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Cardinality and Short-Term Memory Concepts based Novel Feature Extraction for Myoelectric Pattern Recognition

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***Abstract*—The quality of the extracted traditional hand-crafted Electromyogram (EMG) features has been recently identified in the literature as a limiting factor prohibiting the translation from laboratory to clinical settings. To address this limitation, a shift of focus from traditional feature extraction methods to deep learning models was witnessed, as the latter can learn the best feature representation for the task at hand. However, while deep learning models achieve promising results based on raw EMG data, their clinical implementation is often challenged due to their significantly high computational costs (significantly large number of generated models' parameters and a huge amount of data needed for training). This paper is focused on combining the simplicity and low computational characteristics of traditional feature extraction with the memory concepts from Long Short-Term Memory (LSTM) models to efficiently extract the spatial-temporal dynamics of the EMG signals. The novelty of the proposed method can be summarized in a) the memory concept leveraged from deep learning structures, capturing short-term temporal dependencies of the EMG signals, b) the use of cardinality to generate logical combinations of spatially distinct EMG signals and as a feature extraction method and 3) low computational costs and the enhanced classification performance. The performance of the proposed method is validated using three EMG databases collected with 1) laboratory hardware (9 transradial amputees and 17 intact-limbed), and 2) wearables (22 intact-limed using two wearable consumer armbands). In comparison to several other well-known methods from the literature, the proposed method shows significantly enhanced myoelectric pattern recognition performance, with accuracies reaching up to 99%.**

1. INTRODUCTION

The Electromyogram (EMG) signals from the remaining muscles after amputation have long been investigated as a source of control for powered prosthetics, to give an opportunity for people with amputations to live and work in a way that was previously difficult [1]. Advanced commercial prostheses, employing pattern recognition (PR) technologies to revolutionize the way muscles' bioelectrical activity signals are used to control a multifunctional prosthesis, are nowadays available. However, despite the success of EMG driven PR-based prostheses (a.k.a myoelectric prostheses), recent literature has pointed out that limitations arise when exporting such systems from the laboratory to real-life clinical applications, as it is usually found that the clinical accuracy is inferior to that achieved in controlled laboratory environments [2]. For real-time applications, any such controller should theoretically operate under minimal latencies and memory requirements for processing and decision making, all while maintaining the accuracy of movement identification. It has also been reported that the lack of intuitive control renders such a technology to be rejected by amputees given the delays and inaccuracies associated with many systems [3]. Hence, accuracy and reliability are key points to determine the success of such a technology. Several factors contribute to achieving high accuracies for controlling a prosthetic arm and ensure its reliability including for example training and testing the developed algorithms with many datasets, including more subjects (intact-limbed and amputees), selecting more movements, and recording data under different experimental conditions (limb position change, varying contraction force efforts, forearm orientations, etc.). To prove our results, we implement our algorithm using three main databases of surface EMG (sEMG) signals recorded from the forearm: BioPatrec-database, 3DC-database, and Forces- database.

Several traditional EMG feature extraction methods were used in the literature, including (but not limited to): the waveform length (WL), mean absolute value (MAV), sloop sign changes (SSC), number of zero crossings (ZC) [4]; fast Fourier transform (FFT) [5], wavelets and wavelet packet transform (WPT) [6, 7]; cepstral coefficients (CC), Willison amplitude (WAMP) [8]; sample entropy (ENT) [9]; and the autoregressive (AR) model parameters [10]. Feature extraction and selection was also a focus on a number of studies comparing a significant number of features for their suitability in this problem [11,12]. This work examined several well-known feature sets like six-order AR6 model coefficients, WL, ZC, Root Mean Square (RMS), and Hjorth time-domain (HTD) parameters. Other feature sets considered here were Hudgins's feature set consisting of MAV, MAVS (MAV slope), ZC, SSC, and WL [13], Englehart's set excluding MAVS from Hudgins set [14], Hargrove's set which is composed of Hudgins's set plus AR6 and RMS [15], Khushaba's fusion of time-domain descriptors (fTDD) [16], consisting of six features representing the root squared zero-order moments, root squared fourth and eighth order moments,

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sparseness, irregularity factor and WL ratio [16], and Khushaba's temporal-spatial descriptor (TSD) method [17].

