electrode (McManus et al., 2020).

Clinical diagnostics also explore sEMG for differentiating among causes of similar symptoms. Low back pain is a notable example where attempts have been made to use SEMG signals for discriminating nerve root compression syndromes from other etiologies (Pullman *et al.*, 2000). Although current evidence classifies such use as unsupported (Type E recommendation), its investigation underscores how SENIAM-consistent collection combined with transparent ISEK-style reporting stands as a prerequisite before conclusive judgements about diagnostic utility can be reached.

Machine learning integration within rehabilitation is increasingly common, especially for adaptive prosthetic control systems where myoelectric inputs determine grip patterns or joint motions. Weighted Neural Networks and other classifiers demand high input fidelity; inconsistent sensor placements introduce intra-class variance hampering classifier accuracy more than physiological variability itself (Yousefi and Hamilton-Wright, 2014). By keeping electrode placement fixed relative to muscle fiber direction per SENIAM while simultaneously logging device-specific parameters as required by ISEK, training datasets become cleaner, improving both offline model development and real-time responsiveness during patient use.

From an ethical standpoint, detailed acquisition metadata forms part of responsible disclosure to participants about what physiological data is collected and how it is processed. This transparency aligns with medical ethics principles aiming to minimize harm, both physical through careful surface placement avoiding discomfort (Onmanee, 2016) and informational through clear communication about data uses. Rehabilitation settings involving vulnerable populations particularly benefit when participant consent encompasses these specifics. Furthermore, rehabilitation research increasingly addresses ecologically valid testing scenarios outside laboratory confines.

Wearable sEMG systems adhering partially to SENIAM maps provide continuous data streams capturing motor adaptation during real-world tasks such as climbing stairs or carrying objects (Atzori *et al.*, 2014a). Deviations from laboratory precision here are inevitable; nonetheless, explicit documentation using ISEK conventions allows clinicians and researchers alike to separate artifacts induced by uncontrolled conditions from genuine physiological responses. Integrating high-quality sEMG into musculoskeletal modeling supports bespoke therapy plans: multi-muscle activation maps recorded under SENIAM-prescribed electrode positions feed biomechanical simulations predicting optimal exercise regimens for specific impairments. For patients recovering from peripheral nerve injuries, coordinating surface measurements with fine-wire intramuscular recordings helps verify whether deep reinnervation accompanies superficial activity gains (Onmanee, 2016). Such multimodal validation informs whether therapy should intensify efforts targeting deep stabilizing musculature versus focusing on superficial movement generators.

Overall, clinical and rehabilitation contexts demand a synthesis between anatomical rigor in measurement setup, the hallmark of SENIAM, and procedural transparency via exhaustive reporting per ISEK. This synergy ensures that therapeutic insights drawn from myoelectric data rest on reproducible foundations despite environmental variability inherent in long-term patient engagement across diverse settings. By coupling reliable acquisition with clear

documentation, practitioners safeguard both the scientific validity of their evaluations and the practical efficacy of interventions designed to restore or enhance neuromuscular function across a spectrum of rehabilitative needs.

4.2 Application of SENIAM and ISEK standards for Robotic prosthetics design

The integration of SENIAM and ISEK standards into robotic prosthetics research ensures that the myoelectric data powering these systems is both accurate and reproducible, which directly influences device performance and user experience (Gopura et al., 2018). Consistency in electrode placement according to SENIAM's anatomical guidelines enables prosthetic control algorithms to receive stable input signals over repeated sessions. This stability is critical for pattern recognition models tasked with translating muscle activation profiles into discrete movement commands, such as opening a prosthetic hand or rotating its wrist (Stegeman and Hermens, 1999). Variations in electrode orientation or inter-electrode distance introduce non-systematic shifts in signal amplitude and frequency content that can impair classification accuracy, particularly for systems relying on nuanced discrimination between similar gestures. As illustrated in Figure 10, advanced robotic prostheses increasingly draw on multichannel sEMG recordings to enable dexterous, naturalistic motions rather than binary open-close actions.

