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Reliable sEMG Motor Intent Perception for Upper Limb Rehabilitation Robots

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Abstract. For upper limb rehabilitation robots, surface electromyography (sEMG) is an essential signal source to assess motor-intent perception by the patients; however, the signals collected from patients are noisy and are different from person to person. Stable intent recognition is thus important with the use of reliable signal processing. This review poses the question of what denoising and information enhancement can do for sEMG-based motor-intent perception. It first outlines the origins of the instability of intent signals and the measures for denoising assessment, and then presents the performance and cost of three categories of methods, namely the classical denoising methods, the learning-based robustness enhancement methods and the multi-sensor information fusion methods. The three families are used to handle different stages of the problem and are not mutually exclusive—task-level metrics should be used to judge the methods, and they can be added in stages as needed. The comparison shows the amount of signal processing needed for a given task and the underlying evidence that supports translation from fixed filtering to a learned model or to additional sensing, for designers of upper-limb rehabilitation systems. The key questions that remain to be answered are cross-session generalization, cross-subject generalization, quantitative attribution of denoising gains to recognition performance, lightweight online deployment and long-term stability and individual weighting of multi-sensor fusion.

Keywords: upper-limb rehabilitation robot, surface electromyography, motor-intent perception, signal denoising, multi-sensor fusion

1. Introduction

Upper-limb dysfunction is often caused by stroke, spinal cord injury, amyotrophic lateral sclerosis (ALS), and other illnesses. Wearable upper-limb rehabilitation robots support rehabilitation training and assist movement [1]. Their usefulness depends in part on recognizing the patient's intended movement, such as holding a cup, before the movement starts, since this timing affects the safety of assistance and the force applied. Surface electromyography (sEMG) is a commonly used signal source for upper-limb motor-intent perception because it reflects neuromuscular drive before visible movement begins [2].

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The issue has been tackled from several aspects by different studies. Nassour et al. studied ALS patients with severe hand paralysis and achieved a 97.1% sensitivity for detecting grasp-intention from residual (low SNR) EMG [3]. Islam et al. employed transfer learning to enhance the inter-session and inter-subject sEMG gesture recognition [4]. Cimolato et al. integrated fingertip force sensing with neural electrical stimulation in a closed-loop perception-stimulation for hand function, as sEMG alone is not sufficient [5]. The previous reviews are classified according to the modality of the senses or according to the prediction framework [1, 6]; relatively few reviews classify the field from the perspective of denoising and enhancement of the information for the perception of motor-intent. However, patient signals are noisy and this varies from patient to patient, making reliable signal processing an important step towards recognition.

This paper will thus target upper-limb rehabilitation robots and ask the questions of denoising and information enhancement for motor-intent perception using sEMG. The field is organized by first the requirement of the task and second the method to perform the task; the paper first presents the sources of instability on the intention signal and the metrics to evaluate the robustness of the methods, then discusses classical denoising, learning-based robustness enhancement, and multi-sensor information fusion under three task scenarios. Finally, it includes selection criteria and open problems that can be used as a guide to design sensing systems.

2. Electromyography-based motor-intent perception

2.1. Surface electromyographic signal characteristics

The motor neurons are activated by motor commands from the brain or the spinal cord and the action potentials of many muscle fibers propagate through tissue and reach the skin surface, as the surface electromyography (sEMG) signal – before the movement is visible [2]. There are three properties of this signal that are important for denoising. It has a low amplitude and is hard to discern above the noise level. It can be frequency domain filtered as its frequency band is approximately 10–500 Hz with most energy concentrated in the 20–150 Hz region. The waveform is random and varies according to the contraction force and fatigue; therefore, denoising methods need to adapt to the signal over time [6].

2.2. Denoising requirements for intent detection

The tasks can be divided into three categories based on their output and difficulty to recognize, and hence require different denoising actions: Grasp intention decoding produces grasp categories and force for hand exoskeletons and prosthetic hands. In the case of severely paralyzed patients, the residual EMG is weak, and denoising should take care to retain the intention information even in low SNR case [3]. Continuous action recognition is for wrist and elbow exoskeletons to generate the gestures or gesture sequences. Here, the signal can vary from session to session and with fatigue; people are different, so denoising should suppress noise, yet follow the variation of the signal [4]. The movement onset detection only provides the time at which the movement starts (for upper limb exoskeletons). It should be both sensitive and specific, and denoising and detection should be finished within milliseconds [7]. sEMG activation patterns are also not one-to-one with actions and, when a task requires contact force or joint posture, sEMG alone may not be enough and other sensing information is needed [5]. The three task types and differentiated requirements are compared in Figure 1.