One of the recently suggested and promising features is cardinality [18], which is represented by counting the number of elements in a set of items, excluding all the similar items among the elements in that collection [18,19]. Compared with other individual features that are commonly used in the literature, cardinality has been shown as one of the features that can achieve good accuracy despite variations in sampling frequency, window segments, and type and number of classes of movements [19], which makes cardinality a major interest of further developments.

Inspired by the earlier reported performance, we aimed to extend the work on cardinality by adding two major components: 1) a memory component, to overcome the cross-sectional nature of traditional feature extraction, as inspired by the concept of LSTM models [20] and 2) a spatial component, by using the cardinality principle between every possible combination of two spatially distinct EMG channels to consider the synergy between the activities of different muscles/sensors. Once the EMG activities in the channel combinations are translated into a unique set of new EMG values, we then extract three TD features from this combination as will be discussed below.

2. Data Collection

The validation of our approach was achieved through three EMG databases. The first database (Force-database denoted here as D1) was collected from 9 transradial amputees (seven traumatic and two congenital), Six movements, including different grip and finger movements, were investigated; these movements are: 1) Thumb flexion; 2) Index flexion; 3) Fine pinch; 4) Tripod grip; 5) Hook grip (hook or snap); 6) Spherical grip (power) as in [21]. For each of the six movements, three force levels: low, medium, and high, have been produced. Five to eight trials were recorded for each force level and for each amputee. The second database (BioPatrec-database denoted here as D2) was collected from 17 hand intact people acquired using 8 bipolar electrodes to classify six hand and wrist movements [22]; this dataset is made of eleven hand/wrist gestures. The Third database (3DC-database denoted here as D3) used a wearable sEMG acquisition system using ten sEMG recording channels to collect the data for eleven hands/wrist gestures [23], as shown in Fig.1. A brief detail of all databases is illustrated in Table I. The main reason behind using these databases is to provide some level of variability to test the effectiveness of the proposed method on different experimental conditions. In this work, the EMG signals from all sources were filtered using a 4th order Butterworth high pass filter (20Hz) to remove movement artifacts.

3. Methodology

The methodology followed in this study depends mainly on finding the temporal (using the concept of recurrent deep learning LSTM method) and spatial dependencies (using the concepts of cardinality). These methodologies can be summarized as follows:

A. Cardinality (Getting Special dependencies)

The cardinality of a collection like A is represented as *Card* (A) or |A|. Accordingly, for two sets of data, the cardinality between them is the number of unique values within these two sets and denoted as |A ∩ B|. One of the main reasons behind using cardinality as a feature is that it is not affected by DC offsets that are commonly caused by the mismatch of electrode impedance.

Figure.1 The eleven hand/wrist gestures [23].

TABLE I: A BRIEF FACTS FOR THE USED DATASET

	Sub. No.	Chan. No.	Class. No.	Samp. Freq. (Hz)	Intact/Amputees
D1	9	8	6	2000	Transradial amputees
D2	17	8	6	2000	Healthy participants
D3	22	10	11	200	Intact-limbed

An overlapping segmentation scheme was utilized to extract the features from the recorded EMG channels (assuming *NC* to be the total number of available channels). The first step in the analysis is to consider every possible combination of *n* out of *NC* across the current analysis windows ($n = 2$, to simplify analysis). This will end up with a combination of (*NC* x *NC*)-*NC*)/2 logical combinations of two channels. Each two windows from the spatially distinct EMG channels are then concatenated and the number of unique elements is calculated (after normalization and rounding to nearest integer). Three time-domain features are then extracted per each unique set of values, these are: cardinality (the count of the unique elements), mean, and the sum of the first differentiation. The same features are also calculated from each individual channel, ending up with a total number of features (Tot_{fet} = (*NC* x *NFPC*) +((*NC*x*NC*)-*NC*)/2 x *NFPC*) features, where *NFPC* is the number of features extracted per channel. Once these are all calculated, the same procedure is repeated to extract the features from a nonlinear version of the original signals (schematically shown in Fig.2) and the cosine similarity between the two sets is calculated [12] as

$$f_i = \frac{-2a_i b_i}{a_i^2 + b_i^2} \qquad \text{where } i = 1, 2, 3, \ldots Tot_{fet.} \qquad (1)$$

