



RESEARCH ARTICLE

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FROM CLASSICAL FILTERING TO ADAPTIVE AND AI-DRIVEN PARADIGMS: A PRISMA-BASED SYSTEMATIC REVIEW AND BIBLIOMETRIC ANALYSIS OF EMG SIGNAL FILTERING

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ARTICLE INFO

Article History

Received: January 29, 2026

Reviewed: March 30, 2026

Accepted: April 30, 2026

Published: May 29, 2026

Keywords:

Electromyography (EMG),

Bibliometric analysis,

Biblioshiny,

Signal filtering,

Systematic review.

ABSTRACT

Electromyography (EMG) is a widely used technique for assessing muscle activity in response to electrical stimulation of the nervous system. Nevertheless, EMG signals are inherently weak, non-stationary, and highly susceptible to noise contamination, necessitating the use of advanced acquisition and signal processing strategies. This study presents a comprehensive systematic review and bibliometric analysis of EMG signal filtering and data acquisition frameworks. Unlike previous reviews that focus solely on signal processing techniques, this study uniquely integrates Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-based systematic screening with multi-dimensional bibliometric mapping to reveal methodological convergence, research gaps, and future design paradigms for low-cost and embedded EMG systems. Bibliometric analyses were performed using Biblioshiny and VOSviewer to characterize the intellectual structure of the field. The primary objective is to identify recent advances, dominant research trends, and critical knowledge gaps warranting further investigation. Based on PRISMA screening, 173 peer-reviewed articles were included for analysis. The findings reveal a sustained annual growth rate of 3.71% in EMG filtering research and highlight five key analytical dimensions: (1) performance evaluation, (2) science mapping, (3) research collaboration networks, (4) citation dynamics, and (5) emerging trends and future research opportunities.



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I. INTRODUCTION

Electromyography (EMG) is an experimental technique for the acquisition and analysis of electrical signals generated by skeletal muscle contractions [1]. These signals represent the anatomical and physiological activity of motor units and constitute a fundamental diagnostic and research tool in biomechanics, medical rehabilitation, and robotic control systems, including prosthetics. Despite its broad applicability, EMG signal acquisition remains challenging due to the inherently low signal amplitude (microvolt to millivolt range) and its stochastic characteristics [2]. Moreover, EMG recordings are highly susceptible to multiple noise sources, such as power-line interference (50/60 Hz), motion artifacts, electrocardiographic (ECG) interference, and intrinsic electronic noise [3]. Such contamination can severely distort relevant signal features, leading to unreliable estimations of commonly used metrics, including Root Mean Square (RMS) and Mean Frequency [4]. Consequently, effective preprocessing through signal filtering is indispensable for preserving signal integrity. The choice of filtering strategy—including filter type, cutoff frequency, and order—critically influences the quality of the extracted information. Conventional approaches, such as band-pass filtering to isolate the physiological muscle frequency band (20–500 Hz) and notch filtering to suppress power-line hum, are widely adopted, while advanced techniques, including wavelet-based and adaptive filtering, have been increasingly employed to address non-stationary noise components [5]. Despite the availability of numerous EMG signal filtering techniques, suboptimal parameter selection frequently results in the attenuation of physiologically relevant frequency components or the introduction of detrimental phase distortions [6].

Consequently, identifying robust filtering configurations that effectively suppress noise while preserving true muscle contraction information remains a critical challenge. This study addresses this issue by providing a comprehensive analysis of EMG signal filtering methods to determine optimal parameter settings that balance noise reduction and signal fidelity [7], [8]. Motivated by the rapidly growing global research interest in EMG signal processing, as evidenced by bibliometric analyses of Scopus-indexed publications, this work integrates a PRISMA-based systematic review with a bibliometric mapping approach. The analysis reveals dominant research trajectories spanning traditional digital filtering, advanced transformation-based methods for non-stationary signals, and emerging AI-driven denoising techniques [9]. By synthesizing methodological trends, performance insights, and research gaps, this study offers a structured foundation for future developments in high-precision EMG-based control systems, including intelligent prosthetics and human-machine interfaces [10], [11]. Despite the extensive body of literature on EMG filtering techniques, bibliometric evidence highlights critical and underexplored research gaps. Existing studies predominantly rely on high-cost, medical-grade EMG systems, while investigations into computationally efficient filtering strategies tailored for low-cost sensors remain scarce [12]. This limitation restricts the translation of EMG-based solutions to embedded and portable applications. Addressing this gap, the present study evaluates lightweight yet optimal filtering configurations that minimize noise while preserving physiologically meaningful muscle contraction information, enabling practical deployment in resource-constrained systems. This work delivers a focused, systematic, and bibliometric analysis of EMG signal filtering, synthesizing state-of-the-art developments, dominant research trajectories, and emerging opportunities. Specifically, it addresses the following research questions: (Q1) What is the current research landscape in electromyography? (Q2) How is the scientific structure of EMG filtering research organized? (Q3) Which articles, sources, and countries exert the greatest influence and productivity in this domain? (Q4) What trends are shaping contemporary EMG research? and (Q5) What critical gaps and future research directions exist for EMG signal processing in low-cost and embedded systems?

The novelty of this study lies in three aspects: (i) the integration of PRISMA-guided systematic review with advanced bibliometric science mapping, (ii) the identification of methodological fragmentation and lack of filtering standardization in EMG research, and (iii) the formulation of future research directions emphasizing adaptive, interpretable, and computationally efficient filtering strategies for wearable and embedded systems. Collectively, these contributions provide a unified analytical framework that bridges methodological rigor with practical system design considerations, thereby supporting the development of robust, scalable, and application-oriented EMG acquisition solutions.

II. THEORETICAL REFERENCE

II.1 ELECTROMYOGRAPHY (EMG)

Electromyographic (EMG) signals are biomedical signals that capture the electrical activity of muscles during contraction, reflecting neuromuscular function, and depending on the anatomical and physiological properties of muscle tissue [13]. EMG signals are acquired using electrodes that detect muscle electrical potentials and are placed either on the skin surface or within the muscle [14]. Accordingly, EMG electrodes are classified into surface electromyography (sEMG) and intramuscular electromyography (iEMG). sEMG employs non-invasive surface electrodes and records activity from a broader, superficial muscle region, whereas iEMG uses invasive needle or wire electrodes to capture highly localized and deeper muscle fiber activity. As a result, sEMG is well-suited for global assessment of surface muscle activation, while iEMG enables detailed analysis of specific muscles or motor units. Owing to their distinct frequency and amplitude characteristics, EMG signals constitute a critical data source for medical diagnosis, assistive device control, and the investigation of neuromuscular function [15].

