Feature Extraction of Multichannel EMG Signals for Shoulder Joint Movement Patterns

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A B S T R A C T S

Electromyography (EMG) signals provide information about muscle activity and can support rehabilitation and prosthetic control systems. This study aims to extract and analyze features of multichannel EMG signals recorded from seven shoulder joint movement patterns. EMG data were acquired using surface electrodes placed on eight dominant muscles associated with shoulder joint motion, namely Deltoid1, Deltoid2, Infraspinatus, Supraspinatus, Teres Major, Latissimus Dorsi, Pectoralis1, and Pectoralis2. The recorded movements included resting, shoulder flexion, shoulder extension, shoulder abduction, shoulder adduction, external rotation, and internal rotation. The proposed processing procedure consisted of signal acquisition, rectification, transformation into the frequency domain using Discrete Fourier Transform, and feature extraction using Linear Envelope, Modified Mean Frequency (MMNF), and Modified Median Frequency (MMDF). The results show that Linear Envelope can describe temporal energy changes in each movement pattern, while MMNF and MMDF can identify groups of similar signal patterns and distinguish several movements through specific muscle channels. Resting movement had very small amplitude changes, while active shoulder movements produced different dominant energy patterns across subjects. MMNF and MMDF produced two main similarity groups, although the distinguishing muscles differed among subjects. These findings indicate that multichannel EMG feature extraction is useful as an initial basis for shoulder movement pattern analysis; however, further development is required to improve online acquisition, automatic gain adjustment, and classification robustness.

Manuscript received Jun 28, 2026; revised Jun 29, 2025. accepted Jun 30, 2025 Date of publication Jun 30, 2026.

Keywords / Kata Kunci — ***EMG; feature extraction; Linear Envelope; MMNF; MMDF; shoulder joint***

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1. INTRODUCTION

Electromyography (EMG) is a biomedical signal [1], [2], [3], [4] that represents the electrical activity generated by muscle contraction. Surface EMG measurement is commonly used because it is non-invasive and can capture the combined activity of several muscle fibres through electrodes placed on the skin [5], [6]. EMG signals are described as having dominant energy within the 20-500 Hz frequency range and low amplitudes in the millivolt range. These characteristics require an acquisition system that can amplify weak signals, reduce unwanted frequency components, and preserve relevant signal patterns for later analysis.

EMG-based movement analysis has been widely explored for rehabilitation, prosthetic control, and human-machine interface applications [7], [8], [9], [10]. Previous studies have applied neural-network-based and hybrid approaches for myoelectric discrimination and EMG pattern recognition. Nevertheless, a reliable pattern recognition system depends not only on the classifier but also on the quality of signal acquisition and the relevance of extracted features. Therefore, feature extraction remains an important stage before the development of a classification or decision-support system for movement recognition [11], [12], [13], [14], [15].

This study focuses on feature extraction of EMG signals from shoulder joint movements. The shoulder joint was selected because it involves several dominant muscles and has multiple movement directions, including flexion, extension, abduction, adduction, external rotation, internal rotation, and resting position. The main research problems are the design of a multielectrode EMG acquisition system, the preprocessing of EMG signals using rectification and Discrete Fourier Transform (DFT), and the extraction of signal features using Linear Envelope, Modified Mean Frequency (MMNF), and Modified Median Frequency (MMDF).

The contribution of this study is the presentation of a multichannel EMG acquisition and feature extraction procedure for seven shoulder joint movement patterns. Unlike a final movement classifier, this study emphasizes the extraction and interpretation of signal characteristics in the time and frequency domains. The results are expected to provide an early basis for further development of EMG-based movement recognition, especially for rehabilitation and prosthetic hand control systems.

2. Literature Review

2.1. Research Design and Workflow

This research is an experimental study involving EMG signal acquisition, instrumentation testing, signal preprocessing, feature extraction, and pattern analysis. The overall workflow begins with electrode placement on selected shoulder-related muscles. The analogue EMG signal is then amplified and filtered using the designed instrumentation circuit. After that, the signal is converted into digital data using the internal ADC of the microcontroller and transmitted to a computer through serial communication for further processing. The overall workflow of the proposed multichannel EMG acquisition and feature extraction system is shown in Fig. 1.

