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ML/DL Techniques to analyze EMG signal across various domains: Exhaustive Review

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ABSTRACT

Research on Machine Learning (ML) and Deep Learning (DL) applied to Electromyography (EMG) signal analysis shows widespread use in medical and rehabilitation applications for prosthetic control, diagnosis of neuromuscular disorders, and gait analysis, as well as in Human-Computer Interaction (HCI) for gesture recognition and user input systems.

Purpose

The central goal of employing ML and DL for EMG analysis is to accurately and robustly decode human motor intent and neuromuscular activity. Applications include controlling prosthetic devices, diagnosing neuromuscular disorders, guiding rehabilitation, and enabling human-computer interaction.

Methods

The analysis aims to overcome inherent challenges of EMG signals, such as noise, variability due to electrode placement, and changes with muscle fatigue, to achieve reliable, real-time performance.

The standard methodology involves a multi-stage pipeline:

1. **Data Acquisition:** Non-invasive surface EMG (sEMG) using electrodes placed on the skin over target muscles. Invasive intramuscular EMG (iEMG) offers higher selectivity for non-clinical applications.
2. **Preprocessing:** Raw EMG signals are noisy and require filtering to remove artifacts like power-line interference, motion artifacts, and baseline drift, band-pass filtering (e.g., 10–500 Hz), notch filtering (e.g., at 50/60 Hz), rectification, and segmentation.
3. **Feature Extraction:** from frequency domain (e.g., Mean/Median Frequency), or time-frequency domain (e.g., Wavelet Transform coefficients), the Deep learning models, in contrast, and extract these high-level features automatically from raw or minimally processed data.
4. **Classification/Regression:** using ML/DL models for either discrete classification (e.g., gesture recognition) or continuous regression (e.g., joint angle or force estimation).
   Common techniques include Random Forests, Convolution Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Support Vector Machines (SVM)
5. **Evaluation:** Models are evaluated using metrics with ongoing research focused on improving accuracy, reducing latency, handling data imbalance, and enabling real-time control on embedded systems.

Results

- **High Accuracy:** Both ML and DL models with very high accuracy in controlled settings, with some applications classification accuracies exceeding 99%.
- **DL Advances:** Deep learning models, particularly hybrid CNN-LSTM architectures automatically learning more abstract and robust features more efficient.
- **Real-time Performance:** DL models have been optimized for real-time applications in fields like prosthetic control, enabling responsive and intuitive human-machine interfaces.
- **Domain-Specific Outcomes:**
  - **Prosthetics and Robotics:** DL classifies hand and arm gestures, allowing more naturalistic and precise control of robotic hands and exoskeletons.
  - **Clinical Diagnostics:** healthy muscle activity and signals from patients with neuromuscular disorders like myopathy and Amyotrophic Lateral Sclerosis (ALS), achieving high precision.
  - **Rehabilitation:** provides biofeedback for guided rehabilitation exercises.

These advanced methods, combined with techniques like feature extraction in the time and frequency domains (e.g., RMS, MAV, Wavelet Transform) and noise reduction, allow for accurate, real-time detection and classification of muscle activity, leading to more intuitive and responsive control systems.

Conclusion

ML and DL techniques have revolutionized EMG signal analysis, enabling accurate and robust decoding of human intent across diverse domains especially in complex, real-world scenarios. The continued development of these techniques, alongside improved data acquisition hardware, promises more intuitive and effective human-machine interfaces for prosthetics, advanced clinical diagnostics, and targeted rehabilitation therapies.

1. Introduction

Electromyography (EMG) is a diagnostic and monitoring technique used to record and analyze the electrical signals produced by skeletal muscles during contraction. These signals reflect the neuromuscular activities of the body and are widely used in clinical diagnostics, rehabilitation, prosthetic control, sports science, and human-computer interaction. Traditionally, the analysis of EMG signals relied on manual observation and handcrafted feature extraction, which often proved to be time-consuming, error-prone, and inconsistent due to the complex, non-linear, and non-stationary nature of EMG data.