B. Establishing Temporal Dependencies

The Long Short-Term Memory (LSTM) works on processing the previous outputs along with the current inputs, i.e., it allows previous information to be processed, with each chunk of the neural network [24]. LSTMs are mainly designed to overcome the long-term dependency problem and enhance the short-term memory through its cell state. In this work, features were extracted using the inspiration of LSTM. Where the short-term memory concept is applied after applying the process mentioned in section A. In this approach, the features extracted from the current windows are multiplied by those extracted from a previous window (adjacent or non-adjacent), and the results are sigmoid mapped to keep the features' range within acceptable limits. This method allows short-term memory to be captured, i.e., within-trial/gesture memory component, especially when there is a high degree of overlap between adjacent windows (further details in or team's recent work in [12]). The block diagram of the proposed method can be demonstrated in Fig.3, where blocks A & B are the same as in Fig.2.

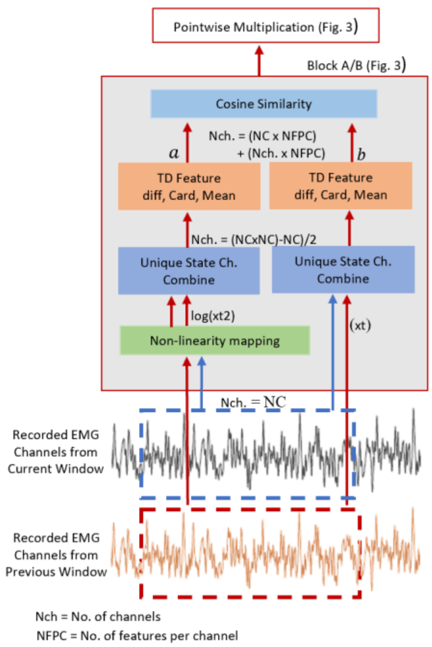

Figure.2 Block diagram of the proposed feature extraction method for each sliding window

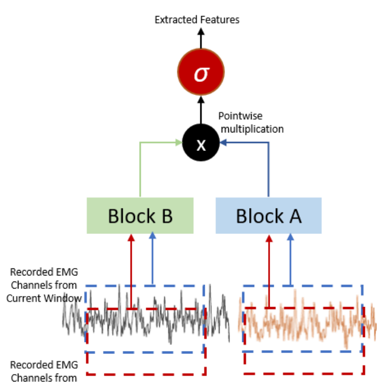

Figure.3 Block diagram of the proposed feature extraction method

After extracting the feature, dimensionality reduction was applied using the Spectral Regression feature projection method (SR) [25], which is utilized to map the original feature set into a new domain with $c-1$ features only, with c being the number of classes, leading to a reduced computational cost.

Finally, two classification methods were evaluated, which are the traditional Linear Discriminant Analysis (LDA) and Support Vector Machines (SVM). As the performance of SVM is susceptible to the kernel function parameter γ and the regularization parameter C, therefore, the parameters for SVM were adjusted and optimized for each dataset.

4. Results and Discussion

To show the superior performance of the proposed method, it is applied to three different databases, with the classification results demonstrated as shown below:

A. Results of Dataset 1 (Force-database)

For the transradial amputee dataset, results were computed for each of the force levels, and each feature extraction and classification method, as shown in Fig.4. Across these results, the proposed method significantly outperformed all other considered methods from the literature ($p < 0.001$).

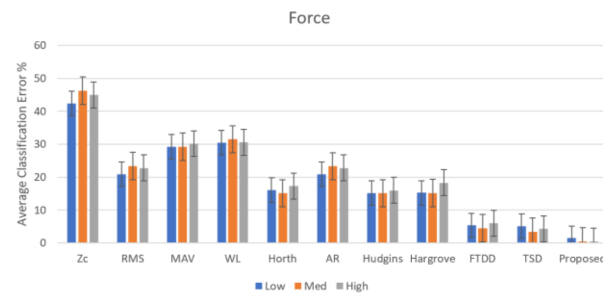

Figure.4 Shows the effectiveness of the proposed method with different TD features using LDA classifier for the Force dataset

B. Results of Database 2 (BioPatrec-Database)

The average classification errors across the 17 participants of the BioPatrec database are shown in Fig.5 for different feature extraction and different classification methods. For the BioPatrec datasets. The SVM classifier performed better in comparison with an LDA classifier.