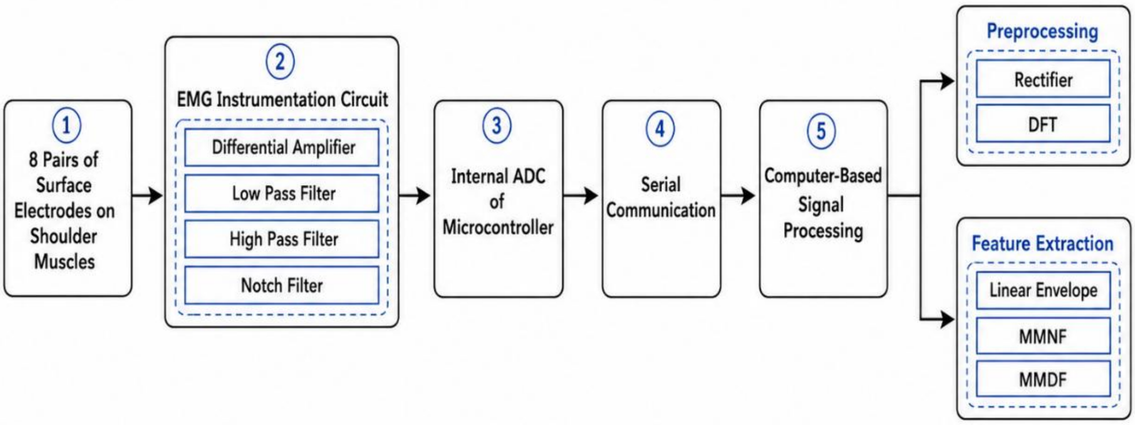

Fig 1. Workflow of multichannel EMG signal acquisition and feature extraction

Table 1. Summary of EMG data acquisition protocol

Aspect	Description
Signal type	Surface electromyography (EMG)
Movement patterns	Resting, shoulder flexion, shoulder extension, shoulder abduction, shoulder adduction, external rotation, internal rotation
Number of channels	8 muscle channels
Muscle channels	Deltoid1, Deltoid2, Infraspinatus, Supraspinatus, Teres Major, Latissimus Dorsi, Pectoralis1, Pectoralis2
Recording duration	4 seconds for each movement
Sampling interval	250 microseconds
Samples per channel	16,000 samples for each movement
Files per subject	56 files (8 channels x 7 movements)
Subjects	Three subjects were involved and anonymized as Subject A, Subject B, and Subject C.

2.2 Electrode Placement and Instrumentation

The EMG signals were recorded from eight muscle channels representing dominant muscles involved in shoulder joint movement. The channels consisted of Deltoid1, Deltoid2, Infraspinatus, Supraspinatus, Teres

Major, Latissimus Dorsi, Pectoralis1, and Pectoralis2. Each muscle point used surface electrodes, while the ground electrode was placed on the nearest bone region, namely the clavicle. The movement patterns consisted of resting, shoulder flexion, shoulder extension, shoulder abduction, shoulder adduction, shoulder external rotation, and shoulder internal rotation. The placement of surface electrodes for the eight-channel EMG acquisition is illustrated in Fig. 2.

