

Signal quality assessment of surface electromyography envelope extraction across multiple noise conditions

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ABSTRACT

Envelope extraction is a fundamental preprocessing step in surface electromyography (sEMG) for myoelectric control, yet its signal quality under varying noise conditions remains insufficiently characterized using classification-independent metrics. This study assessed the signal quality of seven envelope extraction configurations, spanning instantaneous, static low-pass, and adaptive Kalman-based smoothing, using a dual-metric framework combining intrinsic signal-to-noise ratio (SNR) and power-reference correlation (ρ). Twenty subjects from the Ninapro DB2 dataset were examined under clean conditions and four noise types (power-line interference (PLI), motion artifact (MA), white Gaussian noise (WGN), and their combination), all scaled to 10 dB SNR. Static low-pass filtering achieved the highest intrinsic SNR (up to 4.4 dB), whereas the instantaneous tier attained the highest fidelity (ρ up to 0.985) but strongly negative SNR (-6 to -13 dB); the adaptive Kalman tier was intermediate (1.5-1.9 dB, $\rho=0.87$). Within the adaptive tier, a Hilbert-based front-end outperformed rectification under PLI (+0.43 dB), MA (+0.29 dB), and combined noise (+0.22 dB; all $p<0.0083$), but not under WGN (-0.05 dB, $p=0.070$). These findings indicate that the benefit of phase-coherent estimation depends on the deterministic structure of interference rather than its magnitude.

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1. INTRODUCTION

Surface electromyography (sEMG) is widely used for myoelectric control of prosthetic and human-machine interface systems [1], with envelope extraction serving as a fundamental preprocessing step that estimates the slowly varying amplitude trend underlying the raw interference pattern [2], [3]. The quality of this estimated envelope directly constrains the information available to subsequent feature extraction [4]–[6] and classification [7] stages, making its characterization an essential, though often implicit, component of sEMG system design [3].

Classical studies established signal-to-noise ratio (SNR) as the principal metric for evaluating envelope smoothing performance, demonstrating a fundamental trade-off between noise suppression and responsiveness as smoothing window length increases [8]–[10]. However, this body of work was developed primarily under idealized, low-noise laboratory conditions. In realistic deployment environments, sEMG recordings are commonly contaminated by power-line interference (PLI), motion artifact (MA), and broadband electronic noise, each of which degrades envelope quality through distinct mechanisms [11], [12].

Targeted algorithms have been proposed to attenuate specific noise types, particularly PLI [13], but such studies typically evaluate noise removal in isolation rather than characterizing how different envelope extraction strategies behave when several noise types occur individually or in combination.

Adaptive smoothing approaches based on Kalman filtering have been proposed as an alternative to static low-pass filtering for sEMG envelope extraction, demonstrating favorable accuracy when measurement noise exhibits a defined colored spectral structure [14], [15]. Comb-filter-based denoising frameworks combining envelope extraction with explicit artifact suppression have similarly been evaluated, although primarily under PLI and MA considered separately [16]. While these studies established the feasibility of adaptive, noise-aware envelope estimation, each addressed a narrow and largely homogeneous noise scenario, leaving open how such methods compare against simpler static alternatives across a broader and more heterogeneous range of interference conditions.

Multi-metric signal quality assessment frameworks, combining SNR with complementary indices such as motion-artifact ratio and spectral deformation, have been developed for sEMG to support electrode placement and channel selection decisions [17]–[19]. These frameworks demonstrated that single-metric evaluation can be insufficient to characterize signal quality comprehensively. Yet their application has been confined to comparing recording configurations, such as electrode location, rather than comparing envelope extraction methods themselves under controlled, systematically varied noise conditions. Consequently, the intrinsic quality behavior of common envelope extraction tiers, which are instantaneous, static low-pass, and adaptive Kalman-based smoothing, remains uncharacterized across the heterogeneous noise environments relevant to ambulatory and prosthetic applications [20], [21].

