Modern Myoelectric Control – Is it Time to Change the Algorithmic Focus?

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***Abstract*— This paper explores the evolving landscape of Electromyogram (EMG) signal analysis, focusing on the growing prominence of deep learning (DL) algorithms for hand, wrist, and finger movement recognition. Such algorithms often come with high computational costs, potentially limiting clinical translation on resource-limited devices, and igniting more research on reduced complexity models. This prompts the question: is it time to shift the algorithmic focus in EMG pattern recognition, given the reported performance of some light-weight traditional or hybrid methods emphasizing synergy between different EMG signals? A comparative study is implemented between state-of-the-art deep learning extension for time series classification, denoted as Random Convolutional Kernel Transform (ROCKET), and simple, yet effective pattern recognition methods tailored to exploit basic forms of EMG signal synergies—Waveform Length Phasors (WLPHASOR), Root-Mean-Squared Phasor (RMSPHASOR), and the proposed novel Multi-Signal Waveform Length (MSWL). Tests are conducted on EMG data from 22 participants performing 11 hand and wrist movements using two EMG armbands (10 and 8 channels, respectively), utilizing the open-source LibEMG toolbox. Preliminary findings suggest that, while DL algorithms exhibit formidable capabilities, the performance gap with traditional EMG feature extraction methods may not be as substantial as anticipated. The observations of this study revealed no significant differences in average accuracies between ROCKET, WLPHASOR, and RMSPHASOR (87% average across participants). Furthermore, MSWL significantly enhances performance to 90%, and the combination of ROCKET+MSWL achieves 91% on average across all subjects. These findings challenge the narrative of DL dominance in EMG pattern recognition, urging a re-evaluation of the algorithmic focus and contributing valuable insights to the debate on effective approaches for extracting meaningful information from EMG signals.**

Keywords—Electromyography (EMG), Myoelectric control, ROCKET, Deep Learning

I. Introduction

Electromyogram (EMG) signals collected from human forearm muscles have long been investigated as a source of control for powered prostheses and assistive devices. In this approach, it is a common practice to utilize machine learning algorithms, including traditional feature engineering and Deep learning (DL) models, to extract the unique movement signatures from EMG signals to decode the user's intended hand movements or grasps [1]. Recent times have seen a huge rise in the adoption of DL models in many different applications, such as gesture recognition, where they have proven to be more effective than traditional machine learning algorithms because the former do not require domain expertise [2, 3, 4]. It is crucial to realize that Convolutional Neural Network (CNN) and the more general DL class of models have large computational costs, even in spite of the great successes of CNN models in EMG-based hand movement recognition. These expenses are ascribed to the very large number of parameters that must be optimized or learned, as well as the massive volume of data needed to train deep learning models like CNNs. According to earlier studies, there might be anywhere from thirty thousand to millions of parameters in DL models [2, 5, 6]. Allocating memory for weights, activations, gradients, data batches, and workspace is necessary for training deep learning models. This takes at least hundreds of MBs, if not GBs, of memory [7]. Adopting these models in clinical applications is severely hampered by the fact that they are hard to train on and difficult to install on devices with limited resources. Therefore, a crucial component of machine learning-driven prosthetic devices is creating a straightforward and effective model that can operate on platforms with limited computational resources.

Using randomly initialized convolutional kernels, the Random Convolutional Kernel Transform (Rocket) was recently proposed and demonstrated to attain great overall accuracy on various time series data with impressively short training time [8]. Rocket employs a single layer of a large variety of kernels without kernel weights learning, which dramatically reduces the computing cost of CNN compared to learnt convolutional kernels as used in CNN. Usually, two features are derived from the Rocket kernels: the proportion of positive values (PPV) and the maximum values. Rocket was subsequently refined into a compact variant known as MiniRocket, which, on large datasets, may outperform Rocket up to 75 times quicker and be nearly deterministic (using a small, fixed set of kernels) while retaining nearly same accuracy [9]. While been relatively new, the Rocket class of models was applied in different time series classification problems using the Photoplethysmography (PPG) [10], Electroencephalography (EEG) [11], EMG [12], and Speech [13], with performance superiority against many other models.