II.2 ELECTROMYOGRAPHY (EMG) SIGNAL FILTERING

Electromyography (EMG) signal filtering is a fundamental preprocessing step aimed at enhancing signal quality by suppressing acquisition-related disturbances, including motion artifacts, power-line interference, and high-frequency noise. Preprocessing typically consists of filtering and segmentation, with filtering playing a decisive role in isolating physiologically meaningful muscle activity for accurate analysis [16]. EMG filtering commonly employs band-pass filters to confine the signal within its physiological frequency range (20–500 Hz), thereby attenuating low- and high-frequency noise, and notch filters to eliminate power-line interference at 50/60 Hz. Additionally, digital and adaptive filtering techniques, such as Butterworth filters, are widely adopted to preserve critical signal attributes—particularly amplitude and spectral content—while substantially improving the Signal-to-Noise Ratio (SNR), which directly influences the reliability of motion recognition and classification outcomes [17]. The subsequent stage involves EMG smoothing or envelope extraction using low-pass filters with low cutoff frequencies or techniques such as Root Mean Square (RMS) and moving average, producing a stable and interpretable representation of muscle activity [18]. This filtering pipeline substantially enhances EMG signal quality, enabling more accurate and reliable downstream analyses, including both conventional signal processing and machine learning-based approaches. Consequently, the consistent application of appropriate filtering strategies is essential for ensuring analytical validity and robust EMG interpretation across research and clinical applications.

III. MATERIALS AND METHODS

This study employs the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework integrated with bibliometric analysis to systematically identify research trends and gaps within the field [19]. This combined approach is widely adopted for its effectiveness in uncovering emerging themes and underexplored research directions. Bibliometric analyses were conducted using VOSviewer and Biblioshiny implemented in the R environment, which enable both qualitative and quantitative synthesis as well as intuitive data visualization. The PRISMA–bibliometric workflow comprises literature identification, screening, eligibility assessment, and bibliometric synthesis, including quantitative analysis, thematic mapping, research gap identification, and the formulation of future research agendas. The detailed research framework applied in this study is presented in Figure 1.

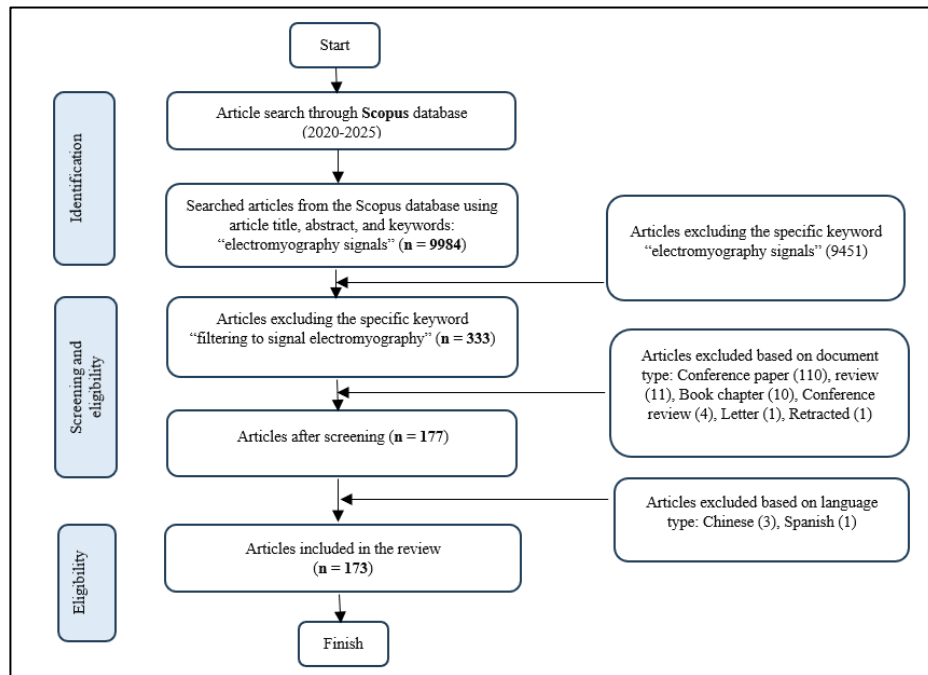


Figure 1: PRISMA research framework.

Source: Authors (2026).

Relevant literature on electromyography (EMG) signal filtering was retrieved from the Scopus database [20]. Study selection followed predefined inclusion criteria: English-language experimental articles published between 2020 and 2025 and identified using targeted EMG-related keywords. After screening and excluding ineligible and closed-access records, 173 articles were retained for analysis. Bibliometric analysis was then conducted to provide a comprehensive overview of EMG filtering research, encompassing research distribution, author productivity, and thematic structures. The results are presented through quantitative, qualitative, and visual analyses, enabling the identification of research trends, key topics, and existing research gaps to guide future investigations.

IV. RESULTS AND DISCUSSIONS

IV.1 PERFORMANCE ANALYSIS

Performance analysis was conducted to assess the quality, consistency, and evolution of EMG signal filtering research using the PRISMA framework, ensuring a transparent and reproducible literature selection process [21], [22]. The analysis focused on eligible publication counts, annual publication trends, and topical relevance to provide a concise overview of the research landscape. A Scopus search (2020–2025) using electromyography-related titles, abstracts, and keywords yielded 9,984 records. After title screening, 9,451 records were excluded, followed by abstract screening of 333 studies and full-text assessment of 191 articles. Ultimately, 173 articles met the inclusion criteria and were retained for analysis. A summary of research performance is presented in Table 1 and Figure 2.

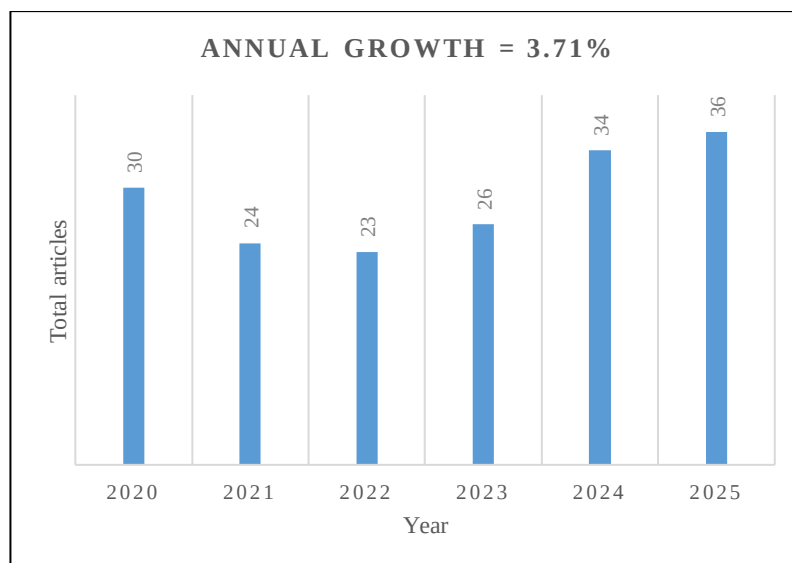


Figure 2: Year-on-year research trends

Source: Authors (2026).