This study addressed that gap by evaluating the signal quality of seven envelope extraction configurations, spanning instantaneous, static low-pass filter-based, and adaptive Kalman filter-based smoothing tiers, using a dual-metric assessment framework that combined intrinsic SNR with power-reference correlation, independent of downstream classification performance. Twenty subjects from the Ninapro DB2 dataset were examined under clean recording conditions and four controlled noise types, namely PLI, MA, white Gaussian noise (WGN), and their combination, at a fixed 10 dB SNR. The principal contributions of this study were: i) a systematic, dual-metric characterization of envelope extraction quality across three methodological tiers and five noise conditions, extending single-metric and single-noise precedents in the literature; ii) empirical identification of a noise-structure-dependent pattern, in which the quality advantage of phase-coherent, Hilbert-based amplitude estimation over conventional rectification was significant under structured interference but not under purely stochastic white noise; iii) quantification of the trade-off space between amplitude fidelity and noise suppression occupied by each methodological tier; and iv) a quantitative basis for anticipating how envelope extraction quality varies with the structural characteristics of interference encountered in practical sEMG acquisition settings.

2. METHOD

2.1. Dataset

Experiments were conducted using the Ninapro DB2 dataset, a publicly available benchmark for sEMG-based hand and wrist movement recognition [22], [23]. The database comprises recordings from 40 intact subjects performing 49 movements across three exercise protocols, acquired at a sampling rate of 2,000 Hz using 12 wireless Delsys Trigno electrodes placed circumferentially around the proximal forearm, supplemented by two additional electrodes positioned at the wrist [23], [24]. The present study used exercise B, comprising 17 movement classes, which are eight isometric and isotonic hand configurations and nine basic wrist movements, each performed in six repetitions with a 5-second active contraction and a 3-second rest interval.

A subset of twenty subjects (S1–S20) was included in the present analysis, selected to provide adequate statistical power for the non-parametric repeated-measures comparisons described in subsection 2.5 while remaining computationally tractable for the full factorial design spanning seven envelope extraction configurations and five noise conditions (subsections 2.2–2.3). Complete data were available for all twenty subjects across all noise conditions. For each subject–configuration combination, 102 movement segments were extracted after the removal of rest intervals and movement transition periods, for a total of $20 \times 7 \times 5 = 700$ subject-level aggregate observations that formed the basis for the statistical analyses reported in section 3.

2.2. Noise augmentation protocol

To characterize envelope extraction quality under conditions representative of practical sEMG acquisition, a controlled noise augmentation protocol was applied to the clean recordings, yielding five experimental conditions.

- a. Clean: the original, unmodified sEMG recordings, representing idealized laboratory acquisition without externally introduced interference.

- b. PLI: a sinusoidal component at 50 Hz together with its second harmonic at 100 Hz was superimposed on the clean signal, simulating capacitive coupling between electrode leads and electrical infrastructure [13], [25]. Because the fundamental PLI frequency falls within the physiologically active band of forearm sEMG (20–150 Hz), this condition presents a structurally challenging case for envelope extraction, as frequency-domain separation cannot isolate the interference without also attenuating genuine motor-unit activity [11], [13].
- c. MA: low-frequency baseline drift, band-limited below 20 Hz, was synthetically introduced to emulate mechanical displacement of the electrode–skin interface during limb movement, consistent with the physiological bandwidth of such artifacts [26], [27], and was likewise calibrated to a fixed SNR of 10 dB (1).
- d. WGN: broadband stochastic noise was superimposed on all channels, simulating electronic noise originating from data-acquisition hardware.
- e. Mixed noise: WGN and MA were applied simultaneously, representing a composite disturbance characteristic of ambulatory or unshielded recording environments.

For all four noise conditions, namely PLI, MA, WGN, and mixed, the injected noise magnitude was calibrated such that the SNR, defined as (1):

$$SNR_{dB} = 10 \log_{10}(P_s/P_n) \quad (1)$$

where P_s and P_n denote the power of the clean signal and the injected noise component, respectively, was fixed at 10 dB. The 10 dB level was selected as a challenging yet practically representative operating point, consistent with noise levels reported in unshielded clinical and prosthetic acquisition environments [11].

2.3. Envelope extraction configurations

Seven envelope extraction configurations were implemented, spanning three methodological tiers: instantaneous amplitude estimation, static low-pass smoothing, and adaptive Kalman-based smoothing. All configurations operated on the raw sEMG signal sampled at 2,000 Hz. Table 1 summarizes the complete set of evaluated configurations.