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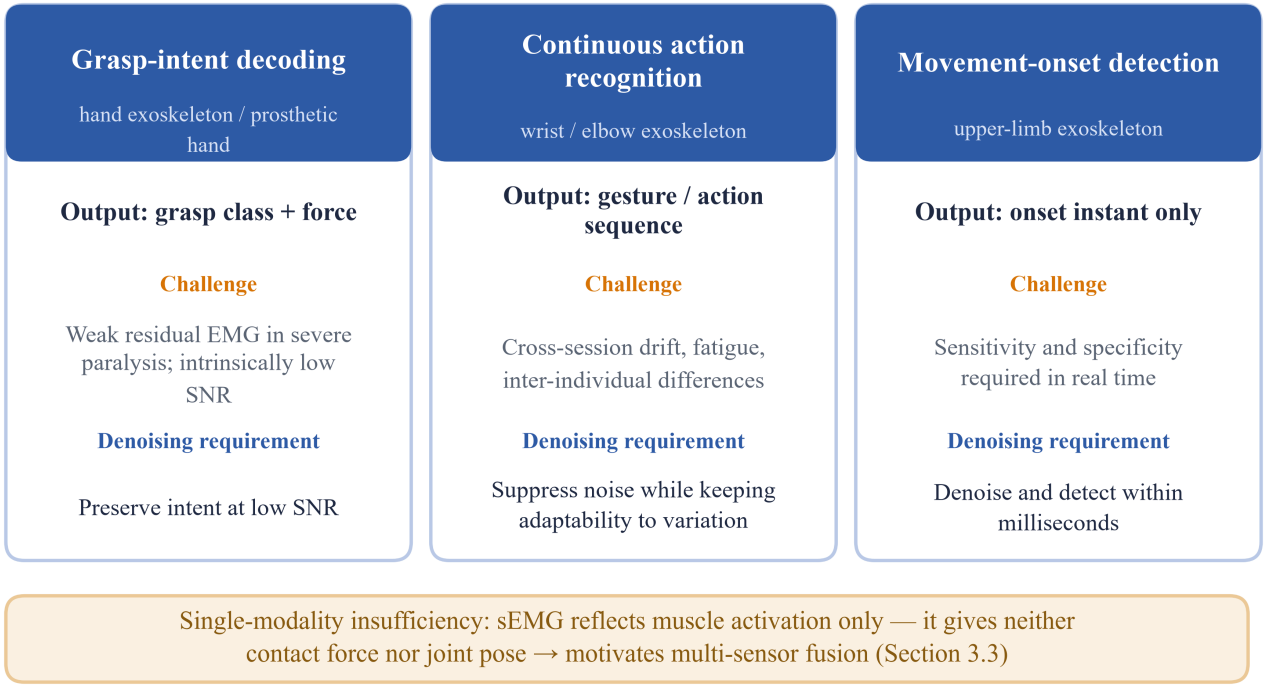


Figure 1. Three task categories in sEMG-based intent detection and their differentiated denoising requirements [3, 4, 7]