Table 1: Descriptive analysis of research performance.

Description	Results
Timespan	2020-2025
Sources (Journals, Books, etc)	103
Documents	173
Annual Growth Rate %	3.71
Document Average Age	3.32
Average citations per doc	9.382
References	1574
Keywords Plus (ID)	1964
Author's Keywords (DE)	672
Authors	725
Authors of single-authored docs	6
Single-authored docs	6
Co-Authors per DoC	4.77
International co-authorships %	24.86
Article	173

Source: Authors (2026).

The Bibliometrix framework was applied to quantitatively assess the literature using key bibliometric indicators, including performance analysis, science mapping, EMG filtering techniques, collaboration networks, and analysis of trends and future research potential. This approach elucidates scientific contributions, research impact, and the evolutionary dynamics of the field. When integrated with PRISMA, Bibliometrix enables a robust evaluation of both the rigor of literature selection and the underlying knowledge structure, resulting in a comprehensive, systematic, and evidence-based review. Electromyography (EMG) signal filtering has emerged as a rapidly advancing research domain. Between 2020 and 2025, 173 publications authored by 725 researchers across 103 sources were identified, reflecting strong scholarly engagement. The field demonstrates notable impact, with an average of 9.38 citations per document and an annual growth rate of 3.71%, underscoring sustained and accelerating research interest. These trends underscore the need for a more in-depth analysis to clarify prevailing research directions and pinpoint critical gaps that warrant further investigation.

IV.2 COMPARISON WITH PREVIOUS REVIEWS

Most existing EMG review studies primarily focus on the comparative evaluation of signal processing and filtering techniques, emphasizing algorithmic performance improvements such as noise suppression and classification accuracy. While these reviews provide valuable insights at the methodological level, they generally overlook broader structural aspects, including methodological consistency, collaboration patterns, and the longitudinal evolution of research themes.

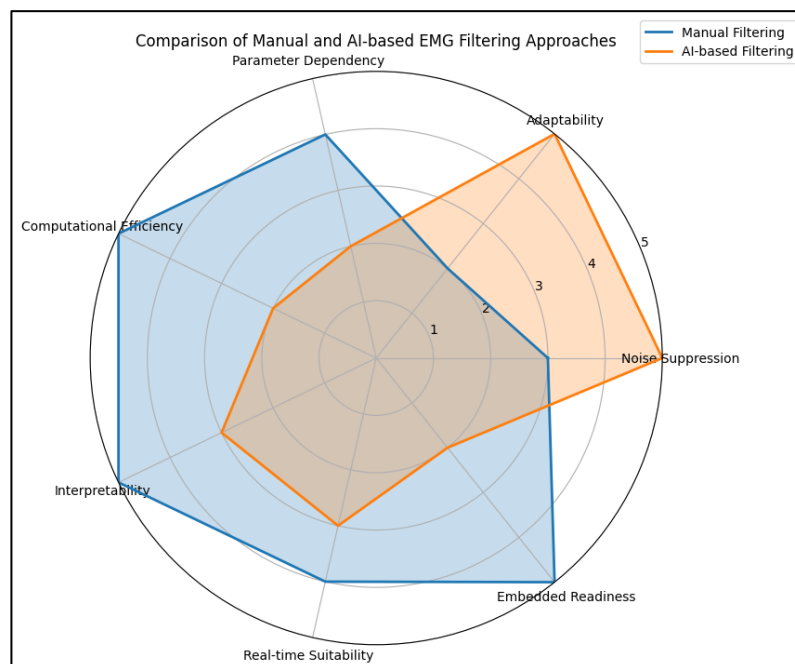


Figure 3: Comparison of manual and AI-based EMG filtering approaches.
Source: Authors (2026).

In contrast, this study delivers a higher-level synthesis by revealing methodological fragmentation across EMG filtering studies, imbalances in research collaboration networks, and a clear transition toward AI-driven filtering paradigms. By integrating PRISMA-guided systematic screening with bibliometric science mapping, this work extends beyond algorithm-centric comparisons to elucidate the intellectual structure and developmental trajectory of EMG filtering research. Consequently, it bridges the gap between signal processing methodologies and practical system design requirements, particularly for adaptive, interpretable, and computationally efficient filtering in wearable and embedded EMG systems. Figure 3 explains that a comparative analysis between conventional and AI-based EMG filtering highlights a clear methodological trade-off aligned with current bibliometric trends. Conventional filtering methods remain dominant in embedded and real-time applications due to their high interpretability, low computational cost, and implementation simplicity. However, bibliometric trend analysis reveals a growing shift toward AI-driven filtering, motivated by superior noise suppression and adaptability to non-stationary EMG signals. This transition is reflected in the increasing prevalence of machine learning and deep learning keywords in recent publications. Despite their performance advantages, AI-based approaches face challenges related to computational complexity, limited interpretability, and embedded deployment constraints. These findings suggest an emerging research direction toward hybrid filtering frameworks that balance AI adaptability with the efficiency and transparency of conventional methods. The life cycle and growth analysis provide important context for understanding the comparative trends between manual and AI-based EMG screening approaches, as seen in Figure 4.