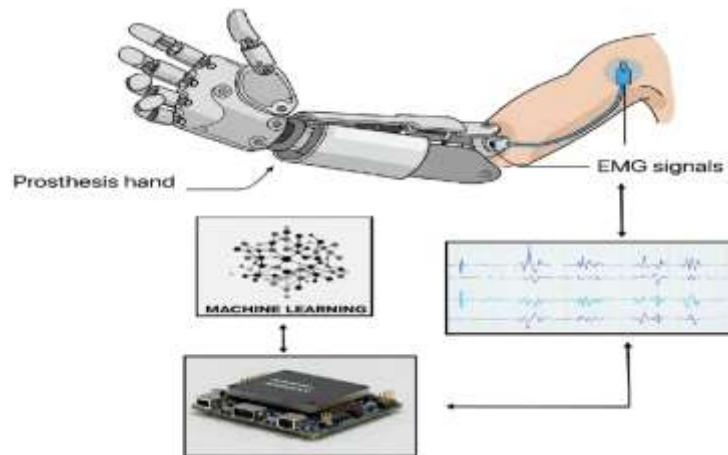


Figure 10: EMG-based prosthetic control (Abdikenov et al., 2025)

When acquired under SENIAM-compliant protocols, these recordings serve as reliable training datasets for machine learning approaches including Weighted Neural Networks (WNNs) and Radial Basis Function Networks (RBNs), which benefit from reduced noise contamination across channels (Yousefi and Hamilton-Wright, 2014). WNNs, in particular, maintain high tolerance for waveform variability while preserving decision accuracy above 90 %, provided channel quality remains consistent. This makes them suitable not only for laboratory evaluation but also for real-time operation in everyday use cases where environmental conditions cannot be fully controlled. The influence of ISEK standards is equally meaningful here. By requiring detailed reporting of acquisition parameters, such as amplifier characteristics, high- and low-pass filter cut-offs, and sampling rates, researchers create comprehensive metadata sets that allow downstream analysts and developers to interpret signal behavior in full context (Pullman et al., 2000). Such contextualization becomes vital when integrating datasets gathered on different hardware platforms or under varied environmental conditions. For example, robotic control algorithms trained using signals filtered at 20 Hz high-pass will differ subtly in responsiveness compared to those trained with a higher cut-off; without explicit documentation of this difference, software adaptation across devices would remain error-prone. In prosthetics applications for trans-radial amputees, the majority group among upper limb loss patients, it is common to depend on myoelectric control driven by sEMG collected from residual forearm muscles (Atzori et al., 2014a).

SENIAM's electrode maps ensure these muscles are targeted consistently across fittings, avoiding misalignment that could mislead machine learning algorithms into mapping incorrect activation patterns to intended movements. As commercial offerings introduce mechanically sophisticated multi-degree-of-freedom hands capable of programmable movements, the value of this consistency grows: each degree of freedom adds potential overlap or confusion between signal classes if inputs vary excessively between sessions. Beyond static laboratory trials, portable acquisition units have opened the possibility for prosthetic control training in real-world contexts outside clinical supervision. This expansion increases opportunities for adaptive learning, where algorithms continuously refine their movement mappings as they accumulate user data, but also elevates susceptibility to noise from motion artifacts and changing electrode contact quality (Atzori et al., 2014b). Here, ISEK's emphasis on transparent recording practices acts as a safeguard: dataset annotations noting the conditions under which signals were captured allow developers to weight observations appropriately during model updates. From a robotics perspective, myoelectric signals acquired under standardized conditions feed directly into force control strategies and movement recognition subsystems. This is especially relevant where prosthetic hands incorporate haptic feedback loops or adjustable grip force settings based on detected muscular effort (Atzori et al., 2014a).

Reliable sEMG recordings collected via SENIAM protocols enable responsive modulation without erratic force spikes that could damage objects or cause discomfort to users. Moreover, combining surface EMG with intramuscular readings provides multi-layered activation profiles: surface channels capture global muscle activity patterns while fine-wire electrodes reveal compartment-specific recruitment details vital for precise control adjustments. Functional Electrical Stimulation (FES) interventions provide an adjacent case highlighting why standardized acquisition benefits robotic rehabilitation aids. In scenarios where FES is used alongside robotic exoskeletons to restore mobility functions, such as

mitigating foot drop, the timing between detected voluntary muscle activity and stimulator output affects gait improvement outcomes (Prenton *et al.*, 2018). Standardized sEMG ensures correct phase detection within gait cycles, enabling synchronized assistive force application rather than misaligned stimuli that might disrupt locomotion. Some studies even suggest neural adaptations following FES use persist without the device present; parsing whether these gains result from direct rehabilitation effects versus mechanical assistance demands precise longitudinal data framed by well-documented acquisition methods.