The rise of artificial intelligence, especially Machine Learning (ML) and Deep Learning (DL) , has transformed the field of EMG signal processing. ML models can learn from data patterns to classify and predict muscular activity, while DL models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), can automatically extract hierarchical features from raw EMG signals. This has led to enhanced accuracy, automation, and robustness in applications such as gesture recognition, muscle fatigue detection, and prosthetic control systems.

With the availability of wearable sensors and real-time processing hardware, the integration of intelligent models has made EMG-based systems more practical and scalable. Despite these advancements, challenges such as inter-subject variability, signal noise, and the need for large annotated datasets remain. This research focuses on addressing these issues by studying existing methods, identifying key influencing factors, and proposing novel or hybrid models for EMG classification and analysis using ML/DL. The goal is to develop efficient, accurate, and real-time EMG systems suitable for practical deployment in healthcare and assistive technology.

Additionally, several machine learning algorithms are evaluated for EMG classification, including Random Forest, KNN, AdaBoost, Decision Tree with and without cross-validation were employed. Moreover, we investigate the impact of class balance on the performance of these models. Model selection and hyper parameter tuning are conducted to optimize the performance. ML/DL techniques for EMG signal analysis involve pre-processing (filtering, normalization), feature extraction (time-omain, frequency-domain, time-frequency methods like EEMD/VMD), and classification/pattern recognition (CNNs, LSTMs, KNN, LDA) to analyze muscle and brain activity for applications in rehabilitation, disease diagnosis, and human-machine interfaces.

These techniques identify muscle activation patterns, decode movement intentions, and monitor neuromuscular conditions like Parkinson's, ALS, and stroke, often outperforming traditional methods by automating feature learning and improving diagnostic accuracy.

2. Key Applications & Domains

The increasing availability of wearable EMG sensors and open-access datasets has further encouraged research in automated EMG signal classification and prediction. Researchers are now capable of modeling human muscular behavior with much higher precision, making real-time applications like smart prosthetics and biofeedback systems increasingly practical. The background of this research thus establishes a strong foundation for developing intelligent, adaptive models that improve the reliability, accuracy, and applicability of EMG-based systems in diverse fields ranging from healthcare to robotics. The integration of AI in EMG signal processing is no longer optional but a necessity for future innovation.

Medical & Rehabilitation:

- *Prosthetics*: ML/DL is used to decode muscle signals for controlling prosthetic arms and legs, restoring motor function for individuals with weakened or paralyzed limbs.
- *Rehabilitation*: EMG signal analysis helps in motor re-education and rehabilitation for stroke patients by detecting muscle activity and controlling assistive robotic devices.
- *Neuromuscular Diagnosis*: ML models can diagnose neuromuscular disorders like Amyotrophic Lateral Sclerosis (ALS) and myopathy by classifying EMG signals.

Human-Computer Interaction (HCI):

- *Gesture Recognition*: EMG signals are analyzed to recognize hand gestures and movements, allowing for physical actions to be used as computer input, according to ResearchGate.
- *Assistive Technologies*: Devices like the MyoPro orthosis detect faint EMG signals to enable natural arm and hand movements, notes the National Institutes of Health (NIH).

Biomechanics & Sports:

- *Movement Analysis*: EMG provides feedback on muscle activity during movement, which can be used by athletes and trainers to enhance coaching and performance.

Applications across Domains

- *Rehabilitation and Assistive Robotics*:

EMG signals are integrated with ML/DL to enable myoelectric control of wearable robotic exoskeletons and exosuits, detecting motion intentions before physical movement for more adaptive control.

- *Disease Diagnosis and Monitoring*:

  i) *Neuromuscular Disorders*: ML/DL models can accurately distinguish between normal and diseased individuals with conditions like Amyotrophic Lateral Sclerosis (ALS), myopathy, and Parkinson's disease.

  ii) *Anomalies*: Models trained on healthy signals can detect deviations, aiding in the early diagnosis of cardiac arrhythmias (from ECGs, though EMG is also used for muscle-related issues) and other critical events.

