Feature extraction for multiclass classification: Application to hand gesture recognition

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Abstract—With the recent advances in the biomedical field, a massive amount of data and records (signals) is collected for diagnosis purposes. The correct interpretation and understanding of these signals presents a big challenge for digital health vision. In this work, Quantization-based position Weight Matrix (QuPWM) for feature extraction for multiclass classification is proposed to improve the interpretation of biomedical signals. This method is validated on surface electromyogram (sEMG) signals recognition for eight different hand gestures. The used CapgMyo dataset consists of high-density sEMG signals across 128 channels acquired from 7 intact subjects. The obtained results show that an accuracy of up to 87% can be achieved for some subjects using a logistic regression model, and an average accuracy of 77% has been reached for all subjects using the CapgMyo dataset. The proposed method can be used to extract relevant features in a wide range of biomedical signals such as electroencephalogram (EEG) and magnetoencephalogram (MEG) signals.

Keywords—position weight matrix, electromyography, hand gesture, EMG, feature extraction

I. INTRODUCTION

Many people are living with limb loss due to traumatic injuries, amputation, and diseases [?]. These people’s daily activities become limited (i.e., picking up objects, typing, clicking a mouse), and they could not easily adapt themselves to this new situation [1]. Prosthetic hands propose a natural extension by providing a robotic arm that can perform complex hand gestures based on their motor abilities [2]. The prosthetic hand is controlled according to the muscles move to perform a specific gesture. Muscles contraction/detraction is sensed using different modalities such as the sounds produced by the muscles also known as acoustic myography (AMG) [3], or their electrical activities so called surface electromyogram (sEMG) [4], [5], etc. Since it has been first discovered, sEMG signals helped to sense the electrical activity of the muscles in a non-invasive way. The correct interpretation of these sEMG signals will allow performing multiple gestures and will open the door toward fully restoring hand functionality. Researchers tend to use sEMG signals because these records are reliable and provide accurate measurements. However, the sEMG records depend on the subject and his physical conduction, such as skin conductivity or to the external noise related to the electrodes placement and electronic noise. For hand gesture classification, the use of sEMG signals presents additional challenges such as similar electrical activities for different types of gestures. In addition, the implementation constraint, such as low cost and real-time response, imposes the use of low processing capacity, in terms of computation and memory, to interpret these signals. Several methods have been proposed to understand the sEMG signals in order to control the prosthetic arm efficiently. These methods can be divided into two main categories: first, traditional machine learning combined with feature extraction based methods. These techniques aim at extracting inherent and discriminative patterns in the sEMG signals using signal processing and statistical techniques [6]–[9]. Second, deep learning (DL) based methods that employ different DL typologies and models such as recurrent neural networks [10], [11], convolutional neural network [12]. In this work, we propose a novel feature generation method for multi-class sEMG signal classification. This method is based on the well-known Position Weight Matrix (PWM) combined with a uniform quantization scheme. The approach named Quantization-based PWM (QuPWM) was recently proposed for binary classification [13] to extract some of the hidden discriminative patterns related to the common pattern between each two classes. In this work, the QuPWM is extended to cover multi-class classification representing eight hand gestures.

This paper is organized as follows. Section II includes a description of the used CapgMyo dataset [14] and the proposed feature extraction framework based on the QuPWM method. Section III presents and discusses the obtained results for eight classes classification with different standard classifiers using four different subjects. Finally, section V summarizes our findings with concluding remarks.

II. METHODS

The proposed technique for multi-class classification method consists of three steps:

- **Quantization**: sEMG signals are converted into sequences using a uniform quantizer.
- **Features extraction**: a set of QuPWM features are extracted using the quantized sEMG signals based on the Position Weight Matrix (PWM) method [13].
- **Classification**: the extracted features are fed to standard classifiers for multiple hand gestures classification.
The proposed framework is illustrated in Fig. 1 and described in detail in the following sections.