Table 1. Evaluated envelope extraction configurations

Category	Configuration	Stage 1	Stage 2
Baseline	Raw EMG	—	—
Instantaneous	Rectify	Full-wave rectification	—
Instantaneous	Hilbert	Hilbert transform	—
Static smoothing	Rectify+LPF	Full-wave rectification	Low-pass filter (5 Hz)
Static smoothing	Hilbert+LPF	Hilbert transform	Low-pass filter (5 Hz)
Adaptive	Rectify+Kalman	Full-wave rectification	Kalman filter
Adaptive	Hilbert+Kalman	Hilbert transform	Kalman filter

Stage 1—instantaneous amplitude estimation. Two alternative approaches were evaluated. Full-wave rectification computed the absolute value of the raw signal:

$$s_{rect}(t) = |x(t)| \quad (2)$$

while the Hilbert transform-based approach computed the modulus of the analytic signal representation. For a real-valued sEMG signal $x(t)$, the analytic signal $z(t)$ is given by (3):

$$z(t) = x(t) + j\tilde{x}(t) \quad (3)$$

where $\tilde{x}(t)$ denotes the Hilbert transform of $x(t)$ [28], [29]. The instantaneous amplitude envelope was then obtained as (4):

$$s(t) = |z(t)| = \sqrt{x(t)^2 + \tilde{x}(t)^2} \quad (4)$$

This formulation preserves phase coherence and yields an analytically exact instantaneous amplitude estimate without introducing the phase delay characteristic of linear filtering [28], [29].

Stage 2—smoothing. For the unsmoothed configurations (raw EMG, Rectify, and Hilbert), the Stage 1 output constituted the final envelope directly. For the static low-pass tier (Rectify+LPF, Hilbert+LPF), a

second-order Butterworth low-pass filter with a 5 Hz cutoff frequency was applied, consistent with conventional envelope smoothing practice [8], [26]. For the adaptive tier (Rectify+Kalman, Hilbert+Kalman), a scalar Kalman filter modeled the envelope as a latent state evolving under a random-walk process, following the recursive prediction–update formulation in (5)–(9) [14], [15]:

$$\hat{s}_{k|k-1} = \hat{s}_{k-1|k-1} \quad (5)$$

$$P_{k|k-1} = P_{k-1|k-1} + Q \quad (6)$$

$$K_k = P_{k|k-1} / (P_{k|k-1} + R) \quad (7)$$

$$\hat{s}_{k|k} = \hat{s}_{k|k-1} + K_k (z_k - \hat{s}_{k|k-1}) \quad (8)$$

$$P_{k|k} = (1 - K_k) P_{k|k-1} \quad (9)$$

where $\hat{s}_{k|k-1}$ and $P_{k|k-1}$ denote the predicted state and error covariance, K_k the Kalman gain, z_k the stage-1 measurement at sample k , and Q and R the process and measurement noise covariances, respectively. Both covariances were implemented as fixed scalars, held constant across all subjects and noise conditions, with $Q = 1 \times 10^{-5}$ and $R = 1 \times 10^{-2}$, yielding a ratio $Q/R \approx 1 \times 10^{-3}$. These values were determined heuristically rather than through per-subject or per-condition optimization: the ratio was selected so that the implicit response time of the filter would approximate the timescale over which voluntary motor-unit recruitment modulates sEMG amplitude during contraction onset and offset [9]. A low Q/R ratio weights the internal random-walk model more heavily than the instantaneous Stage-1 measurement, thereby suppressing residual high-frequency fluctuation while retaining sufficient responsiveness to track genuine activation transients, consistent with the smoothing behavior reported for adaptive EMG amplitude-tracking implementations [15], [26]. Holding these covariances fixed rather than adapting them per condition was a deliberate design choice, ensuring that the comparison across configurations isolated the effect of the Stage-1 front-end and the smoothing tier rather than of parameter tuning.

Among these, the Hilbert+Kalman configuration was of particular analytical interest, as the contrast between it and Rectify+Kalman isolates the effect of the instantaneous-estimation front-end within the adaptive smoothing tier, while the contrast across tiers situates adaptive smoothing relative to the instantaneous and static low-pass alternatives.