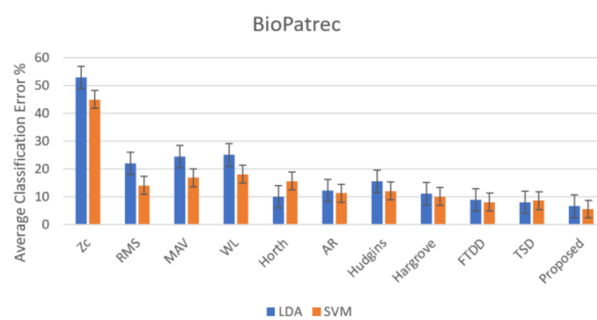

Figure.5 shows the effectiveness of the proposed method with different TD features using LDA and SVM classifier for BioPatrec Dataset

C. Results of Database 3 (3DC-Database)

Fig.6 shows the averaged classification error results across all the 22 subjects of the EMG 3DC database. In this figure, the proposed method is compared with other well-known features and feature sets using SVM and LDA classifiers.

5. CONCLUSION

In this paper, we proposed a novel approach to utilize cardinality to generate a logical combination of spatially distinct EMG channels and combined that with the concept of memory as inspired by LSTM. The benefits of the proposed method included the simplicity by which the method is implemented based on time-domain features without any complicated processes and the achieved low levels of classification errors based on testing with EMG signals acquired from different databases. This study aims to reduce the gap between academia and industry/clinical implementation by providing reliable performance that competes with state-of-the-art deep learning models. We believe that there is a great potential for this method to enhance the performance of feature extraction by changing some parameters, such as the selected n^{th} previous window, and use different TD features. We are further developing this method and carrying on real-time performance tests to generalize the outcomes.

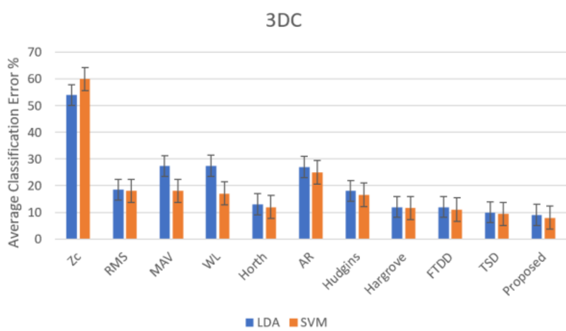

Figure.6 shows the effectiveness of the proposed method with different TD features using LDA and SVM classifier for 3DC dataset

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The quality of the extracted traditional hand-crafted Electromyogram (EMG) features has been recently identified in the literature as a limiting factor prohibiting the translation from laboratory to clinical settings. To address this limitation, a shift of focus from traditional feature extraction methods to deep learning models was witnessed, as the latter can learn the best feature representation for the task at hand. This paper is focused on combining the simplicity and low computational characteristics of traditional feature extraction with the memory concepts from Long Short-Term Memory (LSTM) models to efficiently extract the spatial-temporal dynamics of the EMG signals. The novelty of the proposed method can be summarized in a) the memory concept leveraged from deep learning structures, capturing short-term temporal dependencies of the EMG signals, b) the use of cardinality to generate logical combinations of spatially distinct EMG signals and as a feature extraction method and 3) low computational costs and the enhanced classification performance. The performance of the proposed method is validated using three EMG databases collected with 1) laboratory hardware (9 transradial amputees and 17 intact-limbed), and 2) wearables (22 intact-limed using two wearable consumer armbands). In comparison to several other well-known methods from the literature, the proposed method shows significantly enhanced myoelectric pattern recognition performance, with accuracies reaching up to 99%.

III. Nominator (Advisor) Information

Name: Prof Tanveer Zia Email: tzia@csu.edu.au

Signature:* Tanveer Zia PIN: _160740__ Present Affiliation: Charles Sturt University

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