Ethical considerations intersect strongly with device usability in this domain. Data privacy provisions gain tangible importance when prosthetic control systems record continuous bioelectrical data during routine activities. Detailed sensor metadata, mandated through ISEK reporting, not only supports technical troubleshooting but also forms part of informed consent disclosures explaining what physiological signals are recorded and how they may be processed or stored (Pullman *et al.*, 2000). User trust hinges on transparency regarding measurement scope and duration, particularly when recordings might inadvertently capture sensitive patterns revealing health status changes. Ultimately, robotics and prosthetics research leveraging SENIAM and ISEK standards achieves a dual objective: building reliable control architectures capable of fine-grained human-machine interaction while maintaining interpretive clarity across evolving technological environments. The structured anatomical placement protocols anchor signal integrity over time; the rigorous documentation requirements preserve analytical coherence regardless of hardware innovation or situational constraints. This combination allows iterative algorithmic refinement without sacrificing reproducibility, a requirement not just for scientific rigor but also for ensuring daily-life usability where adaptive intent decoding must operate seamlessly amid inevitable variations in usage context (Gopura *et al.*, 2018).

5 Ethical Considerations

Ethical concerns in myoelectric research branch directly from the intimate nature of the physiological data being collected, as well as the context in which such data is acquired, stored, and analyzed. The recording of electromyographic activity, whether through surface electrodes or invasive fine-wire techniques, constitutes the capture of sensitive biological information that may carry implications beyond immediate research goals (Glannon, 2016). These signals can reveal neuromuscular health status, subtle changes in motor control indicative of disease progression, or unintended insights into participant behavior patterns. Because of this potential, ethical protocols must treat EMG data not merely as anonymous numerical sequences but as personally identifying physiological profiles warranting protection both at acquisition and after analysis (Campel *et al.*, 2020). A foundational principle is informed consent, which must be more than a formality. Participants should comprehend not only the general purpose of the study but also the specific types of physiological signals recorded, the anatomical sites involved, and any associated discomforts or risks, particularly with invasive methods like fine-wire EMG (Onmanee, 2016). For surface recordings guided by SENIAM positional maps, risks are minimal compared to needle-based insertions; however, transparency around electrode placement remains important for ensuring participants' comfort and agency (Hermens *et al.*, 2000). Consent processes should explicitly cover how raw EMG files and extracted features will be stored, processed, and potentially shared across institutions. ISEK's reporting conventions indirectly support this by requiring detailed acquisition documentation (Pullman *et al.*, 2000), yet ethical practice dictates that such documentation is also conveyed to participants where relevant. This transparency cultivates trust and aligns with medical ethics principles aiming to minimize harm. The use of standardized frameworks has another ethical dimension: they impose procedural discipline that inherently reduces risks linked to poor technique. For instance, correct placement under SENIAM decreases chances of unnecessary discomfort due to repeated repositioning attempts and helps avoid inadvertent stimulation of adjacent tissue during FES trials (Prenton *et al.*, 2018).

In rehabilitation settings where electrode configurations evolve over time due to patient mobility constraints (Atzori *et al.*, 2014a), deviations from standard layouts should be carefully documented along ISEK lines so that any observed changes in clinical outcomes can be interpreted without conflating them with methodological inconsistency. Ethical responsibility thus extends into methodological rigor; sloppiness can obscure genuine treatment effects and mislead clinicians when adjusting therapy plans. Data privacy takes on heightened importance when prosthetics or robotics applications employ continuous sEMG monitoring during daily activities (Stegeman and Hermens, 1999).

Persistent recording systems inevitably capture incidental moments outside intended trial tasks, gestures conveying emotional states or involuntary muscle twitches, and these could be sensitive if linked to other personal identifiers. Secure storage protocols must therefore consider encryption both in transit and at rest, with access restricted to authorized personnel whose roles are defined within institutional review board (IRB) agreements (Zuhri *et al.*, 2025). An ethically sound workflow involves anonymizing datasets before algorithmic training so that no residual markers remain tying activation profiles to individual identities. Participant autonomy also intersects with device usability ethics. In scenarios where machine learning algorithms progressively adapt prosthetic responses based on accumulated sEMG patterns (Yousefi and Hamilton-Wright, 2014), users should retain choices over whether their ongoing bio-data feeds back into model refinement beyond initial calibration phases. Opt-out mechanisms need technical feasibility built into device firmware rather than existing only as informal verbal agreements; absent such design considerations, consent becomes static rather than dynamic over the life cycle of participation. Vulnerability in certain populations, such as post-stroke patients undergoing gait evaluation, imposes further obligations. For example, when assessing foot drop correction via FES-assisted walking trials (Prenton *et al.*, 2018), differences between neural recovery and purely mechanical assistance require clear communication.