2.4. Dual-metric quality assessment framework

Signal quality was assessed directly from the envelope waveform, independent of any downstream classification stage, using two complementary metrics that jointly define a two-dimensional quality space. Each envelope $s(t)$ was first segmented into successive windows of 30 samples with 50% overlap, producing a discrete power series.

$$E_i = (1/W) \sum_{k=1}^W s^2(t_k), i = 1, \dots, N_w \quad (10)$$

where $W = 30$ is the window length and N_w the total number of windows. A physiologically grounded reference power series R_i was constructed by applying a second-order Butterworth low-pass filter with a 2 Hz cutoff frequency directly to the power of the raw sEMG signal, isolating the slow-varying trend associated with macroscopic neuromuscular activation; this reference is inherently robust to high-frequency stochastic noise and does not require concurrent force or kinematic measurement [26], [30].

– Intrinsic SNR. The trend component $\hat{E}_i$ of the envelope power series was extracted using the same 2 Hz low-pass filter applied to the reference, and the residual series was obtained as $D_i = E_i - \hat{E}_i$. The intrinsic SNR was then defined as (11):

$$SNR_{int} = 10 \log_{10} (\sum \hat{E}_i^2 / \sum D_i^2) \quad (11)$$

a positive SNR_{int} indicates that the physiologically meaningful trend dominates the envelope power series, whereas a negative value indicates that residual stochastic fluctuations remain dominant.

– Power-reference correlation (ρ). The fidelity with which the envelope power series tracked the reference series was quantified using the Pearson correlation coefficient:

$$\rho = [\sum (E_i - \bar{E})(R_i - \bar{R})] / \sqrt{[\sum (E_i - \bar{E})^2 \cdot \sum (R_i - \bar{R})^2]} \quad (12)$$

values of ρ approaching 1.0 indicate faithful tracking of neuromuscular activation dynamics, whereas values near zero or negative indicate decorrelation arising from excessive smoothing or noise-induced temporal distortion.

– Optimal zone. Following established conventions in biomedical signal quality assessment, an envelope configuration was classified as occupying the optimal zone of the (SNR_{int}, ρ) quality space when it simultaneously satisfied $SNR_{int} > 0$ dB and $\rho > 0.75$ [8], [17].

2.5. Statistical analysis

For each of the 35 envelope–noise combinations (seven envelope configurations $\times$ five noise conditions), the mean intrinsic SNR and mean ρ were computed across the 102 segments of each subject, yielding one aggregate value per metric, per subject, per configuration ($N = 20$ per combination).

The Friedman test, a non-parametric alternative to repeated-measures ANOVA suitable for non-normally distributed repeated measurements, was applied to assess whether statistically significant differences existed among the seven envelope extraction configurations within each noise condition [31]. Separate Friedman tests were conducted for each metric and each noise condition, yielding ten omnibus tests in total.

Where the Friedman test indicated a significant overall difference, pairwise post-hoc comparisons were conducted using the Wilcoxon signed-rank test between the Hilbert+Kalman configuration and each of the six alternative configurations [32]. These post-hoc comparisons were restricted to intrinsic SNR, which is the primary metric for the front-end contrast examined in subsection 3.3; the ρ was assessed at the omnibus (Friedman) level only. To control the family-wise error rate across the six pairwise comparisons per metric per noise condition, a Bonferroni-corrected significance threshold of $\alpha = 0.05/6 \approx 0.0083$ was applied [33].

3. RESULTS AND DISCUSSION

3.1. Dual-metric quality landscape and the fidelity–suppression trade-off

Figure 1 presents the joint distribution of the two-quality metrics across all seven envelope configurations and five noise conditions. Rather than ordering the configurations along a single axis of quality, the two-dimensional space defined by intrinsic SNR and ρ resolves them into three distinct clusters that correspond to the three methodological tiers, revealing a systematic trade-off between amplitude fidelity and noise suppression. In this space, the optimal zone is defined by the shaded region (intrinsic SNR > 0 dB and $\rho > 0.75$).