2.3. Noise propagation paths and key sources of instability

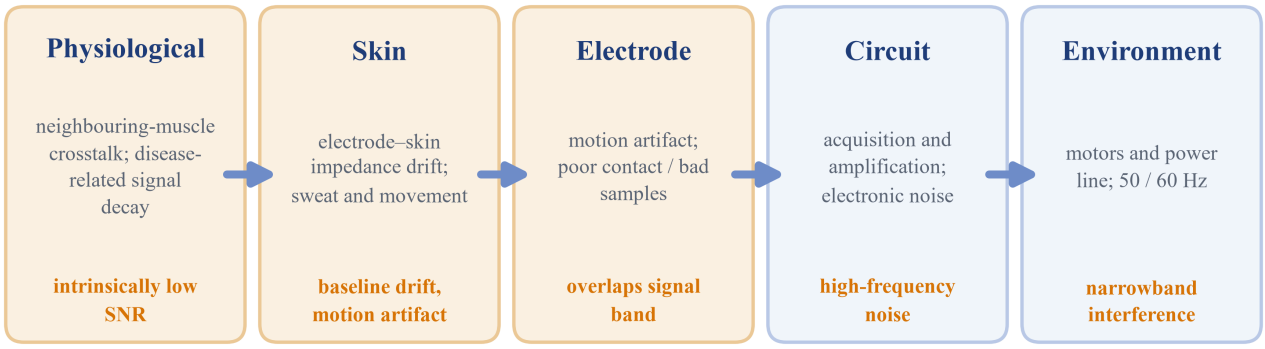


Figure 1. Three task categories in sEMG-based intent detection and their differentiated denoising requirements [3, 4, 7]

Disturbances of sEMG can be added at three stages: generation, conduction, and acquisition. Physiologically, SNR can be intrinsically low due to signals from adjacent muscles and degradation of the EMG signal due to the disease (e.g. very weak EMG signal in severely paralyzed patients) [3]. A significant source of instability is the skin-electrode interface: this changes with sweating and movement of the electrode resulting in baseline drift and motion artifacts. The frequency range of these artifacts overlaps the signal and they are most obvious during limb movement, and cannot be filtered out by itself [8]. The addition of acquisition and amplification introduces electronic noise while environmental motor and power-line interference at 50/60 Hz introduce narrowband interference [6]. In addition to signal contamination, non-stationarity also impacts recognition;

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fatigue causes the spectrum to move towards lower frequencies, while electrode displacement alters the statistics of the signal to the same action across sessions [4]. The significant interferences along the generation-conduction-acquisition path are illustrated in Figure 2.

2.4. Core evaluation metrics for denoising performance

The denoising performance is evaluated at two levels (Table 1). Signal-level metrics reflect the amount of contamination that is removed; task-level metrics assess the extent to which denoising helps in motor-intent perception.

Table 1. Evaluation metrics for denoising performance

Level	Metric	What it measures	Applicabletask	Reference
Signal	Signal-to-noise ratio (SNR); mean squared error (MSE)	SNR quantifies signal strength relative to noise; MSE quantifies deviation from a reference or clean signal when available	General; continuousestimation	[9]
Task	Classificationaccuracy (or F1)	Accuracy is the proportion of correct classifications; F1 is the harmonic mean of precision and recall	Grasp intention decoding	[10]
Task	Sensitivity, specificity	Reliable triggering when required, without false triggers	Movementonset detection	[3]
Task	Decision latency	Processing time, determining whether real-time closed-loop control is met	Onset detection, real-time control	[7]
Task	Inter-session, inter-subject accuracy	Whether accuracy holds across subjects and sessions	Continuous movementrecognition	[4]

Three points matter. A cleaner signal does not always give more accurate recognition, so the method comparison below uses task-level metrics as its benchmark. If SNR improvement is reported for grasping, amplitude and waveform fidelity should also be examined as smoothing can result in loss of signal as well as noise and lead to a false impression of improvement. In movement onset detection, the sensitivity and specificity will be in a compromise as the threshold varies, and denoising will only work if it increases both at once [3, 7]. The different number of channels in the existing methods, the different definition of the task and the different inputted data set, are also the limitations to make cross-study comparison and clinical application difficult, and are discussed in Section 4.

3. sEMG denoising and information enhancement

3.1. Classical denoising for low-snr signals

This group of scenarios includes grasp intention decoding and movement onset detection in hand exoskeletons. Patients with severe paralysis have weak residual EMGs, with an inherently small SNR, and the wearable side has limited computing power; thus, processing should add as little latency as possible [3]. Classical denoising methods do not require training and have fixed parameters; thus, they are a natural baseline for the present problem. Moving average and sliding window root mean square (RMS) each averages a time window to reduce random jitter and provide an approximation of the amplitude of the EMG. Median filters take the median value of the window and are used to remove the bad-sample jumps caused by poor electrode contact [6]. Frequency-domain filtering uses the frequency gap between signal and noise: most EMG energy lies in 20–150 Hz, so low-pass filtering removes high-frequency electronic noise and notch filtering removes 50/60

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Hz power-line interference. Wavelet denoising is appropriate for any application that requires maintaining the sharpness of the onset of motion since it involves time-frequency analysis and shrinking noise while maintaining the sharpness of the edges of waveforms [6]. Table 2 provides a list of the methods of all three routes combined, the problem each addresses and the primary limitation.