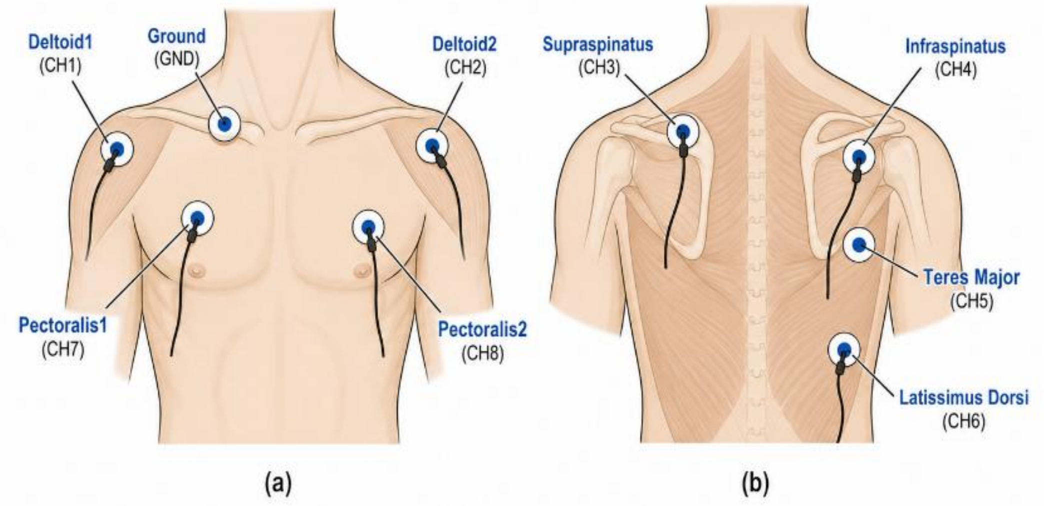

FIG 2. Electrode placement for eight-channel EMG acquisition

The instrumentation consisted of a differential amplifier, low pass filter, high pass filter, notch filter, data acquisition circuit, and computer-based processing program. The differential amplifier was designed to amplify weak EMG signals. In the developed system, the amplifier was prepared with a gain of 240 times for EMG signals in the range of 5-10 mV. The filter units were used to condition the EMG signal before digitization. The low pass filter, high pass filter, and notch filter were tested to verify their responses before the signal recording process.

2.3. Data Acquisition and Signal Processing

The data acquisition system used the internal ADC of the ATXMega128A1 microcontroller. The ADC was set to acquire data from eight channels with a sampling interval of 250 microseconds. Each movement was recorded for 4 seconds, producing 16,000 data points per channel. For one subject, the data consisted of 8 channels multiplied by 7 movements, resulting in 56 files. Three trials were performed for several feature extraction analyses. An example of raw EMG processing through full-wave rectification and Linear Envelope extraction is shown in Fig. 3.

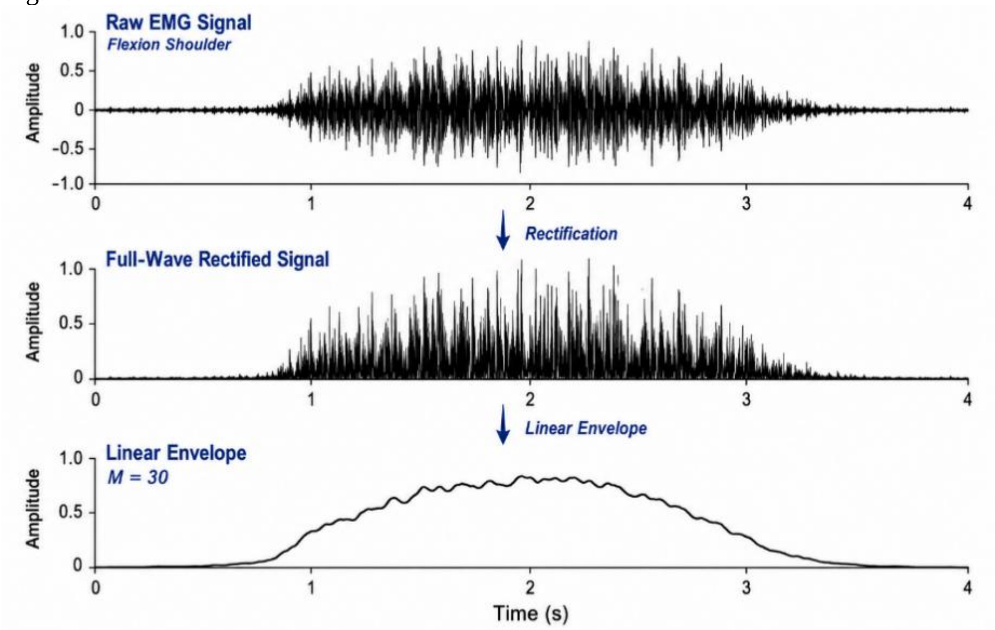

FIG 3. Example of raw EMG, full-wave rectified EMG, and Linear Envelope for shoulder flexion

