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# Feature extraction and selection for the classification of myoelectric signal

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**ABSTRACT** – Recently, electromyography (EMG) pattern recognition has been widely investigated for rehabilitation purpose. Advance in EMG pattern recognition allows the patients to recover their hand functionality. This paper aims to investigate two popular features including Mean Absolute Value (MAV) and Autoregressive Coefficient (AR) extracted from reconstructed wavelet coefficient in the classification of multiple hand movement types. Two classifiers, namely Linear Discriminate Analysis (LDA) and Support Vector Machine (SVM) are employed in the performance evaluation. According to findings, AR feature outperforms MAV not only in term of classification performance, but also robustness of the model.

## 1. INTRODUCTION

Electromyography (EMG) has been widely used in rehabilitation and clinical applications. In recent days, EMG pattern recognition provides the opportunity for the patients to recover their hand functionality, especially for trans-radial amputee. Due to high potential and nature characteristic of EMG signals, it has been successfully applied in myoelectric prosthetic control [1].

Current EMG pattern recognition usually involves 3 important steps. There are signal processing, feature extraction and classification. Signal processing transforms the signal into time and frequency representation to obtain valuable information. Feature extraction attempts to extract hidden information from the signal. At last, classifier is used to differentiate the EMG signals based on the extracting features [2].

Based on our previous work in [3], Root Mean Square (RMS) extracted from the reconstructed Discrete Wavelet Transform (DWT) achieved better classification performance compared to other conventional methods. However, it is interesting to know whether different feature extracted from reconstructed DWT is able to produce an accurate EMG signals classification. For this reason, this study aims to investigate the classification performance of two popular features, namely Mean Absolute Value (MAV) and Autoregressive Coefficient (AR) in the classification of 17 hand movement types.

## 2. METHODOLOGY

Figure 1 illustrates the flow diagram of the proposed EMG pattern recognition system. Firstly, the EMG data is acquired from NinaPro database. After that, RDWT is used to transform the signals into multiresolution coefficient. Then, features are extracted from each wavelet coefficient and fed into LDA and SVM for the classification of 17 hand movement types.

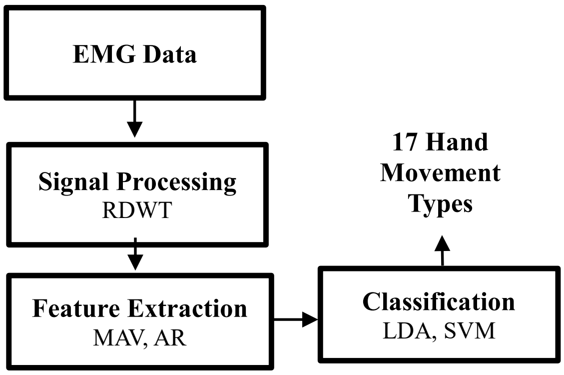


Figure 1 Flow diagram of proposed system.

### 2.1 Reconstructed Discrete Wavelet Transform

Based on our previous work in [3], reconstructed DWT (RDWT) with Db4 at fourth decomposition level outperformed spectrogram in EMG signals classification. Thus, RDWT is applied in this research. RDWT is the estimated DWT that can be achieved by performing the inverse wavelet transform on each wavelet coefficient according to the level of decomposition. For example, the reconstructed detail at level 2, $rD_2$ is obtained by computing inverse wavelet transform on detail, $D_2$ at second decomposition level.

### 2.2 Feature Extraction

RDWT decomposes and reconstructs the signal into multi coefficients, which consists of high dimension. To reduce the dimensionality, feature extraction is employed. Feature extraction is an essential step to extract the hidden information from the signal. In this work, 2 features including Mean Absolute Value (MAV) and fourth order Autoregressive Coefficient (AR) are extracted from each wavelet coefficient [4], [5]. In total, 96 features (MAV) and 384 features (AR) are acquired from each movement from each subject.

## 3. RESULTS AND DISCUSSIONS

The EMG data of 10 healthy subjects are collected from the NinaPro database 4 [6]. RDWT transforms the EMG signals into time-scale representation in order to obtain more valuable information. Next, features are extracted from each wavelet coefficient to form a feature vector. Finally, machine learning algorithms are used to evaluate the performance of extracting features for the classification of 17 hand movement types. In this work, two classifiers namely Linear Discriminate Analysis (LDA) and Support Vector Machine (SVM) are used in performance evaluation since LDA and SVM often offer promising results in EMG pattern recognition [3], [5], [7]. Note that 6-fold cross-validation is used in the performance evaluation.

Table 1 demonstrates the results of LDA and SVM for both MAV and AR feature set. As can be seen, SVM provides better result compared to LDA. By applying AR+SVM, all 10 subjects have the classification accuracy of above 90%, especially subject 5, who achieves the 100% recognition rate. On the contrary, subject 3 achieves the accuracy lower than 90% in AR+LDA. On the other hand, MAV offers a competitive result, which is slightly worse than AR. The reason AR achieves better classification performance might be due to larger number of features (384 features), thus improving the classification performance.

Based on the obtained mean classification accuracy in Table 1, it can be inferred that AR+SVM is the overall best combination, which gives the highest mean accuracy of 95.98% in this work. Concerning the robustness of model, AR+SVM achieves the highest consistency due to smallest standard deviation value (2.332%). Evidently, AR features contributes significant improvement in classification accuracy for both LDA and SVM models.

Table 1 Experimental results of LDA and SVM.

| Subject | Classification accuracy (%) | | | |
|---|---|---|---|---|
| | LDA | | SVM | |
| | AR | MAV | AR | MAV |
| 1 | 96.08 | 91.18 | 97.06 | 91.18 |
| 2 | 97.06 | 96.08 | 95.10 | 84.31 |
| 3 | 89.22 | 92.16 | 95.10 | 86.27 |
| 4 | 97.06 | 83.33 | 97.06 | 85.29 |
| 5 | 96.08 | 90.20 | 100 | 91.18 |
| 6 | 95.10 | 94.12 | 95.10 | 91.18 |
| 7 | 98.04 | 95.10 | 97.06 | 96.08 |
| 8 | 93.14 | 87.25 | 92.16 | 89.22 |
| 9 | 96.08 | 94.12 | 98.04 | 93.14 |
| 10 | 98.04 | 91.18 | 93.14 | 88.24 |
| **Mean** | 95.59 | 91.47 | 95.98 | 89.61 |
| **STD** | 2.665 | 3.868 | 2.332 | 3.674 |

## 4. CONCLUSIONS

In this paper, the performance of MAV and AR features extracted from RDWT have been examined. The experimental results show that AR outperforms MAV not only in term of classification accuracy, but also consistency. Moreover, the superior classifier is found to be SVM, which offers the optimum classification performance in this work. On the whole, it is concluded that AR+SVM is the best combination to achieve the optimal performance and it is recommended to be used in rehabilitation and clinical application.


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