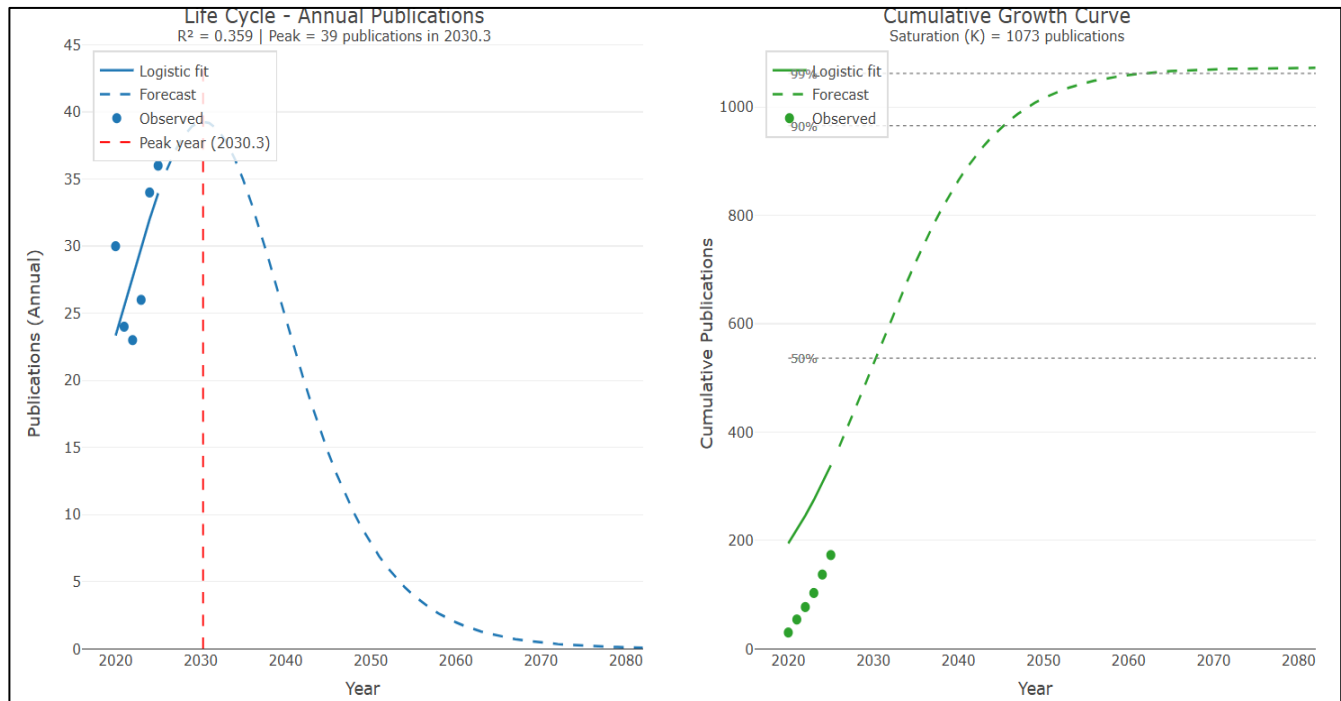


Figure 4: Life cycle of scientific production.
 Source: Authors (2026).

The life-cycle and cumulative growth analyses provide important context for interpreting the comparative trends between manual and AI-based EMG filtering approaches. The projected peak in annual publications around 2030 indicates that the field is approaching a maturity phase, in which foundational techniques—largely represented by conventional manual filtering methods—have been extensively explored and stabilized. This maturation explains the continued relevance of manual filtering in the literature, particularly for embedded and real-time systems, where interpretability, low computational cost, and implementation robustness remain critical design requirements. At the same time, the steep rise observed in the cumulative growth curve before reaching saturation reflects a paradigm shift rather than simple incremental growth. This acceleration coincides with the increasing prominence of AI-based filtering methods, as also revealed by bibliometric keyword and trend analyses. As the field approaches saturation, research emphasis is moving away from developing entirely new manual filtering schemes toward leveraging AI to enhance adaptability and noise robustness in non-stationary EMG signals. Consequently, the life-cycle analysis supports the view that future advances in EMG filtering will likely be driven by hybrid and AI-assisted approaches that build upon established manual methods, rather than by purely conventional filtering paradigms.

IV.3 SCIENCE MAPPING

Science mapping of EMG signal filtering research was performed using Biblioshiny to elucidate the conceptual and intellectual structure of the field [22], [23]. Co-word analysis and thematic mapping reveal well-defined clusters encompassing both conventional filtering techniques (band-pass and notch filters) and advanced approaches, including wavelet-based and adaptive filtering, with increasing integration into clinical applications and machine learning-driven systems.

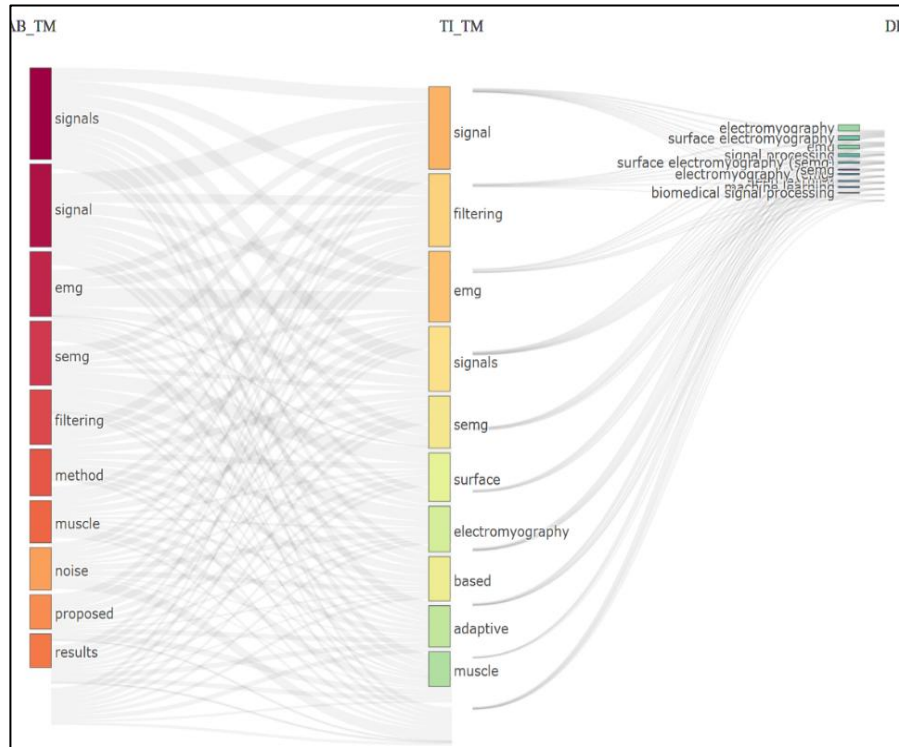


Figure 5: Three field plots.
Source: Authors (2026).