The preprocessing stage included full-wave rectification to eliminate negative values in the EMG signal. For frequency-domain processing, the rectified EMG signal was divided into five segments for each movement pattern. Since each movement generated 16,000 samples, each segment contained 3,200 samples. The DFT process was then applied to transform time-domain EMG data into frequency-domain representation. The frequency index used for MMNF analysis was within the 20-500 Hz range.

Feature extraction was performed using three approaches. Linear Envelope was used to observe temporal changes in signal amplitude and energy. The Linear Envelope process used an order of M = 30. MMNF was used to calculate the average frequency-related energy characteristic of the EMG signal in the frequency domain. MMDF was used to obtain the median frequency characteristic from the accumulated signal energy. The extracted feature values were analysed based on mean values, standard deviations, and overlapping or non-overlapping ranges between movement patterns.

TABLE 2. Signal processing and feature extraction stages

Stage	Purpose	Output
Signal acquisition	Record EMG signal from eight surface electrode channels	Multichannel raw EMG signal
Rectification	Remove negative components of the EMG waveform	Rectified EMG signal
Segmentation	Divide 16,000 samples into five segments	3,200 samples per segment
DFT	Transform the signal from time domain to frequency domain	Frequency-domain representation
Linear Envelope	Analyse temporal energy or amplitude changes	Time-domain envelope feature
MMNF	Calculate modified mean frequency-based feature	Frequency-domain mean feature
MMDF	Calculate modified median frequency-based feature	Frequency-domain median feature

Table 2 summarizes the main stages of the signal processing and feature extraction procedures implemented in this study. To provide a clearer description of the computational process, the mathematical formulations corresponding to each processing stage are presented below. The EMG signals were processed sequentially through full-wave rectification, frequency-domain transformation, Linear Envelope computation, and frequency-based feature extraction using the Mean of Mean Frequency (MMNF) and Mean of Median Frequency (MMDF).

The first preprocessing stage converts the bipolar EMG signal into a unipolar signal using full-wave rectification:

$$x_r(n) = | x(n) | \quad (1)$$

where $x(n)$ denotes the original EMG signal and $x_r(n)$ represents the rectified signal. After rectification, the signal is transformed into the frequency domain using the Discrete Fourier Transform (DFT), expressed as

$$X(k) = \sum_{n=0}^{N-1} x_r(n) e^{-j2\pi kn/N} \quad (2)$$

The Linear Envelope is obtained by applying a moving-average filter with a window length of $M = 30$, as described by

$$LE(n) = \frac{1}{M} \sum_{k=0}^{M-1} x_r(n-k) \quad (3)$$

where $LE(n)$ is the Linear Envelope signal and M is the moving-average window length. Frequency-domain features were then extracted from the processed EMG signals. The Mean of Mean Frequency (MMNF) was calculated as

$$MMNF = \frac{\sum_{i=1}^{N} f_i P_i}{\sum_{i=1}^{N} P_i} \quad (4)$$

The Mean of Median Frequency (MMDF) corresponds to the frequency that divides the total spectral power into two equal halves and is determined by

$$\sum_{i=1}^{MMDF} P_i = \frac{1}{2} \sum_{i=1}^{N} P_i \quad (5)$$

The extracted Linear Envelope, MMNF, and MMDF features were subsequently analysed to identify characteristic activation patterns associated with seven shoulder joint movements. These features formed the basis for the qualitative comparison and discussion presented in the Results and Discussion section. The acquired EMG signals were analysed using their original amplitudes without amplitude normalization such as Maximum Voluntary Contraction (MVC) normalization or z-score normalization. Therefore, comparisons among subjects were interpreted qualitatively rather than quantitatively, while the feature extraction focused on identifying relative activation patterns across different shoulder movements.