- **Human-Machine Interaction:**

  i) *Hand Gesture Recognition*: sEMG signals are used to decode and classify hand gestures for applications in silent speech recognition and other human-computer interfaces.

  ii) *Silent Speech Recognition*: Decoding intentions from EMG signals to enable communication for individuals who are unable to speak.

3. Exhaustive Review

Zaim , T., Abdel-Hadi, S., Mahmoud, R., Khandakar, A., Rakhtala, S. M., & Chowdhury (2025) conducted a comprehensive systematic review focusing on myoelectric control systems for upper limb rehabilitation using EEG and EMG signals. The study explored the integration of machine learning (ML) and deep learning (DL) for improved neuron-rehabilitation, revealing their potential in decoding motor intentions and enhancing assistive technologies. The authors categorized existing systems, highlighted signal processing techniques, and examined classification methods like CNNs, RNNs, and hybrid architectures. Schonhaut , E. B., Scherpereel, K. L., & Young, A. J. (2025) examined whether electromyography (EMG) data is essential for deep learning-based estimation of joint and muscle states. Utilizing advanced neural network models, they compared performances of estimations using EMG with those that relied solely on kinematic or kinetic data. Barigala, V. K., Swarubini, P. J., Ganapathy, N., Karthik, P. A., Kumar, D., Ronickom, J. F. A. (2025) evaluated machine learning approaches for identifying the optimal placement of facial electromyography (fEMG) sensors for emotion detection. Using algorithms like SVM, KNN, and Random Forest, the study assessed signal quality and classification accuracy from various facial zones. Gao J., Niu, H., Li, Y., & Li, Y. (2025) introduced a machine-learning-enabled biocompatible capacitive-electromyographic (c-EMG) bimodal flexible sensor for facial expression recognition. The sensor integrates mechanical flexibility with high sensitivity and real-time signal acquisition. Zafar, M. H., Moosavi, S. K. R., & Sanfilippo, F (2025) proposed a federated learning-enhanced edge deep learning framework for real-time EMG-based gesture recognition in human-robot interaction. Their approach addresses privacy concerns and computational latency by training models locally on edge devices.

Khader, A., Zyout, A. A., & Al Fahoum, A. (2024) explored a novel approach to diagnose knee pathologies by combining enhanced spectral resolution of EMG signals with a deep learning model. Their method incorporated signal transformation techniques to improve feature richness and CNN architecture for classification.

Salazar, S. V. H., Preciado, J. C., & Muñoz, S. A. (2024) conducted a comparative analysis of machine learning and deep learning models for hand gesture recognition using surface EMG signals. Models like CNNs and LSTMs were compared with classical ML algorithms. da Silva, D. A., Branco, N. F. L. C., de Andrade Mesquita, L. S., Branco, H. M. G. C., & de Alencar Barreto, G. (2024) proposed a deep learning system based on residual learning for classifying lower-limb motion using EMG signals. Their architecture demonstrated improved accuracy and generalization over conventional models. H., & Youssef, S. M. (2023) developed a motion control system combining EEG and EMG signals using deep learning models. The research aimed to fuse multi-modal bio signals for more accurate human motion classification, leveraging CNN and LSTM networks. Their results showed that combining EEG and EMG improved the reliability and precision of movement detection. Ekinci, , E., Garip, Z., & Serbest, K. (2023) explored by extracting time-domain and frequency-domain trained models such as Decision Trees, SVM, and k-NN. Their system showed satisfactory accuracy in distinguishing different gestures and emphasized the effectiveness of well-processed EMG signals. Kim, P., Lee, J., Jeong, J., & Shin, C. S. (2023) developed a deep learning algorithm to detect transitions between walking environments using only EMG signals. Their model, which used CNN-LSTM hybrid architecture, successfully identified terrain changes, such as level ground to stairs, improving prosthetic adaptability.