Table 2. Overview of the three method routes: representative methods, problems addressed, and main limitations

Category	Representative method	Problem addressed	Main limitation	Representative reference
Classical denoising	Moving average; sliding-window RMS	Random jitter; amplitude estimation	Blurs abrupt transients; adds latency	[9]
Classical denoising	Median filtering	Bad samples and jumps	Limited effect on Gaussian noise	[6]
Classical denoising	Low-pass and notch filtering	High-frequency noise; power-line interference	Fails when signal and noise bands overlap	[8]
Classical denoising	Wavelet denoising	Keeps the abrupt onset of movement	Basis choice relies on experience	[6]
Learning-based robustness enhancement	Deep learning	Non-stationarity; fine-grained decoding; class imbalance	Needs labeled data and compute; performance may drop under distribution shift	[10]
Learning-based robustness enhancement	Transfer learning / domain adaptation	Cross-session and cross-individual drop	Transfer between individuals is incomplete	[4]
Multi-sensor information fusion	Complementary filtering	Stabilizes IMU posture/orientation features before fusion	No strict optimality; relies on parameter tuning	[11]
Multi-sensor information fusion	Kalman filter (KF) family: EKF / AKF	Combines model predictions and measurements; smooths state estimates	Needs noise statistics; nonlinear cases need variants	[12]
Multi-sensor information fusion	Force/tactile sensing with closed-loop feedback	Adds contact information	Adds hardware and synchronization; feedback strategy is application-specific	[13]

Two studies exemplify the application limits, not denoising performance per se. Nassour et al. proposed a two-stage strategy of adaptive-threshold coarse detection and CNN error correction for ALS patients with severe hand paralysis for grasp-intent decoding [3]. The threshold is dynamically moved together with a reference window to capture weak grasp intent, and the network then reconsiders the threshold output to rule out false triggering. The sensitivity and specificity were 97.1% and 99.6%. To detect movement onset, Trigili et al. identified movement onset in grasping tasks using an EMG-based upper-limb exoskeleton and provided millisecond-level real-time criteria for triggering [7]. These studies give the lower bounds for the SNR and latency requirements the front-end denoising stage must meet. However, classical denoising also has some obvious drawbacks: sharp transients are blurred by moving averages, latency is introduced by filtering in the time domain, frequency-domain filtering is not applicable if the motion artefacts overlap the signal band, and the wavelet basis is to be determined by experience [6]. It hence adapts best as a baseline under low SNR conditions and is unsuitable by itself to cope with the time-varying nature and inter-individual differences of the signal.

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3.2. Learning-based enhancement for signal variability

In this group, the recognition of continuous gestures and movements is addressed in wrist and elbow exoskeletons and prosthetic hands. It is not weak signal strength that is the issue here, it is signal variability. The EMG for the same movement varies across sessions due to fatigue and as the electrodes move, the distribution of the signal in each patient may be very different, and samples of important transitional movements may be rare, leading to class imbalance [10]. The least mean squares (LMS) or recursive least squares (RLS) adaptive filters are better thought of as adaptive signal processing as opposed to machine learning: they are continuously modified with the error signal, and thus represent an intermediate step between fixed filtering and error-driven robustness enhancement through learning.

The deep learning model can discriminate gestures directly from the signal and it can learn representations from large labeled data sets. To reduce performance degradation from one session/one subject to another, transfer learning or domain adaptation refers to adapting patterns learned from source data to a new session or subject with limited target data [4]. The primary learning-based techniques are included in Table 2 with the other two paths.

Here are two recent examples. Ni et al. overviewed the methods of hand-gesture recognition using sEMG, along with the challenges of robustness, public databases, application and deep learning [10]. Islam et al. demonstrated that using transfer learning technique with lightweight conv model can enhance the inter-session and inter-subject gesture recognition [4]. The boundaries of learning-based enhancement are also well known: the need for training data, the need for computation and the possibility of a drop in accuracy from session to session and from one subject to another. Therefore, validation on the targeted patient population and deployment condition is key. Learning-based methods can better cope with distribution change, but are more data and computation intensive than fixed filters. The overall results of adaptive filtering and transfer-learning-based adaptation are summarized as in Figure 3.