These results indicate a clear methodological evolution from classical linear filtering toward data-adaptive and intelligent filtering frameworks. The three-field plot (Figure 5) demonstrates strong thematic consistency across countries, title–abstract keywords, and author keywords, with dominant terms such as signal, EMG, sEMG, and filtering, underscoring the sustained and concentrated research focus on EMG signal filtering. Complementarily, the VOSviewer co-occurrence network (Figure 6) highlights tightly connected keyword clusters, reflecting mature research streams in traditional filtering and emerging clusters centered on wavelet methods and AI-driven filtering. The proximity and density of these clusters suggest a growing convergence between advanced signal processing techniques and machine learning paradigms, while simultaneously revealing opportunities for further exploration in adaptive and real-time EMG filtering for practical applications.

Table 2: Descriptive analysis of research performance using keywords.

Keywords	Number of Keywords
Bandpass filters	19
Butterworth filters	19
Low-pass filters	19
Notch filters	19
High-pass filters	15
IIR (Infinite Impulse Response) filters	15
Wavelet transforms	15
Median filters	14
Wavelet decomposition	14
Adaptive filters	10
Signal-to-noise ratio	10
Noise	4
Impedance	4

Source: Authors, (2026).

VOSviewer-based mapping reveals the underlying knowledge structure of EMG signal filtering research. Dense clusters with large nodes indicate mature and dominant themes, whereas smaller, sparse clusters reflect emerging or niche directions. Overlay visualization further highlights a clear temporal shift from classical filtering techniques toward adaptive and data-driven approaches. These results demonstrate that bibliometric visualization functions not merely as descriptive mapping, but as a robust analytical framework for identifying thematic dominance, research evolution, and future research opportunities in EMG filtering [24], [25].

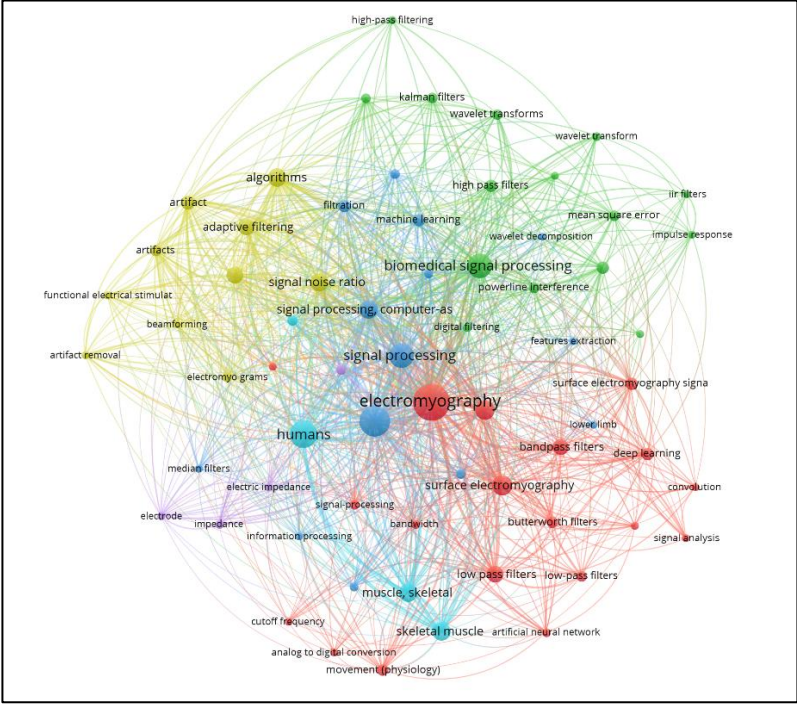


Figure 6: Keyword analysis and its development.

Source: Authors, (2026).

Overall, the findings confirm that EMG signal filtering research is fundamentally driven by the need to suppress motion artifacts, power-line interference, and high-frequency noise while preserving essential temporal and spectral characteristics of muscle activity signals. As EMG applications expand into biomechanics, rehabilitation, and human-machine interfaces, filtering has transitioned from a routine preprocessing step to a critical design factor that directly impacts system accuracy, robustness, and interpretability, particularly in machine learning and deep learning-based frameworks.

IV.4 RESEARCH COLLABORATION ANALYSIS

Bibliometric collaboration analysis reveals that research on electromyography (EMG) signal processing remains largely nationally clustered, with limited effective international collaboration. Co-authorship networks indicate that most research interactions occur within domestic or regionally proximate groups, suggesting that global knowledge integration in EMG research is still suboptimal. At the country level, China, the United States, India, and Germany emerge as the dominant contributors, functioning as primary research hubs with the highest publication output and collaboration intensity. Although collaborative activity is distributed across Asia, Europe, and the Americas, cross-continental linkages remain sparse, reflecting fragmented collaboration structures rather than a fully interconnected global research network.

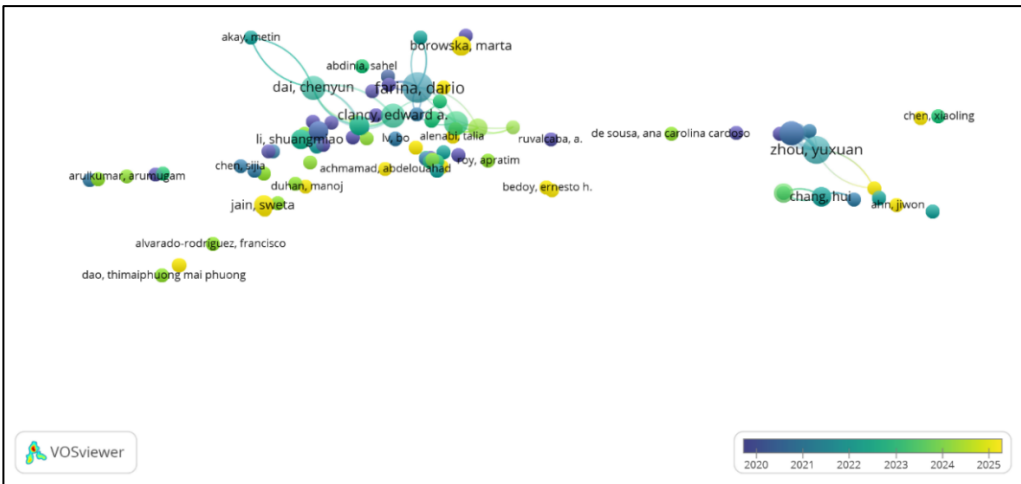


Figure 7: Collaboration among researchers.

Source: Authors, (2026).

Clustering analysis identifies three major country clusters (11, 11, and 8 countries, respectively), highlighting the presence of regional collaboration blocs. This pattern suggests that scientific exchange is driven more by geographical and institutional proximity than by thematic or methodological convergence. Notably, Indonesia is integrated into the global collaboration network, indicating growing participation from emerging research economies, although its role remains peripheral compared to leading hubs.