Common ML/DL Techniques & Challenges

Electromyography (EMG) is a powerful biomedical technique used to measure and analyze the electrical activity produced by skeletal muscles. Traditionally, interpreting EMG signals requires significant expertise due to their nonlinear, non-stationary, and noisy nature. This complexity limits the real-time and wide-scale application of EMG in domains such as prosthetic control, rehabilitation, sports science, and neuromuscular disease diagnosis. Although Machine Learning (ML) and Deep Learning (DL) offer robust techniques for pattern recognition and time-series analysis, effectively applying these methods to EMG data remains challenging. Issues such as inter-subject variability, sensor placement sensitivity, limited training datasets, and the high dimensionality of EMG signals hinder the performance and generalization of ML/DL models.

The core problem, therefore, is to develop accurate, efficient, and generalizable ML/DL models that can automatically interpret EMG signals in real-time, while addressing challenges related to noise reduction, feature extraction, classification accuracy, and adaptability to different users and applications.

Algorithms:

- Tree-based methods: like Random Forests are effective for classifying muscle activation patterns
- Deep Learning models, including CNNs and RNNs (like LSTMs), are used for their ability to learn complex patterns directly from raw EMG data

Essential Signal Processing Steps

Feature Extraction: Extracting meaningful information from the raw EMG signal:

1) Time-Domain Features: Simple statistical features like Mean Absolute

Value (MAV) and Root Mean Square (RMS) are frequently used.

2) Frequency-Domain Features: Techniques like Wavelet Transform and Fourier Transform are applied to analyze the frequency components of the signal.

3) Combined Features: Hybrid approaches combine time and frequency-domain features for a more comprehensive analysis.

Noise Reduction and Artifact Removal: EMG signals are susceptible to noise from electronics and motion artifacts:

4) Adaptive Filters: Employ reference signals to cancel out interference like Electromyography (ECG) artifacts.

5) Singular Value Decomposition (SVD): Used for denoising signals and enhancing feature detection.

Challenges:

- **Data requirements:** Deep learning models often require large datasets, which can be difficult to acquire, motivating research into transfer learning.
- **Real-time processing:** Reducing latency for real-time applications on embedded systems is a key challenge, as complex models can increase processing time.
- **Noise and artifacts:** Motion artifacts and general noise from electrode placement can significantly affect signal quality and require robust filtering methods.

EMG signal analysis Framework

The automation of EMG signal analysis is critical in transforming how muscular activity is interpreted and utilized across various applications. Manual analysis methods suffer from multiple limitations, including dependence on expert knowledge, inconsistency in interpretation, time inefficiency, and difficulty in handling large-scale or real-time data. These constraints hinder the scalability and reliability of EMG-based applications, especially in fields such as neuro rehabilitation, prosthetic control, and real-time motion monitoring. Moreover, the dynamic and noisy nature of EMG signals requires techniques that can adapt to changing inputs and perform consistently without manual intervention. Automation provides a robust solution by utilizing intelligent algorithms that can process EMG data quickly and accurately. In wearable healthcare devices, for example, real-time automated systems can detect muscle fatigue, evaluate rehabilitation progress, or control robotic limbs based on EMG signals without requiring a clinician to constantly interpret the data. Additionally, automation facilitates the integration of EMG analysis into edge computing and IoT systems, expanding its applications in remote monitoring and smart environments.

1. **1. Signal Acquisition:**

Raw EMG signals are collected using surface (sEMG) or invasive needle electrodes.

2. **2. Pre-processing:**

Raw signals are cleaned and prepared using techniques like filtering, normalization, and signal segmentation to remove noise and enhance quality.

There are two major types of electrodes used to measure EMG signals—the needle electrode and the surface electrode. Needle electrodes are further classified into three subtypes: mono-polar single electrodes, single-fiber EMG electrodes, and concentric-EMG electrodes. Needle electrodes are approximately 1 mm2 wide. Surface electrodes are 0.5–2.5-cm wide and due to their positioning are non-invasive (Merlo . 2003).