2.4. Evaluation Scenario

The evaluation was arranged to verify both the acquisition hardware and the extracted signal features. Hardware evaluation included the differential amplifier, low pass filter, high pass filter, notch filter, and data acquisition unit. Feature evaluation focused on the interpretation of Linear Envelope, MMNF, and MMDF values for each movement pattern and muscle channel. The reported analysis used maximum energy, average dv/dt, mean feature values, standard deviation, and overlapping or non-overlapping feature ranges as the main basis for int erpretation.This study did not include a supervised classification experiment. Therefore, the evaluation in this article is limited to feature behavior and movement similarity analysis. This limitation is important for the formulation of the article claim: the study demonstrates the potential of multichannel EMG feature extraction, but it does not yet prove complete recognition accuracy for the seven shoulder joint movements

3. Results And Discussion

3.1. Instrumentation and Signal Recording Results

The first evaluation was performed on the EMG instrumentation circuits. The differential amplifier, low pass filter, high pass filter, and notch filter were tested to ensure that the hardware could support EMG signal acquisition. The differential amplifier was prepared for weak EMG signals and used a gain of 240 times. The filter responses were tested before the recording of multichannel EMG signals. These hardware tests indicate that the developed acquisition system was able to support the recording of EMG signals from eight muscle channels. Representative multichannel EMG recordings for the seven shoulder joint movement patterns are presented in Fig. 4.

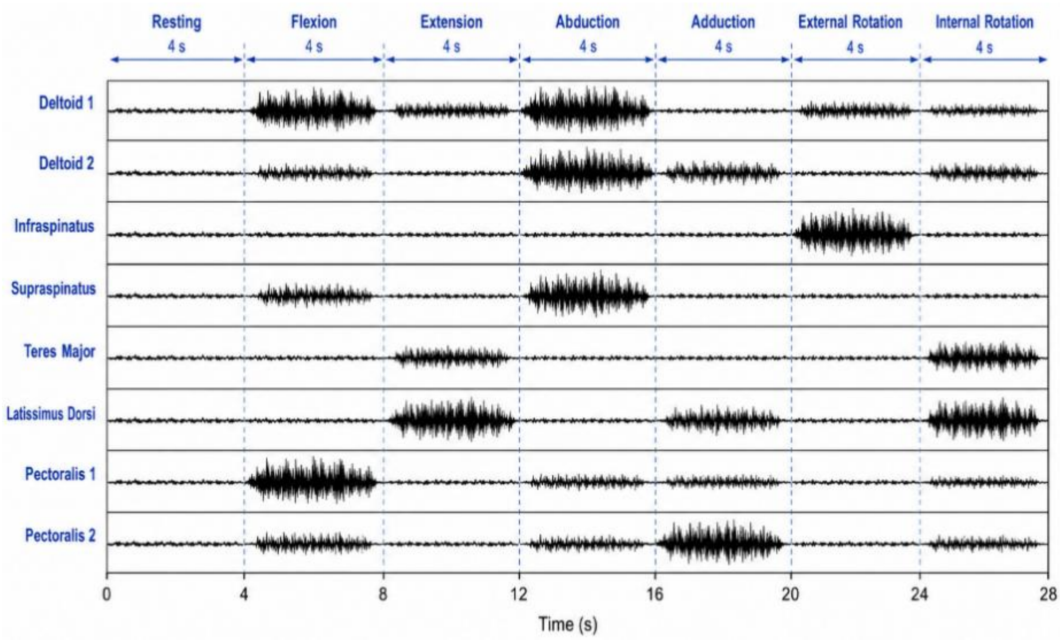

FIG 4. Representative multichannel EMG signals for seven shoulder joint movement patterns

The EMG recording process was conducted on eight muscle points located around the shoulder joint. Each movement was recorded for 4 seconds, and the signal patterns were observed for all channels. A cardiac artifact appeared in the Deltoid2 channel during data acquisition. This condition is important because artifacts can influence feature extraction results, especially when the channel is used to distinguish movement patterns. Therefore, the interpretation of Deltoid2 results must be treated carefully.