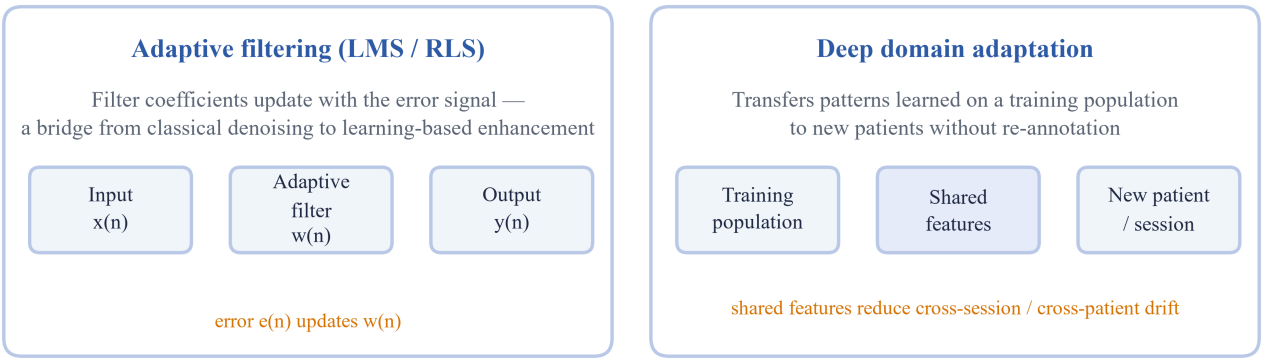


Figure 3. Learning-based robustness enhancement: adaptive filtering and deep domain adaptation [4, 14]

3.3. Multi-sensor fusion for missing information

This group covers hand-intent perception and grasp contact feedback. There the problem is missing information, because EMG just measures the activation of the muscles, and not their contact force or the posture of the joints, and the signal is influenced by sweating and fatigue, which makes it unfeasible to use EMG for fine-grained hand control [2]. Multi-sensor fusion serves to bridge this gap, whereby sources are combined that complement each other. These are the three types of

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sensing: EMG for the lead time of intent, inertial measurement unit (IMU) for long-term stable posture, and force or tactile sensing for contact feedback.

Two types of processing should be distinguished. The first concerns sensor-state estimation. Complementary filtering combines low- and high-frequency information from inertial sensors and can provide a more stable posture estimate before that information is combined with sEMG [11]. The Kalman filter (KF) family combines model predictions with measurements according to their uncertainty; extended Kalman filter (EKF) and adaptive Kalman filter (AKF) variants are used for nonlinear models or uncertain noise statistics [12]. The second is a closed-loop application extension rather than a fusion algorithm itself. Fingertip force sensing with neural electrical stimulation can return contact information during grasping [5]. Mechanical multi-axis force sensing can also link contact sensing to compliant actuation [13]. These examples show how information missing from sEMG can be supplied by additional sensing and feedback pathways.

There is an economic cost to fusion enhancement too. Multi-source data needs to be synced, modality-specific errors need to be addressed, and mechanisms for robustness against sensor failure are needed [14]. The Kalman family also needs to make proper state model and noise assumptions [12]. Table 2 lists the main fusion methods alongside the other two routes, and Figure 4 shows the complementary sources and the two method families.