Misinterpretation might lead participants to believe they have achieved permanent improvement when in fact gains rely on ongoing device support, a scenario touching upon psychological harm if reality later contradicts expectation. Ethical reflection also reaches meta-research stages. Public repositories aggregating sEMG datasets can accelerate scientific progress but must balance openness against privacy concerns. Following ISEK's emphasis on methodological transparency ensures datasets contain rich metadata about acquisition parameters without embedding participant-

identifiable content (Pullman *et al.*, 2000). When cross-site pooling involves invasive measurements like fine-wire EMG, additional sensitivity arises from the potential linkage between anatomical specificity of insertion sites and unique individual traits such as scar patterns or injury history. In training classifiers for rehabilitation robotics under SENIAM-compliant recordings (Stegeman and Hermens, 1999), equitable performance across demographic groups forms part of fairness ethics: algorithms must not inadvertently bias control accuracy toward specific muscle morphologies or skin impedance ranges common among certain ethnicities or age brackets. This calls for diverse participant sampling during dataset construction and disclosure within methodological reports regarding population composition, a requirement that dovetails with ISEK's structured documentation standards.

Finally, adapting experimental setups for ecologically valid scenarios outside laboratory confines raises situational ethics questions (Atzori *et al.*, 2014a). Portable units deployed at home collect data under less controlled conditions where ambient noise or daily routines may introduce atypical artifacts; ensuring participants understand these factors can affect interpretation prevents misattribution in therapeutic reviews. Recording environmental context alongside EMG readings aids both scientific clarity and ethical obligation to avoid misleading conclusions about intervention success. Ethics in myoelectric research is thus woven tightly through every operational stage, from preparatory disclosure and procedural adherence aligned with SENIAM maps to rigorous metadata logging per ISEK guidance, culminating in secure stewardship of sensitive neuromuscular records. The confluence of technical standardization and ethical diligence creates conditions where innovation in prosthetics, rehabilitation, and related fields proceeds without compromising participant welfare or autonomy while retaining analytical credibility grounded in reproducible science (Onmanee, 2016).

6 CONCLUSION

The integration of standardized frameworks for electromyographic data acquisition and reporting has established a foundational platform that enhances the reliability and comparability of neuromuscular research across diverse applications. By adhering to precise anatomical electrode placement protocols, consistent inter-electrode distances, and alignment relative to muscle fibers, researchers and clinicians can minimize variability introduced by operator-dependent factors and environmental influences. This spatial consistency is essential for generating reproducible datasets that support advanced computational modeling, machine learning classification, and biomechanical analyses.

Complementing these procedural standards, comprehensive documentation of acquisition parameters, including sensor types, filtering characteristics, and sampling rates, ensures transparency and interpretive clarity. Such detailed reporting enables effective integration of heterogeneous datasets, facilitates meta-analyses, and supports the development of adaptive algorithms capable of functioning reliably in both controlled laboratory settings and real-world environments. The synergy between precise physical setup and exhaustive metadata recording addresses challenges posed by portable acquisition systems and variable testing conditions, preserving data integrity despite practical constraints.

Clinical and rehabilitation contexts benefit from this dual approach by enabling accurate monitoring of neuromuscular function over time, supporting therapeutic decision-making, and enhancing the efficacy of interventions such as functional electrical stimulation and prosthetic control. The ability to distinguish genuine physiological changes from methodological artifacts is critical for tracking recovery trajectories, assessing disease progression, and tailoring individualized treatment plans. In robotics and prosthetics, standardized myoelectric inputs underpin the development of intuitive control systems that translate muscle activation patterns into precise device movements, improving user experience and functional outcomes. Consistent electrode placement and detailed acquisition metadata reduce classification errors and facilitate algorithmic refinement, which is especially important for multi-degree-of-freedom prosthetic devices operating in dynamic, everyday contexts.