**A. sEMG signals quantization**

As the PWM method deals only with sequences, the sEMG of the CapgMyo dataset, which is described in details in section III-A, are converted into sequences using uniform quantization scheme \[15, 16\]. The quantization step converts the real-valued signals \(X\) into a sequences \(Q = \mathcal{F}(X)\) containing a discrete set or levels \(\Omega = \{q_1, q_2, \ldots, q_M\}\) of size \(M\) of resolution \(\bar{\sigma} = k \times \sigma\) is defined as \(\mathcal{F}: R \rightarrow \Omega\) as follows:

\[
\mathcal{F}(X) = \begin{cases} 
q_1 & \text{if } X < \mu + \frac{(2 - M) \bar{\sigma}}{2} \\
q_{(k+M/2)} & \text{if } \mu + (k - 1) \bar{\sigma} \leq X < \mu + k \bar{\sigma} \\
q_M & \text{elsewhere}
\end{cases}
\]

such that:

\[
k = \frac{-M}{2} + 2, \frac{-M}{2} + 3, \ldots, \frac{M}{2} - 1,
\]

where \(\mu\) and \(\sigma\) are the mean value and the standard deviation of the real-valued signals used for quantization. The choice of these specific values was motivated by the 3-sigma rule \[17, 18\]. Therefore, every signal sample \(X(n)\) of the input sEMG signals will be converted into a specific level \(q \in \Omega\), as illustrated in Fig. 1.

**B. QuPWM-based features extraction**

The position weight matrix (PWM) is a well known method for motifs characterization and discovery in biological sequences such as DNA/mRNA \[19, 21\]. Inspired by the PWM method, QuPWM was recently proposed for binary classification and it showed great potential in motifs extraction \[13\]. In this work, we extended the QuPWM method to multi-class classification by building a PWM, \(PWM^C\), for each class "C" derived from the corresponding training set of this class. The PWM matrices indicate the significance of each position within input sequences for each class. For instance, PWM matrice of class "A" is denoted \(PWM^A\) and defined as:

\[
PWM^A[i, q_j] = \sum_{s=1}^{N^A_s} \xi(Q^A_s(i), q_j)
\]

where \(N^A_s\) is the total number of sequences of the class "A". The \(\xi(a, b)\) function is defined as follows:

\[
\xi(a, b) = \begin{cases} 
1 & \text{if } a = b \\
0 & \text{elsewhere}
\end{cases}
\]

In this work, we derived features from what we call motif-based PWMs (mPWM), which can be built using new extra motifs extracted from the same sequence as shown in Algorithm 1 and Fig. 2. In other words, the input sequence is decomposed into different binary sequences, where each is reflecting the presence of a specific motif of levels along the input sequence.
corresponding to the motif $m$ in Algorithm 1, to be in the class "A" as as follows:

$$\bar{S}_m(n) = \begin{cases} q_{m2} & \text{if } Q(n) = q_2 \text{ and } Q(n+1) = q_3 \\ 0 & \text{elsewhere} \end{cases}$$

For instance, the motif sequence $m_{q_2q_3}$ or di-mers sequence is defined as follows:

$$m_{q_2q_3}(n) = \begin{cases} 1 & \text{if } Q(n) = q_2 \text{ and } Q(n+1) = q_3 \\ 0 & \text{elsewhere} \end{cases}$$

Therefore, the mPWM matrix of a specific motif, i.e., motif of di-mers $q \in \Omega_k$, of the class "A" is denoted $PWM_{m2}^A$ and defined as:

$$PWM_{m2}^A[i, q] = \sum_{s=1}^{N^+} m_q^{A,s}(i),$$

where $m_q^{A,s}(i)$ denotes $i^{th}$ sample of the $s^{th}$ motif sequences $m_q$ of the class "A".