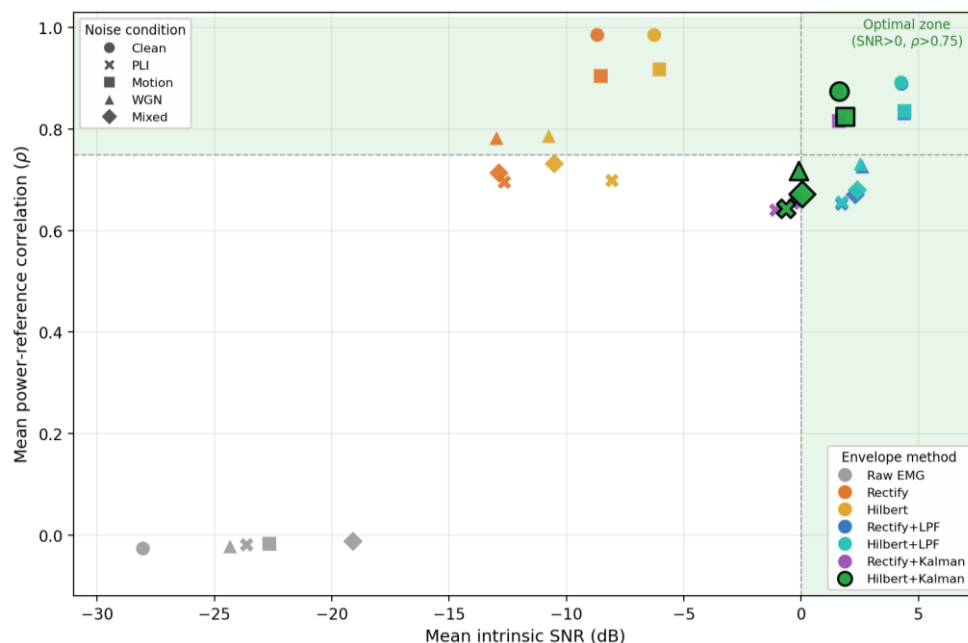


Figure 1. Fidelity–suppression trade-off across seven envelope methods and five noise conditions, in the joint space of intrinsic SNR and power-reference correlation

The instantaneous-estimation tier (rectify Hilbert) attained the highest ρ of any tier, reaching $\rho=0.985$ under clean conditions, yet its intrinsic SNR remained strongly negative (-6.3 dB for Hilbert and -8.7 dB for rectify under clean conditions). This indicates that although these envelopes faithfully followed the slow activation trend, they retained substantial high-frequency fluctuation that the intrinsic-SNR criterion penalizes. Conversely, the static low-pass tier (Rectify+LPF and Hilbert+LPF) achieved the highest intrinsic SNR of any configuration, up to 4.4 dB under clean and motion conditions, but at a measurable cost in correlation, which declined to approximately 0.89 . The raw-EMG baseline, lacking any amplitude-estimation stage, occupied the extreme low-fidelity corner with near-zero correlation and deeply negative intrinsic SNR (-19 to -28 dB), confirming that envelope extraction is a prerequisite for any meaningful amplitude representation.

The adaptive Kalman tier (Rectify+Kalman and Hilbert+Kalman) occupied an intermediate region, combining a positive intrinsic SNR under low-noise conditions (1.5 – 1.9 dB) with correlation values close to 0.87 , only marginally below those of the static tier. Critically, this trade-off structure would be invisible to a single-metric evaluation: ranking the configurations by intrinsic SNR alone would identify the static low-pass tier as uniformly superior and obscure the fact that the instantaneous tier tracked neuromuscular activation dynamics most faithfully. The dual-metric formulation thus exposes a design tension, between suppressing residual fluctuation and preserving activation dynamics, that is intrinsic to envelope extraction and cannot be captured by noise-suppression criteria alone [8], [17].

3.2. Quality degradation across noise structures

Figure 2 summarizes the intrinsic SNR of each configuration across the five noise conditions; the raw-EMG baseline is omitted for scale, and its values are reported in Table 2. Two patterns are evident. First, the tier ordering established under clean conditions persisted across all noise types: the static low-pass tier consistently yielded the highest intrinsic SNR, the adaptive tier remained near the 0 dB boundary (indicated by the dashed line in Figure 2), and the instantaneous tier stayed strongly negative. Second, the noise conditions imposed markedly different degrees of degradation.