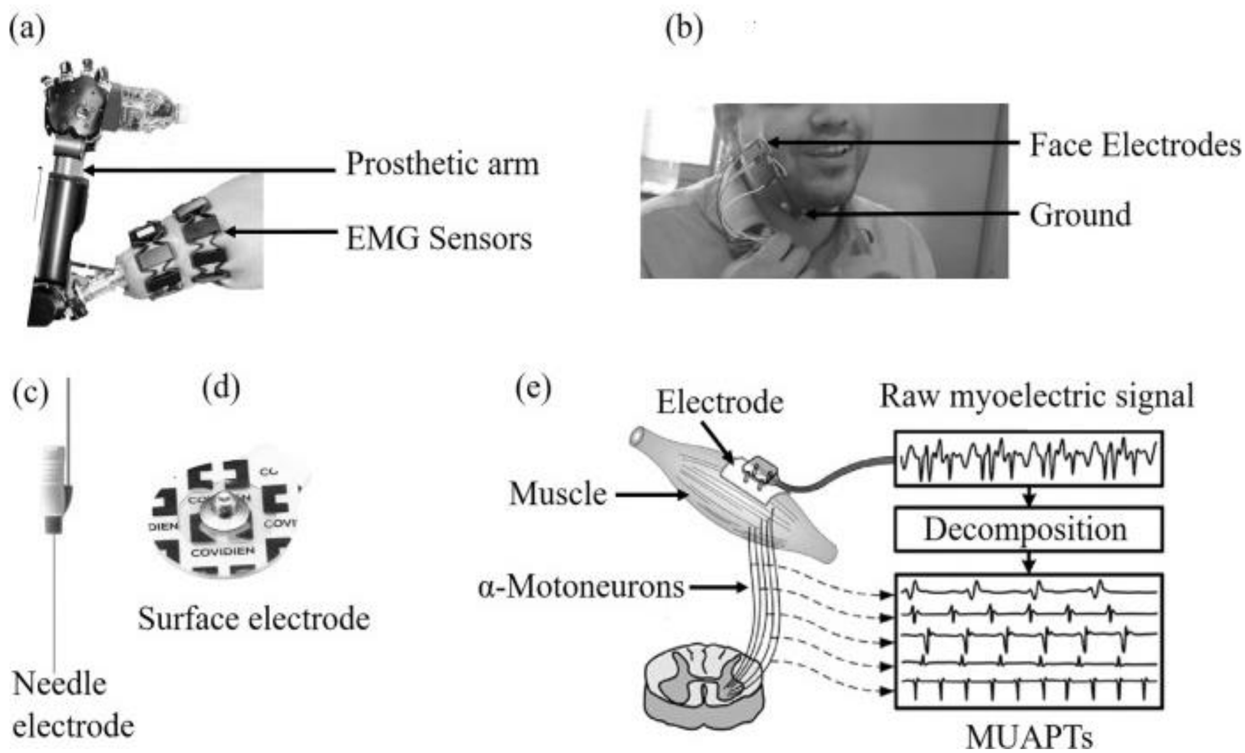

Figure-1: Electrodes used to measure EMG signals

Surface electrodes work on the principle of chemical equilibrium detecting the change between the muscle surface and body skin through electrolytic conduction. Surface electrodes are of two types: gelled EMG electrodes and dry EMG electrodes. There are 3 main types of electrograms, viz. electroencephalogram (EEG), electrocardiogram (ECG), and EMG. The advantage of using EMG over ECG and EEG is that ECG and EEG signals are below 100 Hz whereas EMG signals cover the range from 5 Hz to 2 kHz.

3. Feature Extraction:

Meaningful features are extracted from the processed signals, including:

- **Time-domain features:** Root Mean Square (RMS), Mean Absolute Value (MAV).
- **Frequency-domain features:** Waveform Length (WL), Zero Crossing (ZC).
- **Time-frequency domain features:** Empirical Mode Decomposition (EMD), Ensemble EMD (EEMD), Empirical Wavelet Transform (EWT), and Variational Mode Decomposition (VMD).