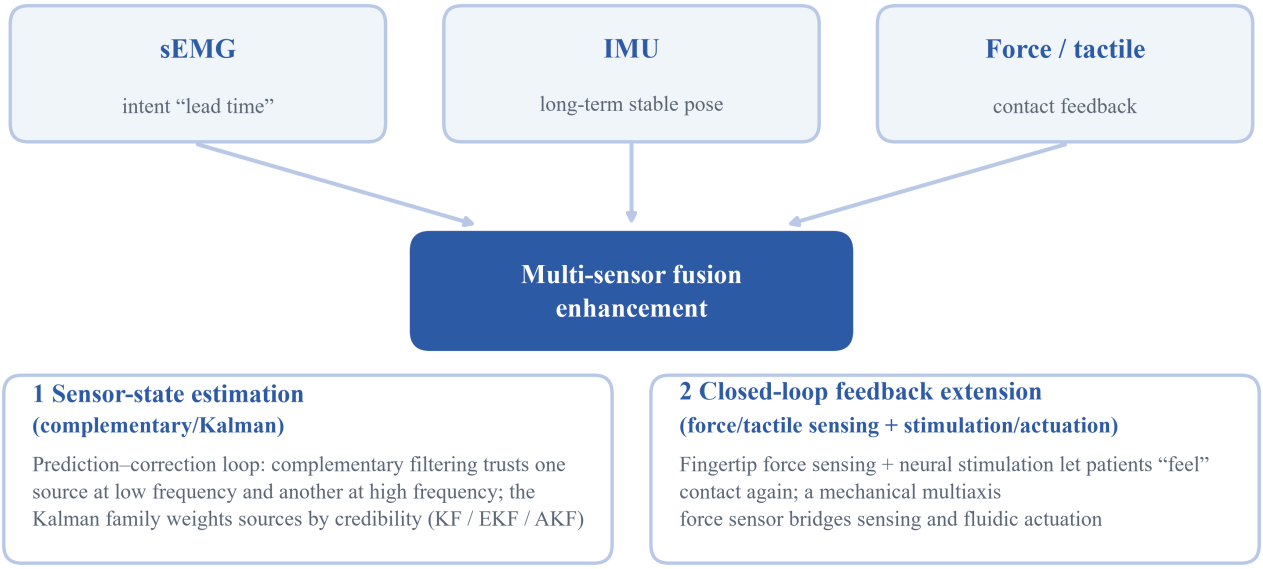


Figure 4. Multi-sensor fusion enhancement: complementary sources and the two method families [5, 13]

3.4. Method comparison and summary of recognition performance

The three classes of methods correspond to three different scenarios and thus it is best to compare them on task-level measures; a cleaner signal does not necessarily correspond to more accurate recognition. This section thus compares them on the basis of the main effect as opposed to SNR improvement alone. There is a compromise in every route. Classical denoising is non-trainable, has fixed parameters, and is interpretable. It is used in constrained wearable devices due to its low computation complexity; however, it is not very adaptive to time-varying signals. Learning-based enhancement is good for non-stationarity and inter-individual differences, but requires data and computation and may not be accurate in the presence of distribution shift. Multi-sensor fusion can

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close the gap of one sensor, and it can enhance the robustness, while the problems of sensor synchronization and sensor weighting and sensor fault tolerance are increased. A summary of the comparison is given in Table 3.

Table 3. The three routes compared by problem, typical route, main advantage, and main limitation

Problem	Typical route	Main advantage	Main limitation
Weak signal (low SNR)	Classical denoising	No training, interpretable, low cost on wearable hardware	Adapts poorly to time-varying signals; fails when noise overlaps the signal band
Changing signal (non-stationarity, inter-individual differences, class imbalance)	Learning-based robustness enhancement	Adapts to distribution change; fine-grained discrimination	Needs data and computation; performance may drop under distribution shift
Insufficient information (missing contact force or joint posture)	Multi-sensor information fusion	Fills in posture and contact information; supports a perception–motor closed loop	Requires synchronization, weighting, and fault tolerance

The three routes are not mutually exclusive, but complement each other, each resolving a single issue in the intent-perception pipeline: weak signal, changing signal, and inadequate information. When choosing the method to use, practical considerations must also be taken into account as detailed in Section 4.

4. Discussion

4.1. Method selection criteria

The method selection for upper-limb rehabilitation robots is restricted by three factors: the limited computing power on the wearable side, safety, and the large difference between patients. The classical denoising is a low complexity starting point. Low-pass, notch and median filtering are the methods that address the noise directly if the noise consists primarily of known frequencies or patterns, as in the case of power-line frequency noise, high-frequency electronic noise, or bad-sample jumps [6, 8]. Wavelet denoising may be preferable to simple smoothing if one wants to denoise without destroying the sharpness of the sudden beginning of the movement [6]. Because its behavior is predictable, classical denoising also makes a useful baseline: reporting the gains from learning-based and fusion methods relative to it shows whether the additional complexity is justified [3, 7]. When the signal is clearly time varying, when there is individual drift or class imbalance, an upgrade should be considered, but this is an additional cost of computing and data with little reward.

Learning-based robustness enhancement is an upgrade for situations of signal variability. When the EMG for the same movement drifts with sessions, fatigue, and electrode shift, or when patients' signal distributions differ greatly and important movements are scarce, learning-based enhancement adapts to the change in a data-driven way and can reduce performance loss across sessions and individuals [4, 10]. Its costs are also clear: it needs training data and computation, and its performance must be validated under the intended session, subject, and patient conditions. It is therefore most useful when there is a real distribution shift that fixed filtering cannot address.