3.2. Linear Envelope Feature Analysis

The Linear Envelope results indicate that the resting shoulder movement produced very small amplitude changes over time. The average dv/dt values for resting movement were 0.0067 mV/s for Subject A, 0.0048 mV/s for Subject B, and 0.0058 mV/s for Subject C. This finding is consistent with the nature of the resting position, where muscle activity is relatively low compared with active shoulder movement patterns.

For shoulder flexion, Subjects B and C showed an energy pattern that increased from a low level to a higher level in almost all muscles except Deltoid2. Subject A showed a different pattern, where several muscles decreased in energy around the third second. The maximum energy during flexion reached 6.669 mV in the Pectoralis2 muscle of Subject A, 2.892 mV in the Infraspinatus muscle of Subject B, and 3.47 mV in the Infraspinatus muscle of Subject C. These differences show that the dominant muscle response may vary among subjects even under the same movement category. Because signal normalization was not performed, the reported amplitudes mainly reflect subject-specific muscle activation characteristics, electrode placement, and recording conditions. Consequently, comparisons of absolute amplitudes among subjects should be interpreted with caution. Therefore, the discussion focuses on identifying relative activation patterns associated with different shoulder joint movements rather than making direct quantitative comparisons between subjects.

For shoulder extension, the Linear Envelope produced several signal energy patterns. Subject A mostly showed increasing energy until the second and decreasing energy afterwards. Subjects B and C showed different decreasing patterns, and the highest energy for extension occurred in Pectoralis2 for Subject A, while Subjects B and C showed the highest energy in the Infraspinatus muscle. For shoulder abduction, Subjects A, B, and C had a similar tendency in which EMG energy increased from the beginning to the end of the movement, except in Deltoid2. The dominant muscles were Pectoralis2 in Subject A, Supraspinatus in Subject B, and Infraspinatus in Subject C.

The Linear Envelope results for adduction, external rotation, and internal rotation also showed variation across muscles and subjects. Adduction had diverse energy patterns similar to extension. External rotation showed varied patterns, but the most common tendency was increasing energy from the beginning to the fourth second. The highest energy of external rotation was reported in Supraspinatus for Subject A at 1.83 mV, Teres Major for Subject B at 0.9 mV, and Teres Major for Subject C at 1.3 mV. For internal rotation, the highest energy was consistently found in Teres Major, with values of 1.15 mV for Subject A, 1.046 mV for Subject B, and 1.288 mV for Subject C.

TABLE 3. Summary of Linear Envelope findings

Movement	Main finding
Resting	Very small amplitude change; average dv/dt values were 0.0067 mV/s (Subject A), 0.0048 mV/s (Subject B), and 0.0058 mV/s (Subject C)
Flexion	Energy increased in Subjects B and C for almost all muscles except Deltoid2; maximum energy was 6.669 mV in Pectoralis2 for Subject A
Extension	Several energy patterns were observed; Subject A increased until the second and then decreased; highest energy was in Pectoralis2 for Subject A and Infraspinatus for Subjects B and C
Abduction	Energy increased from the beginning to the fourth second for Subjects A, B, and C, except in Deltoid2
Adduction	Energy patterns were diverse, similar to extension; dominant muscles differed among subjects
External rotation	Most common pattern was increasing energy until the fourth second; dominant muscle differed among subjects
Internal rotation	Highest energy was consistently found in Teres Major across Subjects A, B, and C