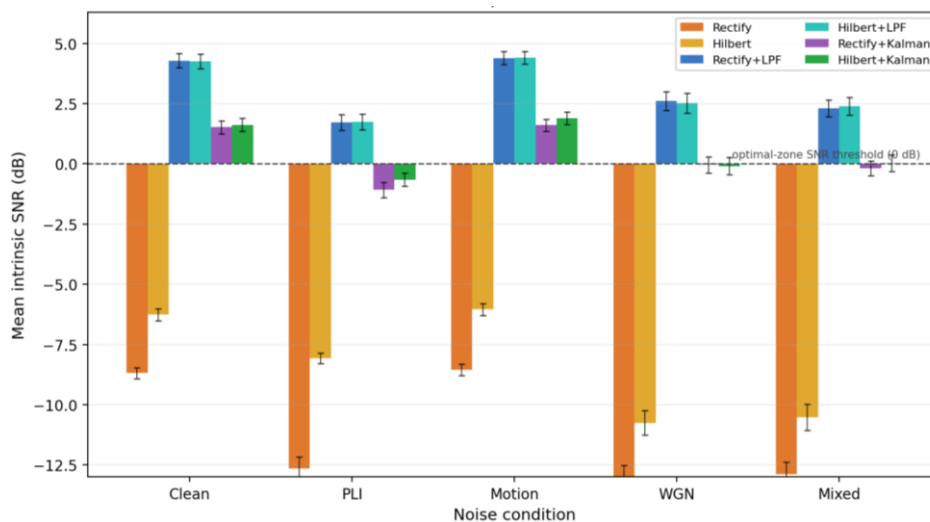


Figure 2. Mean intrinsic SNR of each envelope configuration across the five noise conditions (error bars denote the standard error of the mean across 20 subjects)

PLI emerged as the most disruptive condition. Under PLI, the intrinsic SNR of the adaptive tier fell below zero (-1.08 dB for Rectify+Kalman and -0.65 dB for Hilbert+Kalman), and even the static low-pass tier, while remaining positive, declined to its lowest values across all noise types (1.73 – 1.74 dB, compared with 4.3 dB under clean conditions). This disproportionate degradation reflects the spectral overlap between the 50 Hz interference and the physiologically active sEMG band, which prevents the smoothing stages from attenuating the interference without also distorting genuine activation [11], [13]. MA, by contrast, produced the least degradation, with several configurations retaining clean-condition quality, consistent with its concentration in a low-frequency band largely separable from the activation trend.

Table 2 reports the mean intrinsic SNR and correlation for every configuration and noise condition, with cells satisfying the joint optimal-zone criterion (intrinsic SNR > 0 dB and $\rho > 0.75$) shown in bold.

Optimal-zone membership was restricted to the four smoothed configurations and, among noise conditions, to the clean and motion cases only. No configuration, including the static low-pass tier that maximized intrinsic SNR, satisfied the joint criterion under PLI, WGN, or mixed noise. This finding indicates that under structurally challenging interference, no single envelope configuration simultaneously achieved adequate noise suppression and faithful activation tracking, and that the choice of configuration under such conditions necessarily entails a compromise between the two quality dimensions.

Table 2. Mean intrinsic SNR (dB) and ρ per configuration and noise condition (N=20)

Configuration	Clean	PLI	Motion	WGN	Mixed
Raw EMG	-28.04/-0.03	-23.63/-0.02	-22.65/-0.02	-24.33/-0.02	-19.09/-0.01
Rectify	-8.69/0.985	-12.64/0.695	-8.54/0.904	-12.98/0.782	-12.88/0.713
Hilbert	-6.26/0.985	-8.06/0.698	-6.04/0.917	-10.75/0.786	-10.52/0.732
Rectify+LPF	4.28/0.889	1.73/0.652	4.39/0.831	2.61/0.726	2.31/0.671
Hilbert+LPF	4.26/0.892	1.74/0.656	4.41/0.835	2.52/0.731	2.40/0.680
Rectify+Kalman	1.52/0.873	-1.08/0.640	1.60/0.815	-0.04/0.714	-0.19/0.659
Hilbert+Kalman	1.62/0.874	-0.65/0.643	1.89/0.824	-0.09/0.717	0.03/0.672

Note: each cell shows SNR/ ρ ; cells meeting the optimal-zone criterion are in bold.

3.3. Structure-dependent value of phase-coherent estimation

The factorial design permits the contribution of the instantaneous-estimation front-end to be isolated by comparing Hilbert- and rectification-based configurations that share an identical smoothing stage. This contrast revealed that the value of phase-coherent, Hilbert-based amplitude estimation depended systematically on the spectral structure of the prevailing noise.