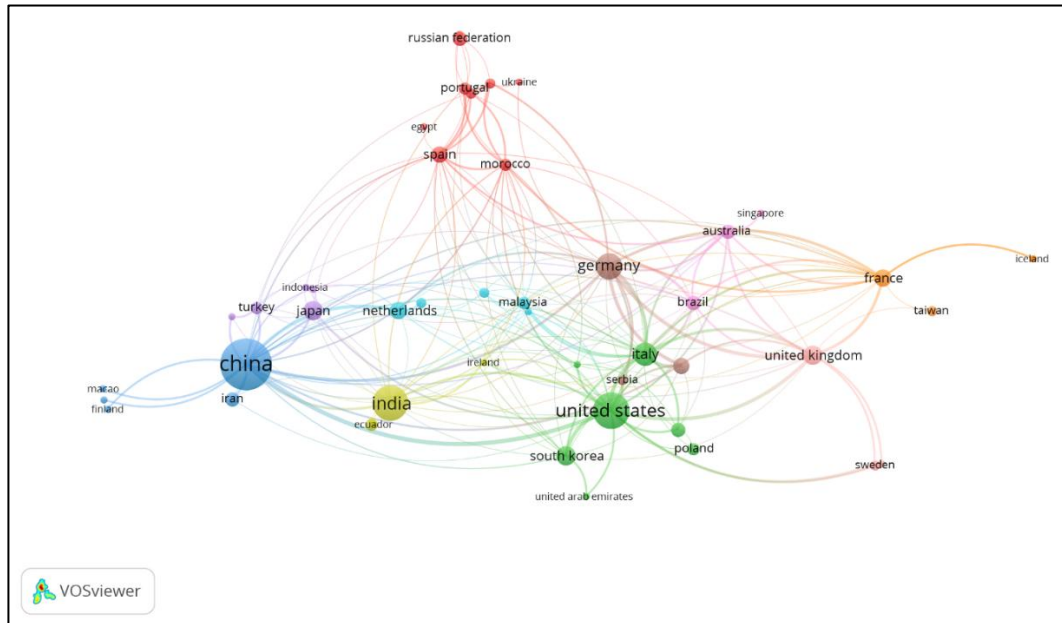


Figure 8: Collaboration between countries.
Source: Authors, (2026).

Overall, these findings underscore a structural imbalance in global EMG research collaboration, where scientific output is concentrated among a few dominant countries while international cooperation remains underdeveloped. Strengthening cross-border and cross-cluster collaboration is therefore critical to accelerating methodological innovation, improving research quality, and fostering more robust knowledge transfer in EMG signal filtering and analysis.

IV.5 RESEARCH CITATION ANALYSIS

Citation analysis reveals a highly concentrated and hierarchical knowledge structure in EMG signal filtering research. A limited number of journals act as primary dissemination hubs, with *Sensors* emerging as the most prolific outlet (15 publications, 2020–2025), indicating its central role in shaping and sustaining research momentum in this domain. This concentration reflects both thematic specialization and the consolidation of EMG filtering research within high-visibility publication venues [26]. Highly cited articles form a set of landmark studies that define the conceptual and methodological foundations of the field. Their dominant citation footprints demonstrate sustained relevance across theoretical modeling, signal processing pipelines, and application-driven EMG analysis. These works function as intellectual anchors, guiding subsequent research trajectories and reinforcing dominant methodological paradigms.

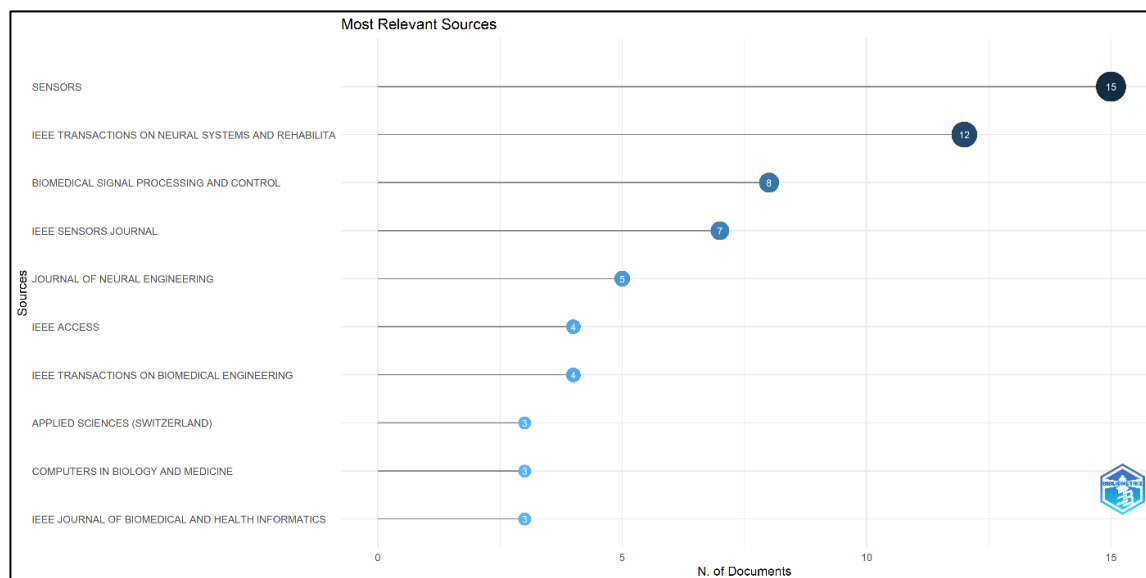


Figure 9: Most relevant sources.
Source: Authors, (2026).

As illustrated in Figure 9, EMG signal filtering research is concentrated within a limited set of Scopus-indexed journals, with *Sensors* ranking as the most prolific source between 2020 and 2025. The dominance of these top-ranked journals indicates their role as core publication venues and primary knowledge dissemination channels in the field. The consistent output across these sources reflects a sustained editorial focus on signal processing, biomedical instrumentation, and EMG-based applications.