3.3. MMNF Feature Analysis

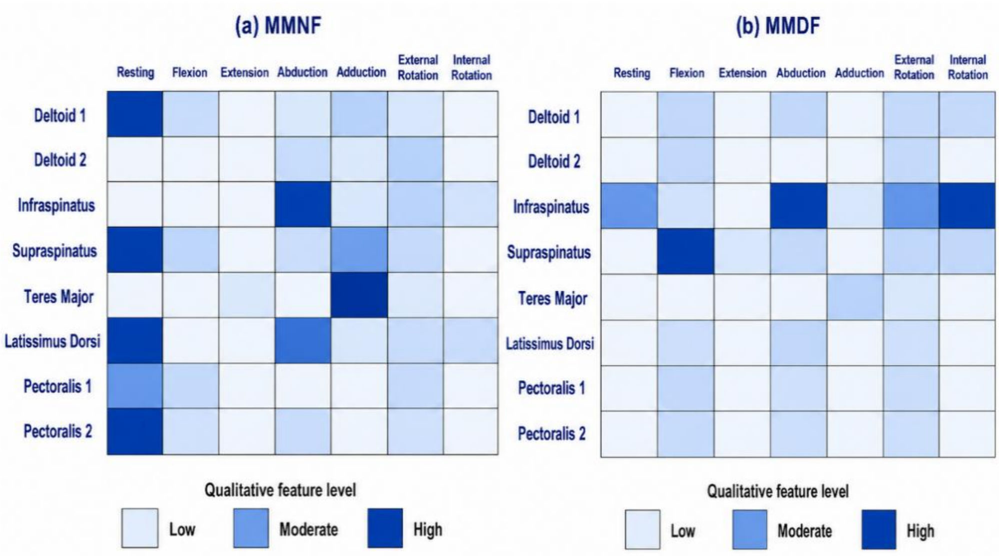

FIG 5. Qualitative MMNF and MMDF feature patterns for seven shoulder joint movements

The MMNF analysis revealed that similar movement patterns can be grouped based on frequency-domain features. In Subject A, the combination of all channels produced two groups of similar patterns. The first group consisted of flexion, extension, and adduction, while the second group consisted of resting, internal rotation, external rotation, and abduction. In the first group, adduction could be distinguished using non-overlapping MMNF values in Teres Major and Supraspinatus. In the second group, resting could be distinguished using Deltoid1, Supraspinatus, Latissimus Dorsi, Pectoralis1, and Pectoralis2, while abduction could be distinguished using Infraspinatus and Latissimus Dorsi. A compact qualitative summary of MMNF and MMDF feature patterns across the seven shoulder joint movements is shown in Fig. 5.

For Subject B, MMNF also produced two similarity groups. The first group consisted of abduction, adduction, and extension, while the second group consisted of resting, flexion, external rotation, and internal rotation. The first group could be distinguished using Pectoralis2, whereas the second group could be distinguished using Latissimus Dorsi. For Subject C, the same group structure as Subject B was observed; however, movement differences could not be determined clearly because overlapping MMNF values occurred across all muscles. This indicates that MMNF performance is subject-dependent and may require additional normalization or more robust classification procedures.

3.4. MMDF Feature Analysis

The MMDF analysis also produced two groups of similar signal patterns. In Subject A, the first group consisted of flexion, extension, and adduction, while the second group consisted of resting, abduction, external rotation, and internal rotation. Flexion could be distinguished using the MMDF value of Supraspinatus, while the four movements in the second group showed significant differences in Infraspinatus. For Subject B, flexion, adduction, and extension could be distinguished using Supraspinatus, and resting, abduction, external rotation, and internal rotation could be distinguished using Infraspinatus. For Subject C, flexion could be distinguished using Teres Major, while resting and abduction could be distinguished using Infraspinatus.