Each of these mPWMs matrices are used to generate two scores representing the projection of the input sequence into this specific class. For example, the two scores $S_{m2}^A(Q, q_2q_3)$ and $S_{m2}^B(Q)$ gives an intuition/probabilities of a given motif $m - q_2q_3$, extracted from the sequence and $Q$ as defined in Algorithm 1, to be in the class "A". These two scores corresponding to the motif $m_q$ in the class "A" are defined as as follows:

$$S_{m2}^A(Q, q) = \frac{\sum_{i=1}^{N^+} m_q(i) \times PWM_{m2}^A[i, q]}{\sum_{j=1}^{M} PWM_{m2}^A[j, q]},$$

$$S_{m2}^B(Q) = \sum_{q \in \Omega} S_{m2}^A(Q, q).$$

For instance, the features vector $V$ to be extracted using di-mers motifs from the input signal $Q$ is defined as follows:

$$V = [S_{m2}^A, \bar{S}_{m2}^A, S_{m2}^B, \bar{S}_{m2}^B, S_{m2}^C, \bar{S}_{m2}^C, \ldots]$$

### C. Classification models

The extracted feature vector $V$ is fed to different scikit-learn models followed by their used parameters: Logistic Regression (LR) with (default parameters) K-Nearest Neighbors with ($K=3$), Support Vector Machine (SVM) with (C=0.025), Decision Tree (DT) with (max_depth=5), Random Forest (RF) with (max_depth=5), Naive Bayes (NB) with (default parameters). In this study, the pair trials are used for the training and the odd trials for testing. The classification performance is calculated using the average accuracy, recall, and precision of all eight classes based on the confusion matrix (see Fig. 3). Finally, the best model is determined by the highest average accuracy achieved.

### III. RESULTS AND DISCUSSION

#### A. CapgMyo Dataset

The CapgMyo database is benchmark database of High-density sEMG (HD-sEMG) recordings of hand gestures performed by 23 participants (able-bodied subjects ranging in age from 23 to 26 years), based on an 8x16 electrode array by using a newly developed acquisition device [14].
The included set of gestures was a subset of the NinaPro database, with the acquisition device having a matrix-type (8 × 16) differential electrode array with wet silver electrodes. We used eight different hand gestures, as illustrated in Fig. 4. Each gesture was held for 3 to 10 seconds and repeated 10 times. To avoid fatigue, the gestures were alternated with a resting posture lasting 7 seconds. Because the gestures were performed in order, repetitive, almost unconscious movements were encouraged, as in the NinaPro database.

B. The effect of the quantization parameters

The quantization scheme affects classification performance. This is because the different classes have different distributions. Therefore, it is very important to choose a suitable quantization scheme that covers all these variables and produces low feature vector’s dimension by reducing the number of levels $M$. Table I shows that for a resolution factor $k = 2$, the optimal number of quantization levels is $M = 10$ using di-mers features.

<table>
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<th>M</th>
<th>$\sigma$</th>
<th>0.5$\sigma$</th>
<th>1$\sigma$</th>
<th>2$\sigma$</th>
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C. Sensitivity analysis of the classification performance

To study the robustness of the method on different subjects, the optimal quantization scheme is used for each subject. Fig. 5 shows the performance of different classifiers for subject 1. The figure shows that the logistic regression model gives better results compared to the other classifier. The same classification model is applied to other subjects, as shown in Table II. The Table shows that the QuPWM method can achieve an average accuracy for all subjects around 77%). The main advantage of these new features combined with standard classifiers, as opposed to deep classifiers, is their straightforward hardware implementation.

D. Comparison to existing methods

IV. CONCLUSION

We propose a new feature extracting method based on the Quantization-based position Weight Matrix (QuPWM) method designed explicitly for multiclass classification on biomedical signals. For validation, the method is applied to multiple hand gestures classification using sEMG signals. The obtained results are promising and achieve good average accuracy for different subjects using different classifiers. It is worth mentioning that the variability between the different classes distribution makes the choice of the quantization scheme crucial and sensitive for this method. Therefore, an optimal non-uniform quantization scheme might be used in order to improve the efficiency of the method and build a subject-independent model for real applications.

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