In the instantaneous tier, Hilbert-based estimation yielded a substantial and uniform improvement in intrinsic SNR over full-wave rectification across all noise conditions (mean improvement 2.2–4.6 dB; all $p < 10^{-5}$, Wilcoxon signed-rank test). This advantage is attributable to the harmonic distortion introduced by rectification, a nonlinear operation that generates spurious high-frequency components, whereas the modulus of the analytic signal provides a distortion-free instantaneous amplitude [28], [29]. Once a static 5 Hz low-pass stage was applied, however, this front-end difference was largely removed (absolute difference ≤ 0.09 dB; Table 2), because the smoothing stage attenuated the rectification harmonics that distinguished the two approaches.

Within the adaptive tier, the front-end difference re-emerged in a more revealing form. Figure 3 shows the intrinsic-SNR difference between the Hilbert+Kalman and Rectify+Kalman configurations across the five noise conditions, where green bars indicate statistically significant differences and the grey bar denotes a non-significant result. The Hilbert front-end conferred a statistically significant advantage under clean conditions (+0.10 dB), PLI (+0.43 dB), MA (+0.29 dB), and mixed noise (+0.22 dB; all $p < 0.0083$, Bonferroni-corrected). Under WGN, however, the advantage vanished: the difference was small, slightly negative, and not statistically significant (-0.05 dB, $p = 0.070$).

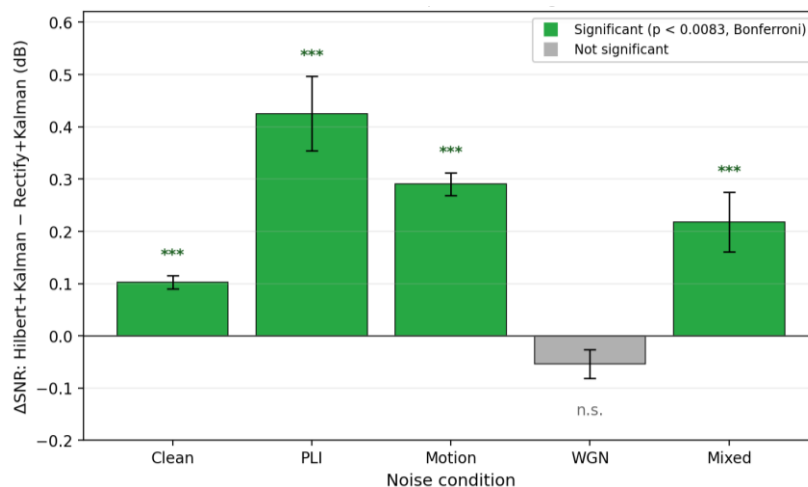


Figure 3. Intrinsic-SNR difference between the Hilbert+Kalman and rectify+Kalman configurations across noise conditions (error bars denote SEM, N=20)

This dissociation is mechanistically informative. The conditions under which phase-coherent estimation conferred an advantage, namely PLI, MA, and their combination with broadband noise, are characterized by deterministic or narrowband spectral structure that the phase information preserved by the analytic signal can exploit. WGN, by contrast, is broadband and phase-incoherent by construction, offering no deterministic structure for phase-aware estimation to recover. The advantage of Hilbert-based estimation within adaptive smoothing therefore depended on the structural character of the interference rather than on its magnitude, since all noise conditions were calibrated to an identical 10 dB level. The largest advantage occurred under PLI, the most spectrally structured condition examined, reinforcing this interpretation.

3.4. Statistical validation

The differences among configurations were statistically robust. Friedman omnibus tests, conducted separately for each metric and noise condition, rejected the null hypothesis of equal central tendency in every case (χ^2 between 115.5 and 120.0; all $p < 1.5 \times 10^{-22}$; Table 3), confirming that configuration choice exerted a highly significant effect on both quality metrics under every noise condition. Post-hoc Wilcoxon signed-rank comparisons between the Hilbert+Kalman configuration and the remaining configurations quantify the trade-off described above: the Hilbert+Kalman configuration significantly exceeded both the instantaneous tier, by 7.4–13.0 dB in intrinsic SNR, and the raw baseline; was in turn significantly exceeded by the static low-pass tier, by approximately 2.5 dB across all conditions; and differed from its rectification-based adaptive counterpart in the structure-dependent manner detailed in subsection 3.3.