TABLE 4. Summary of distinguishing features from MMNF and MMDF

Subject	Method	Similarity groups	Distinguishing muscle/channel reported
A	MMNF	Group 1: flexion, extension, adduction; Group 2: resting, internal rotation, external rotation, abduction	Adduction: Teres Major and Supraspinatus; Resting: Deltoid1, Supraspinatus, Latissimus Dorsi, Pectoralis1, Pectoralis2; Abduction: Infraspinatus and Latissimus Dorsi
B	MMNF	Group 1: abduction, adduction, extension; Group 2: resting, flexion, external rotation, internal rotation	Group 1 distinguished by Pectoralis2; Group 2 distinguished by Latissimus Dorsi
C	MMNF	Same group structure as Subject B	Overlapping MMNF values occurred across all muscles; movement differences were difficult to determine
A	MMDF	Group 1: flexion, extension, adduction; Group 2: resting, abduction, external rotation, internal rotation	Flexion: Supraspinatus; Group 2 differences: Infraspinatus
B	MMDF	Group 1: flexion, adduction, extension; Group 2: resting, abduction, external rotation, internal rotation	Group 1 distinguished by Supraspinatus; Group 2 distinguished by Infraspinatus
C	MMDF	Group 1: flexion, adduction, extension; Group 2: resting, abduction, external rotation, internal rotation	Flexion distinguished by Teres Major; resting and abduction distinguished by Infraspinatus

3.5. Discussion

Overall, the results show that Linear Envelope provides useful temporal information, whereas MMNF and MMDF provide frequency-domain features that can group and partially distinguish movement patterns. However, the results should not yet be interpreted as complete seven-class classification performance because this study did not evaluate classification accuracy, confusion matrix, sensitivity, specificity, or statistical hypothesis testing. Therefore, the strongest claim of this study is feature extraction and similarity analysis of multichannel EMG signals for shoulder joint movements.

The combination of Linear Envelope with MMNF and MMDF is useful because it provides complementary information. Linear Envelope describes the time-domain evolution of muscle activity, while MMNF and MMDF summarize frequency-domain characteristics. In the observed movements, temporal energy patterns alone could describe whether energy increased or decreased during movement, but frequency-domain features were needed to identify specific muscles that could separate movements within similar groups.

The results also show that the same movement does not always produce the same dominant muscle channel across subjects. This may be related to inter-subject variation, electrode placement, muscle activation strategy, or signal artifact. Therefore, future development should consider normalization, repeated trials, artifact handling, and subject-independent evaluation before the method is used in an online recognition system.

3.6. Limitations and Future Improvement

This study has several limitations that should be considered. First, the number of subjects was limited, and the inter-subject variation in muscle activation patterns affected the consistency of the extracted features. Second, the analysis was focused on feature extraction and movement similarity rather than supervised classification; therefore, classification performance metrics such as accuracy, confusion matrix, sensitivity, and specificity were not evaluated. Third, signal artifacts, particularly in the Deltoid2 channel, may have influenced the extracted feature values and should be addressed through improved signal conditioning or artifact removal techniques. In addition, the current analysis was performed on recorded data, so its performance in an online or real-time acquisition system has not yet been validated.

Future work should focus on improving the robustness and practical applicability of the proposed EMG feature extraction approach. Automatic gain adjustment should be implemented before EMG recording to obtain more stable signal amplitudes across subjects and movement patterns. Online data acquisition and real-time feature extraction should also be developed to support practical movement recognition systems. Furthermore, future studies should involve more subjects, repeated trials, signal normalization, artifact reduction, and quantitative classification evaluation using appropriate machine learning methods. These improvements are expected to strengthen the reliability of multichannel EMG-based shoulder movement pattern recognition.

4. CONCLUSIONS

This study has converted multichannel EMG recordings from seven shoulder joint movement patterns into time-domain and frequency-domain features. EMG signals were acquired from eight muscle channels using surface electrodes and processed using rectification, DFT, Linear Envelope, MMNF, and MMDF. The Linear Envelope results show that resting movement has very small amplitude changes, while active movements produce different temporal energy patterns across muscles and subjects. MMNF and MMDF were able to form two similarity groups and identify several distinguishing muscle channels for specific movement patterns. Nevertheless, the distinguishing features were not fully consistent across subjects, and MMNF values in one subject showed substantial overlap, making movement separation more difficult. These findings indicate that multichannel EMG feature extraction can provide an initial basis for shoulder movement pattern analysis, but further research is required to implement automatic gain adjustment, online data acquisition, faster feature extraction, and quantitative classification evaluation

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