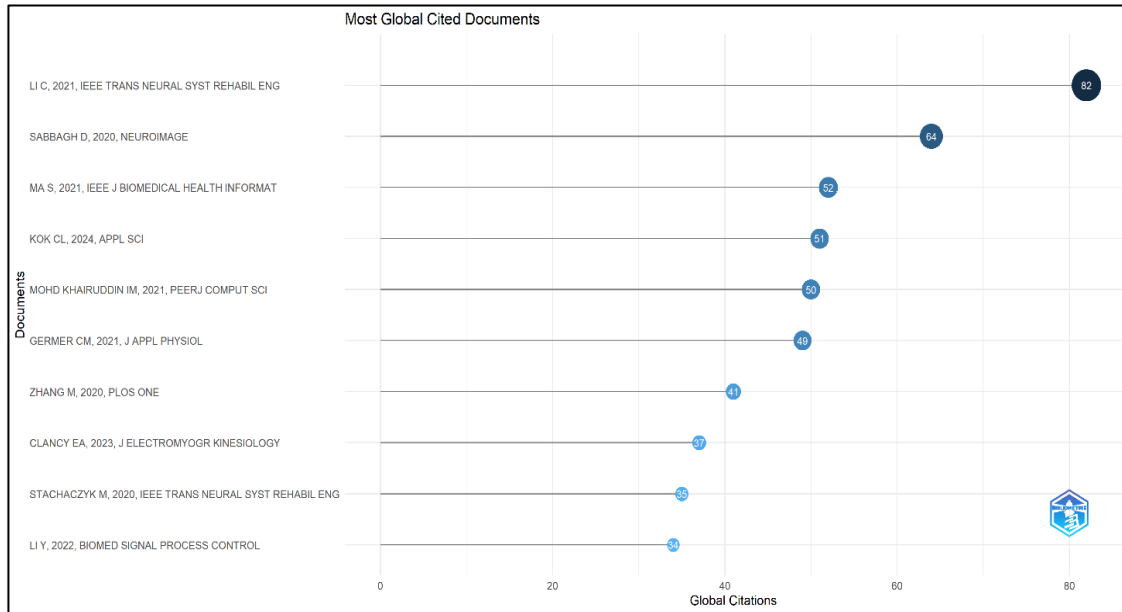


Figure 10: Most globally cited documents.
Source: Authors, (2026).

Figure 8 highlights the globally most cited articles, which represent high-impact and widely adopted contributions that have shaped the conceptual and methodological direction of EMG filtering research. The elevated citation counts of these studies indicate their function as landmark papers, frequently referenced as theoretical foundations, signal processing benchmarks, or methodological baselines in subsequent works [27]. This observation is further corroborated by Table 3, which summarizes the total global citation counts of the most influential articles. The concentration of citations among a small number of publications confirms a skewed citation distribution, where a few seminal studies account for a substantial portion of the field's intellectual influence. Collectively, Figures 9–10 and Table 3 demonstrate that EMG filtering research is structured around a stable core of highly cited journals and articles, which collectively define the dominant research paradigms and guide future methodological developments [28].

Table 3: Most globally cited documents.

No	Author	DOI	Total Citations	TC per Year	Normalized TC
1	Kuang et al. [29]	10.1109/TNSRE.2021.3055276	82	13.67	4.32
2	Sabbagh et al. [30]	10.1016/j.neuroimage.2020.116893	64	9.14	4.25
3	Ma et al. [1]	10.1109/JBHI.2020.2987528	52	8.67	2.74
4	Kok et al. [31]	10.3390/app14135784	51	17.00	7.23
5	Khairuddin et al. [32]	10.7717/PEERJ-CS.379	50	8.33	2.63
6	Germer et al. [33]	10.1152/jappphysiol.01041.2020	49	8.17	2.58
7	Zhang et al. [34]	10.1371/journal.pone.0235330	41	5.86	2.72
8	Clancy et al. [35]	10.1016/j.jelekin.2023.102807	37	9.25	4.24
9	Stachaczyk et al. [4]	10.1109/TNSRE.2020.2986099	35	5.00	2.32
10	Li et al. [36]	10.1016/j.bspc.2021.103344	34	6.80	3.52

Source: Authors, (2026).

The citation network further indicates strong international knowledge diffusion, as top-cited studies are consistently referenced across countries and institutions, underscoring their global influence and cross-disciplinary adoption. Collectively, these findings confirm that EMG filtering research is driven by a core set of influential publications and journals, with citation dynamics highlighting mature research themes while simultaneously delineating the foundational frameworks upon which emerging methods—particularly adaptive and learning-based filtering—are being developed.

IV.6 ANALYSIS OF TRENDS AND POTENTIALS IDENTIFIED FOR FUTURE RESEARCH

The trend analysis reveals a decisive shift in EMG signal filtering research from static, rule-based approaches toward adaptive, data-driven paradigms. As shown in Figure 9, while conventional signal processing remains a foundational component, recent years are characterized by a rapid expansion of machine learning, deep learning, and explainable artificial intelligence (XAI) techniques, signaling a structural transformation in how EMG noise suppression and feature preservation are addressed [37].

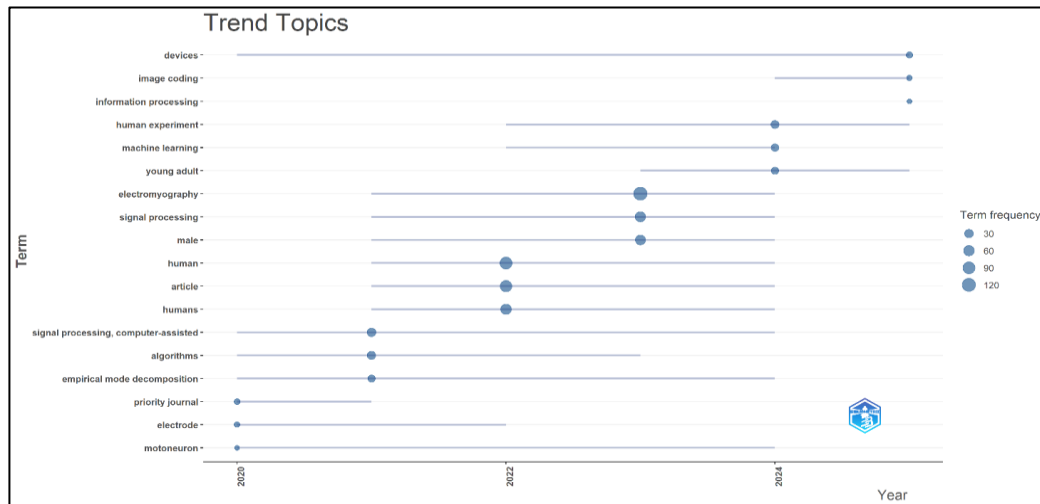


Figure 11: Trend topics diagram.

Source: Authors, (2026).