Ethical considerations are deeply intertwined with these technical standards. Transparent communication about data collection methods, potential risks, and data usage fosters participant trust and aligns with principles of minimizing harm and respecting autonomy. Secure data handling practices and informed consent processes that encompass both procedural details and privacy safeguards are essential, particularly as continuous monitoring and adaptive algorithms become more prevalent. Attention to demographic diversity and equitable algorithm performance further ensures fairness in clinical and assistive technologies.

Overall, the harmonization of spatially explicit acquisition protocols with comprehensive reporting requirements creates a cohesive framework that supports scientific rigor, clinical utility, and ethical responsibility. This integrated approach enables the neuromuscular research community to advance knowledge, improve therapeutic interventions, and develop sophisticated human-machine interfaces while maintaining consistency and transparency across studies and applications. Continued adherence to and refinement of these standards will be instrumental in addressing ongoing challenges and maximizing the impact of electromyographic methodologies in both research and practical domains.

REFERENCES

1. Hermens, H.J., Freriks, B., Merletti, R., Stegeman, D., Blok, J., Rau, G., Disselhorst-Klug, C. and Hägg, G., 1999. European recommendations for surface electromyography. *Roessingh research and development*, 8(2), pp.13-54.
2. Stegeman, D. and Hermens, H., 2007. Standards for surface electromyography: The European project Surface EMG for non-invasive assessment of muscles (SENIAM). *Enschede: Roessingh Research and Development*, 10(8), pp.108-112.
3. Hermens, H.J., Freriks, B., Disselhorst-Klug, C. and Rau, G., 2000. Development of recommendations for SEMG sensors and sensor placement procedures. *Journal of electromyography and Kinesiology*, 10(5), pp.361-374.
4. Onmanee, P., 2016. *Development and Application of a Protocol for Fine-Wire and Surface EMG Data Collection as Part of Clinical Gait Assessment*. University of Salford (United Kingdom).
5. Garikayi, T., Van den Heever, D. and Matope, S., 2018. Analysis of surface electromyography signal features on osteomyoplastic transtibial amputees for pattern recognition control architectures. *Biomedical Signal Processing and Control*, 40, pp.10-22.