4. Classification and Pattern Recognition Model Design & Validation:

Extracted features are used to train ML/DL models to identify patterns or classify muscle activation characteristics.

- **Design and implement ML Algorithms:** Linear Discriminant Analysis (LDA), K-Nearest Neighbors (KNN). SVM, Random Forest
- **Develop DL Algorithms:** Convolutional Neural Networks (CNNs) for pattern recognition, and hybrid CNN-LSTM)) networks for sequential data analysis.

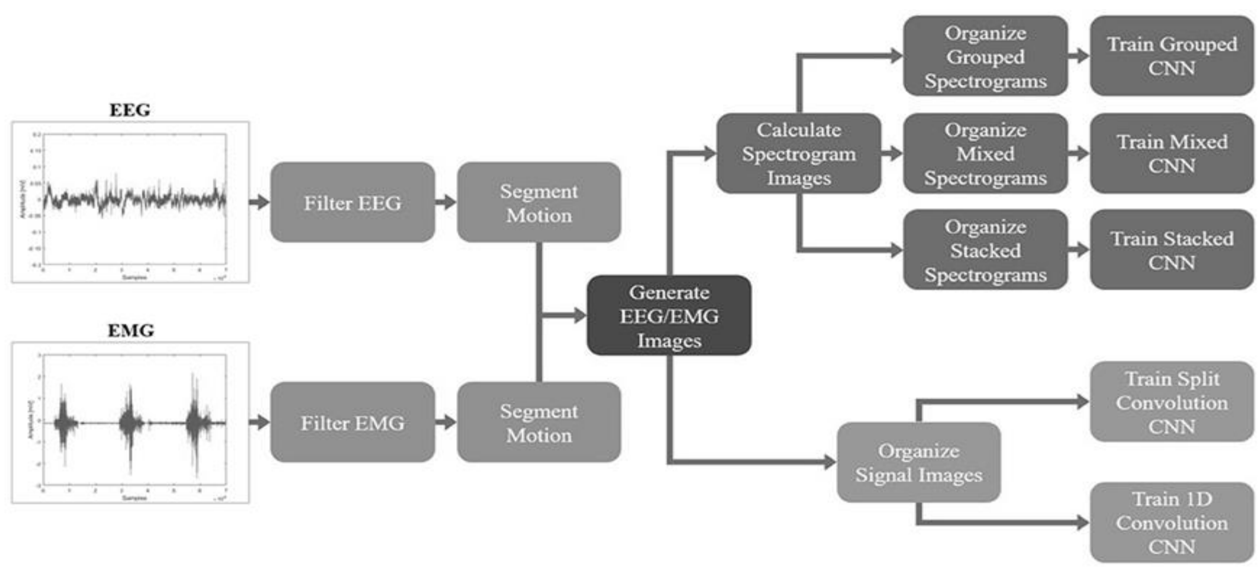

Figure 2: EMG signal analysis Framework

Conclusion

This paper emphasizes the extraction and selection of significant features from time-domain, frequency-domain, and non-linear domains that are crucial for accurate classification. It involves the development of intelligent ML/DL models such as Support Vector Machines (SVM), Random Forest, Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and hybrid architectures to recognize patterns in EMG data.

The proposed models will be applied to various domains including hand gesture recognition, muscle fatigue analysis, prosthetic control, rehabilitation systems, and fall risk prediction

- **Automated Feature Learning:**

DL models, unlike traditional ML, excel at learning features automatically from raw data, reducing the reliance on manual feature extraction.

- **Hyperparameter Optimization:**

Techniques like Grey Wolf Optimizer (GWO) can be used to optimize the hyper parameters of DL models, improving their performance and reliability for EMG-based classification systems. The future research will likely to focus on improving model robustness against real-world variability and integrating multimodal sensor data for more comprehensive and reliable systems.

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