Multi-sensor fusion is an option for filling information gaps. If safe, fine-grained control, or contact force, joint posture, or long-term stable localization is required, the use of additional sensing can complement the use of sEMG and help to implement closed-loop control [5, 13, 14]. The disadvantages are that it requires synchronization and modality-specific error handling and fault

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tolerance, and that Kalman-based estimation relies on a proper state model and noise assumptions [12].

One strategy for creating a sequence of selections is to first determine the primary limitation. Start with classical denoising, if weak signal quality is the major issue. If there is still distribution shift at session or subject level, then add learning-based robustness enhancement. For tasks that involve information other than sEMG (e.g., posture and/or contact force), consider augmenting it with an additional sensing modality and fusion strategy.

The routes are not mutually exclusive. A system typically combines classical denoising with the other two as necessary, as Nassour et al. report with an adaptive-threshold detection using CNN: fixed signal-processing logic and learning-based verification stage [3].

4.2. Research gaps and future directions

Four gaps can be identified in this area based on these criteria. The first is the generalization across individuals and sessions. While transfer learning and domain adaptation can minimize the drop in some cases, the performance may deteriorate for some users/sessions [4]. A common unified benchmark and evaluation protocol for severely paralyzed patients is also lacking, and the number of channels and the definition of tasks are different, making it difficult to compare methods [6]. The methods that require only light annotation, evaluated using common metrics, are a promising direction and it would be better to report inter-individual and intra-individual accuracy, as standard measures, for comparison.

Secondly, the contribution of denoising to the accuracy of recognition is not quantifiable separately. Studies might present SNR or MSE at signal level and accuracy at task level without distinguishing the effect of the denoising step, per se [9, 10]. It would be interesting to see the classification performance before and after denoising, with the same classifier and data partition, to see what the denoising step does rather than just see smoother waveforms.

Third, the existence of lightweight hybrid schemes that can be executed online and still maintain a high degree of robustness to distribution shift is still constrained. Although learning-based methods could enhance adaptation, they are difficult to implement on limited wearable devices, and rehabilitation systems must also have stable behavior and predictable latency. One pragmatic approach is to keep simple signal conditioning at the front end and only introduce a lightweight learning stage at the back end where the fixed processing is not sufficient.

Fourth, the long-term stability and individualized weighting of the multi-sensor fusion is still unsolved. The literature on general sensor fusion focuses on uncertainty management and fault tolerance [15]. However, cross-user variability, sensor placement, fusion design as well as real-world deployment remain practical challenges in recent reviews of upper-limb sEMG-IMU and hybrid-sensor systems [14, 16]. The question is, therefore, not so much whether multimodal fusion can enhance the information content, but whether these enhancements are consistent between patients, sessions, and long-term wear.

5. Conclusion

The comparison implies that the three routes clear obstacles in order. The pertinent question for a particular robot is: What is the place in that sequence where its task fails? Weak activation comes first, and fixed-parameter filtering handles it at negligible computational cost. The variability between sessions, fatigue and subjects follows and the presence of a real distribution shift is what

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justifies the learned stage. Information the surface recording does not contain, such as contact force or joint posture, lies beyond the reach of denoising entirely.

This ordering, used at the system level, allows a rehabilitation device to be specified based on what it must do. Keeping each added stage tied to a named limitation matters more in rehabilitation than in most robotics settings, because every extra stage also consumes power, adds latency, and introduces a failure mode the wearer has to tolerate.

These conclusions are subject to two caveats. This review is limited to non-invasive surface recording; no comments are made about intramuscular or implanted interfaces; the three-route division is a gross simplification because adaptive filtering is already a mixture of fixed filtering and learning, and deployed systems often use a combination of stages. The synthesis is also qualitative, in that the number of channels, the definition of a task, and the data sets reported in the cited studies were not pooled and effect sizes were not calculated. The relative size of the gains reported for each route should therefore be interpreted as indicative. These constraints would have to be lifted by a shared set of benchmarks that incorporate severely paralyzed patients, where the recognition results are reported pre and post denoising using the same classifier and data split, and fusion studies that span multiple months and not just sessions.

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