Unlike the traditional hand-crafted feature engineering methods utilized in EMG classification [14], one of the main benefits of CNN and thereby Rocket/MiniRocket is the ability of the convolution technique to capture the spatial relationships between the activation patterns of the different time series from multiple muscles. Conversely, the conventional method for extracting features from EMGs does not prioritize spatial focus because it treats each muscle separately and concatenates the features obtained before sending them to the classification stage [15] (unless explicit projection techniques such as Nonnegative Matrix Factorization are applied [16]). Nonetheless, a few recent developments in multi-signal EMG feature extraction have been made, such as the Recursive Multi-Signal Temporal Fusions (RMTF) [18] and the phasor represented EMG feature space [17]. Compared to CNN, MiniRocket and Rocket models require a lot less computing power.

The evolution of this field of research suggests the dominance of convolution-based methods, with recent literature indicating significant outcomes from new implementations of traditional and hybrid methods [17,18]. This raises the question of whether it's time to shift the algorithmic focus in EMG pattern recognition, given reported performance of lightweight traditional or hybrid methods emphasizing multi-signal synergy relationships. This paper compares MiniRocket, representing Rocket, with waveform length phasor (WLPHASOR) and root-mean-square phasor (RMSPHASOR) from [17], and a novel Multi-Signal Waveform Length (MSWL) method (inspired by our earlier work on RMTF [18]).

II. Methodology

A. Multi-Signal Waveform Length (MSWL)

The Waveform Length (WL) feature is described intuitively as the cumulative length of the signal of the time segment of interest [19,20]. It specifies a measure of waveform amplitude, frequency, and duration in a single parameter as follows.

$$WL_x = \sum_{i=2}^{N} |x_i - x_{i-1}| \tag{1}$$

where x_i is the i'th sample of the EMG signal $\mathbf{x}$, with i =2, 3, …, N, and N is the total number of samples within the signal segment, or simply the window size. The WLPHASOR [17] adopts this WL concept into a phasor represented EMG feature space (Similarly for RMSPHASOR, with the root-mean-square (RMS) feature). The phasor representation is a distance-based modelling applied on all channels. In this model, the residual limb is depicted as a cylindrical part with Ch channels so that Ch phasors (P_0, P_1, P_2, ….,P_{ch-1}) with π/5 radian spacings are constructed (see Fig.1 for the demonstration of electrodes phasors with 10 channels as an example). The phasor form of WL feature is given as

$$P^{WL} = [WL_0, WL_1 e^{j\frac{\pi}{5}}, WL_2 e^{j\frac{2\pi}{5}}, \dots., WL_{Ch-1} e^{j\frac{9\pi}{5}}] \tag{2}$$

Pairwise Euclidean distances are formed between the phasors above for the original EMG signals resulting in Ch (Ch-1)/2 features and their derivatives (another set of Ch (Ch-1)/2 features) [17].

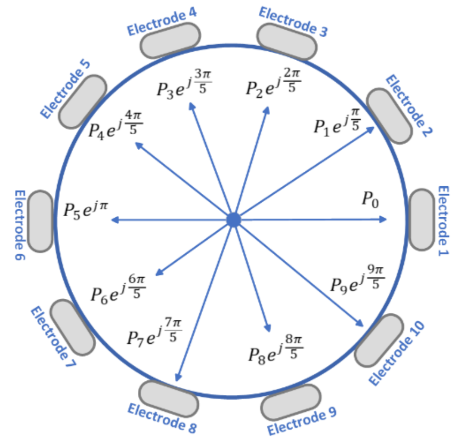

Fig. 1. Phasor representation for a problem with 10 EMG channels

Unlike the work in [17] focusing on single EMG channels WL representations, we focus in this paper on the phasor representations of multi-signal waveform length (≥ 2 channels). A range spatial filter (RSF) [21] is adopted to construct a combined signal representation across the samples of the considered channels. As an example of two channels Ch_X and Ch_Y, the RSF filter is given below using the range equation.