Table 3. Friedman omnibus test statistics (χ^2 , df=6) and p-values for the effect of envelope configuration on each quality metric, per noise condition (N=20)

Noise condition	χ^2 (SNR)	p (SNR)	χ^2 (ρ)	p (ρ)
Clean	118.9	2.8×10^{-23}	117.9	4.6×10^{-23}
PLI	117.9	4.4×10^{-23}	119.2	2.4×10^{-23}
Motion	118.6	3.2×10^{-23}	119.6	2.0×10^{-23}
WGN	117.4	5.7×10^{-23}	120.0	1.6×10^{-23}
Mixed	116.4	9.1×10^{-23}	115.5	1.4×10^{-22}

3.5. Implications, limitations, and method selection

Taken together, these results carry two practical implications for sEMG envelope extraction. First, no single configuration was optimal across all quality dimensions and noise conditions. The static low-pass tier maximized intrinsic SNR and is therefore preferable when smooth, low-variance amplitude estimates are the priority; this advantage, however, was obtained through fixed, aggressive smoothing, this advantage, however, was obtained through fixed, aggressive smoothing that may attenuate rapid activation transients in applications requiring responsiveness. The adaptive Kalman tier, while yielding lower intrinsic SNR, adjusts its smoothing to the local signal dynamics and may therefore be preferable where transient fidelity matters; within this tier, a phase-coherent Hilbert front-end is advisable, as it improved quality at no measurable cost under every condition except phase-incoherent white noise.

Second, the structure-dependence of the Hilbert advantage suggests that envelope-method selection should be informed by the dominant interference expected in a given acquisition setting. In environments dominated by structured interference, such as power-line coupling or MA, as is typical of unshielded clinical and ambulatory recordings, phase-coherent estimation offers a measurable benefit; in settings dominated by broadband electronic noise, it offers none.

Several limitations qualify these conclusions. The analysis was conducted on twenty subjects from a single dataset at a fixed 10 dB noise level; the magnitude, though not necessarily the direction, of the reported effects may vary with noise intensity and across acquisition hardware. The quality assessment was deliberately classification-independent, isolating intrinsic envelope quality from downstream classifier behavior; the relationship between the quality metrics characterized here and end-task performance, such as movement classification, remains to be established. A further limitation concerns the two metrics themselves, which were derived from the signal rather than from an independent ground truth: because both the intrinsic-SNR trend and the correlation reference apply the same 2 Hz low-pass operation, the criterion inherently rewards smoothing, and interference with spectral content below 2 Hz may propagate into the reference. Consistent with this, the motion-artifact condition marginally increased intrinsic SNR across all configurations (Table 2) rather than degrading it, so its apparent robustness should be interpreted with caution. Finally, the Kalman process and measurement noise covariances were held fixed across subjects and conditions; per-condition adaptation of these parameters may alter the adaptive tier's position within the trade-off space and represents a direction for further investigation.

4. CONCLUSION

This study characterized the signal quality of seven sEMG envelope extraction configurations, namely instantaneous, static low-pass, and adaptive Kalman-based smoothing, across five noise conditions, using a classification-independent dual-metric framework combining intrinsic SNR with power-reference correlation. The two metrics revealed a systematic fidelity–suppression trade-off that single-metric evaluation would obscure: static low-pass filtering maximized intrinsic SNR, the instantaneous tier most faithfully preserved activation dynamics, and the adaptive Kalman tier occupied a balanced intermediate position. Under PLI, WGN, and mixed noise, no configuration satisfied both quality criteria, with PLI the most disruptive owing to its spectral overlap with the active sEMG band.

The factorial design further isolated a noise-structure-dependent advantage of phase-coherent estimation: within the adaptive tier, a Hilbert-based front-end significantly outperformed full-wave rectification under PLI, MA, and mixed noise, but not under stochastic WGN. This dissociation indicates that the benefit of phase-coherent estimation depends on the deterministic structure of the interference rather than its magnitude. These findings provide a basis for selecting envelope extraction methods according to the dominant expected interference, and motivate future work relating these intrinsic quality metrics to downstream classification performance and extending the analysis across a wider range of noise intensities.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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Agus Harjoko		✓				✓	✓	✓		✓		✓		✓
Danang Lelono	✓		✓	✓		✓	✓		✓	✓		✓	✓	

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**rganizing - **O**rganizing

E : **E**dit - **E**dit

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in Ninapro at <https://ninapro.hevs.ch/instructions/DB2.html>.

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