6. Putra, D.S., Weru, Y.U.W. and Fitriady, 2019, April. Pattern recognition of electromyography (EMG) signal for wrist movement using learning vector quantization (LVQ). In *IOP Conference Series: Materials Science and Engineering* (Vol. 506, No. 1, p. 012020). IOP Publishing.
7. Wang, L. and Buchanan, T.S., 2002. Prediction of joint moments using a neural network model of muscle activations from EMG signals. *IEEE transactions on neural systems and rehabilitation engineering*, 10(1), pp.30-37.
8. Choi, H.S., 2023. Electromyogram (EMG) signal classification based on light-weight neural network with FPGAs for wearable application. *Electronics*, 12(6), p.1398.
9. Yousefi, J. and Hamilton-Wright, A., 2014. Characterizing EMG data using machine-learning tools. *Computers in biology and medicine*, 51, pp.1-13.
10. Atzori, M., Gijsberts, A., Castellini, C., Caputo, B., Hager, A.G.M., Elsig, S., Giatsidis, G., Bassetto, F. and Müller, H., 2014. Electromyography data for non-invasive naturally-controlled robotic hand prostheses. *Scientific data*, 1(1), p.140053.
11. Merletti, R., 2000. Surface electromyography: The SENIAM project. *European Journal of Physical and Rehabilitation Medicine*, 36(4), p.167.
12. Zieliński, G. and Gawda, P., 2024. Surface Electromyography in Dentistry—Past, Present and Future. *Journal of Clinical Medicine*, 13(5), p.1328.
13. Ladegaard, J., 2002. Story of electromyography equipment. *Muscle & Nerve: Official Journal of the American Association of Electrodiagnostic Medicine*, 25(S11), pp.S128-S133.
14. Pitt, M.C. and Jabre, J., 2018. The problem of lack of normative data in paediatric EMG and possible solutions. *Clin Neurophysiol*, 129(3), pp.672-675.
15. Gentil, M. and Moore, W.H., 1997. Electromyography. *Instrumental clinical phonetics*, pp.64-86.
16. Hermens, H.J., Freriks, B., Merletti, R., Stegeman, D., Blok, J., Rau, G., Disselhorst-Klug, C. and Hägg, G., 1999. European recommendations for surface electromyography. *Roessingh research and development*, 8(2), pp.13-54.
17. Armijo-Olivo, S., Gadotti, I., Kornerup, M., Lagravère, M.O. and Flores-Mir, C., 2007. Quality of reporting masticatory muscle electromyography in 2004: a systematic review. *Journal of Oral Rehabilitation*, 34(6), pp.397-405.
18. Pullman, S.L., Goodin, D.S., Marquinez, A.I., Tabbal, S. and Rubin, M., 2000. Clinical utility of surface EMG [RETIRED] Report of the Therapeutics and Technology Assessment Subcommittee of the American Academy of Neurology. *Neurology*, 55(2), pp.171-177.
19. Garikayi, T., Matope, S. and van den Heever, D., 2015. Development of an Adaptive Controller for Lower Limb Rehabilitation Device. *Int. J. Mech. Eng. Autom*, 2(6), pp.245-256.
20. De Luca, C.J., Adam, A., Wotiz, R., Gilmore, L.D. and Nawab, S.H., 2006. Decomposition of surface EMG signals. *Journal of neurophysiology*, 96(3), pp.1646-1657.
21. Semciw, A.I., Neate, R. and Pizzari, T., 2014. A comparison of surface and fine wire EMG recordings of gluteus medius during selected maximum isometric voluntary contractions of the hip. *Journal of Electromyography and Kinesiology*, 24(6), pp.835-840.
22. Polachan, K., Chatterjee, B., Weigand, S. and Sen, S., 2021. Human body–electrode interfaces for wide-frequency sensing and communication: A review. *Nanomaterials*, 11(8), p.2152.
23. Garikayi, T., Van Den Heever, D. and Matope, S., 2017. Investigating the effects of passive mechanical ankle on unilateral osteomyoplastic transtibial amputees. *Journal of Musculoskeletal Research*, 20(03), p.1750015.
24. Prenton, S., Hollands, K.L., Kenney, L.P. and Onmanee, P., 2017. Functional electrical stimulation and ankle foot orthoses provide equivalent therapeutic effects on foot drop: A meta-analysis providing direction for future research. *Journal of rehabilitation medicine*.
25. Hermens, H.J., Freriks, B., Disselhorst-Klug, C. and Rau, G., 2000. Development of recommendations for SEMG sensors and sensor placement procedures. *Journal of electromyography and kinesiology*, 10(5), pp.361-374.
26. Rainoldi, A., Melchiorri, G. and Caruso, I., 2004. A method for positioning electrodes during surface EMG recordings in lower limb muscles. *Journal of neuroscience methods*, 134(1), pp.37-43.
27. Day, S., 2002. Important factors in surface EMG measurement. *Bortec Biomedical Ltd publishers*, pp.1-17.
28. Merlo, A., Bo, M.C. and Campanini, I., 2021. Electrode size and placement for surface EMG bipolar detection from the brachioradialis muscle: a scoping review. *Sensors*, 21(21), p.7322.
29. McManus, L., De Vito, G. and Lowery, M.M., 2020. Analysis and biophysics of surface EMG for physiotherapists and kinesiologists: Toward a common language with rehabilitation engineers. *Frontiers in neurology*, 11, p.576729.
30. Gopura, R., Kiguchi, K., Mann, G.K. and Torricelli, D., 2018. Robotic Prosthetic Limbs. *J. Robotics*, 2018, pp.1085980-1.
31. Abdikenov, B., Zholtayev, D., Suleimenov, K., Assan, N., Ozhikenov, K., Ozhikenova, A., Nadirov, N. and Kapsalyamov, A., 2025. Emerging frontiers in robotic upper-limb prostheses: Mechanisms, materials, tactile sensors and machine learning-based EMG control: A comprehensive review. *Sensors*, 25(13), p.3892.
32. Glannon, W., 2016. Ethical issues in neuroprosthetics. *Journal of Neural Engineering*, 13(2), p.021002.
33. Campbell, E., Phinyomark, A. and Scheme, E., 2020. Current trends and confounding factors in myoelectric control: Limb position and contraction intensity. *Sensors*, 20(6), p.1613.
34. Zuhri, S., Suhendrianto, S. and Erwan, F., 2025. Designing a myoelectric prosthetic arm for trans-radial amputation based on Indonesian anthropometric data. *International Journal of Product Development*, 29(3-4), pp.299-310.