Looking forward, the results suggest several strategic research directions that will shape the next phase of EMG filtering studies. First, future work is expected to prioritize adaptive and context-aware filtering frameworks capable of handling non-stationary noise under real-world conditions, particularly for wearable and embedded EMG systems [38]. Second, the increasing dominance of machine learning and human-centered experiments indicates a growing demand for end-to-end EMG pipelines, in which filtering, feature extraction, and classification are jointly optimized rather than treated as independent stages. Third, the emergence of XAI-related themes highlights a critical need for interpretable filtering and denoising models, especially in clinical and rehabilitation applications where transparency and trust are essential. Moreover, the sustained growth of the electromyography keyword (120 publications through 2025) underscores the field's maturity, while the rising trajectories of signal processing, machine learning, and human experiment point toward application-driven and user-adaptive research agendas. Collectively, these trends indicate that future EMG filtering research will move beyond noise suppression alone, evolving into a strategic system-level component that directly influences performance, reliability, and clinical usability. Consequently, research efforts should focus on scalable, interpretable, and computationally efficient filtering solutions that can be deployed in real-time human-machine interfaces, smart prosthetics, and next-generation rehabilitation technologies. Building upon the trend analysis, a strategic mapping was conducted to identify high-impact and underexplored research opportunities in EMG signal filtering. The strategic diagram classifies themes into four quadrants according to their centrality and density, thereby revealing not only the current structure of the field but also its future growth trajectories.

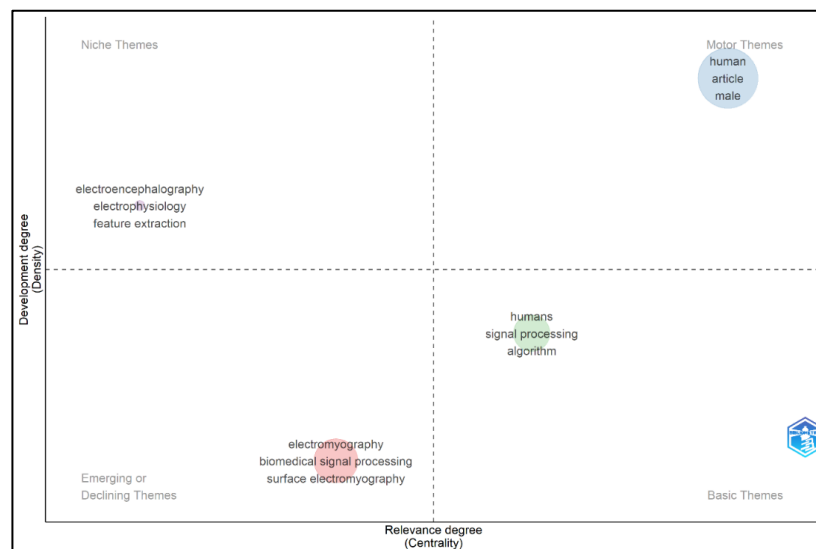


Figure 12: Identify potential future research with a strategic diagram.

Source: Authors, (2026).

As shown in Figure 12, Quadrant 1 contains highly influential driving themes (*human*, *article*, *male*) that dominate the literature and define the empirical backbone of EMG research. These themes are mature and saturated, suggesting that while they remain essential, they offer limited novelty unless coupled with methodological innovation. Quadrant 2 consists of highly developed yet isolated topics such as *electroencephalography*, *electrophysiology*, and *feature extraction*, indicating advanced but siloed research streams that require stronger integration with EMG-specific filtering frameworks to maximize their broader impact. In contrast, Quadrant 3 (electromyography, biomedical signal processing, surface electromyography) represents emerging and transitional themes with low density but high strategic relevance. These topics signal a critical opportunity for methodological breakthroughs, particularly in redefining filtering paradigms that address non-stationarity, inter-subject variability, and real-world noise conditions.

Similarly, Quadrant 4, which includes foundational concepts (humans, signal processing, and algorithms), serves as the methodological substrate of the field and offers fertile ground for innovation through the integration of adaptive algorithms, explainable models, and computationally efficient implementations. Taken together, the strategic map indicates that future EMG filtering research should deliberately shift its focus toward Quadrants 3 and 4, where the potential for high-impact contributions is greatest. Advancing these themes through adaptive, interpretable, and application-driven filtering strategies is expected to redefine EMG signal analysis and accelerate its translation into wearable systems, intelligent prosthetics, and human-machine interfaces.

V. CONCLUSIONS

This study provides a definitive bibliometric and thematic synthesis of electromyography (EMG) research with a focused examination of signal filtering methodologies. The results clearly demonstrate that EMG preprocessing is dominated by a diverse yet fragmented set of techniques—including band-pass, Butterworth, low-pass, notch, high-pass, median, and adaptive filters—reflecting both the methodological richness and the lack of convergence within the field. Bibliometric evidence confirms a sustained and accelerating growth in publications, alongside increasing methodological diversification, driven by the rapid expansion of EMG applications in biomedicine, rehabilitation, intelligent prosthetics, and machine learning-enabled systems. Critically, the absence of a universally accepted EMG filtering standard represents a structural limitation that continues to constrain reproducibility, comparability, and system-level optimization across studies. These findings indicate that future research must move beyond ad hoc filter selection toward application-aware, adaptive, and performance-driven filtering frameworks. A rigorous and systematic understanding of EMG filtering should therefore be regarded as a strategic prerequisite, not merely a preprocessing choice, for advancing analytical accuracy, enhancing system robustness, and enabling the reliable deployment of next-generation EMG-based technologies.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Samsul Arifin, Nuryani, and Mohtar Yunianto.
Methodology: Samsul Arifin and Mohtar Yunianto.
Investigation: Samsul Arifin and Mohtar Yunianto.
Discussion of results: Samsul Arifin, Nuryani, and Mohtar Yunianto.
Writing – Original Draft: Samsul Arifin.
Writing – Review and Editing: Samsul Arifin and Mohtar Yunianto.
Resources: Samsul Arifin, Nuryani, and Mohtar Yunianto.
Supervision: Nuryani and Mohtar Yunianto.
Approval of the final text: Samsul Arifin, Nuryani, and Mohtar Yunianto.

VII. ACKNOWLEDGMENTS

The authors acknowledge the Doctoral Program in Physics at Universitas Sebelas Maret (UNS) for academic support and the Ministry of Education, Culture, Research, and Technology of Indonesia (Kemendikristek) through the Doctoral Program for Indonesian Lecturers (PDDI) for funding and institutional support.

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