$$C = [\mathbf{max}(Ch_X, Ch_Y) - \mathbf{min}(Ch_X, Ch_Y)] \tag{3}$$

Once the combined signal is formed, the WL_{XY} of the combined signals is then calculated as shown below, where the WL of the generated signal is normalized by the logarithm of the integral squared values of the samples in each of the channels been combined.

$$WL_{XY} = \frac{\sum_{i=2}^{N} |C_i - C_{i-1}|}{\log(\sum_{i=1}^{N} Ch_X^2 + \sum_{i=1}^{N} Ch_Y^2)} \tag{4}$$

The phasor representing MSWL is then give by

$$D^{WL} = \left[\left\| WL_{01}\left(1 - e^{j\frac{\pi}{5}}\right) \right\|, \left\| WL_{02}\left(1 - e^{j\frac{2\pi}{5}}\right) \right\|, \dots, \left\| WL_{12}\left(e^{j\frac{\pi}{5}} - e^{j\frac{2\pi}{5}}\right) \right\|, \dots, \left\| WL_{89}\left(e^{j\frac{8\pi}{5}} - e^{j\frac{9\pi}{5}}\right) \right\| \right] \tag{5}$$

Similarly, the above analysis is repeated on the derivatives of the EMG signals to generate ∇D^{WL} . A set of logarithmically scaled final feature vector is generated by the following equation

$$\mathrm{F} = [\log(D^{WL}), \log(D^{WL}/\nabla D^{WL})] \tag{6}$$

This is the extracted feature set that is then supplied to the classifier stage. For the analysis in this paper, an LDA classifier is utilized from within the LibEMG toolbox [14]. Several feature extraction methods are considered in the experiments, including WL, normalized WL, denoted as WLN (by dividing by the total sum of WL from all channels), the proposed MSWL, WLPHASOR, RMSPHASR, Rocket, Rocket concatenated with RMSPHASOR (Rocket+RMSPHASOR), Rocket concatenated with WLPHASOR (Rocket+WLPHASOR), and Rocket concatenated with MSWL (Rocket+MSWL). We have further added an implementation of MiniRocket [9] from the sktime library (https://www.sktime.net/en/stable/index.html). For the Rocket class of methods, our experimental results showed that no significant differences were found when using 10000 kernels (default value for Rocket methods) versus 500 kernels, and hence we stick with 500 kernels for MiniRocket. It is also important to mention here that an overlapping windows scheme is utilized for feature extraction on the 3DC datasets with a window size of 200 ms and increments of 100 ms. The Wilcoxon Signed Rank test is applied to test the statistical significance of the results of different methods. All analyses were carried out using Anaconda Spyder 5.4.2, Python=3.9, LibEMG=0.0.2, on a laptop with 16 GB RAM.

B. *3DC Dataset Description*

The EMG data was collected using a bespoke 3DC armband that has a 9-axis Inertial Measurement Unit (IMU) and 10 EMG recording channels at a 1000 Hz sampling frequency [5]. In parallel, MYO armband with 8 EMG channels sampled at 200 Hz was also utilized to verify the MSWL performance across different sampling rates. In this study, only EMG data were used. The armbands were affixed to each participant's dominant arm prior to recording as shown in Fig. 2. Eleven hand/wrist movements seen in Fig. 2 are included in the proposed dataset. Following an auditory cue, subjects began with neutral gestures and held each one for five seconds. For 55 seconds, a full cycle consisting of all eleven movements was captured. A total of 220 seconds without any breaks were recorded during four consecutive cycles. After that, participants had five minutes to unwind without taking off their armbands. Subsequently, four additional cycles were recorded, forming the test dataset, while the initial four cycles constituted the training dataset.

Fig. 2. The 3DC EMG datasets collection hardware and gestures included (images adopted from [5], under the Creative Commons Attribution License).

III. Results and Discussion

The classification results shown in Fig. 3 represent the average across 22 subjects, reporting results of the two armbands. These results depict a few important points. Firstly, both RMSPHASOR and WLPHASOR got an average of roughly 87% with the 3DC armband (83.4% for RMSPHASOR and 82% for WLPHASOR using MYO armband), with Rocket achieving an average of 87.7% and 82.8% with 3DC and MYO armbands, respectively ($p > 0.5$ indicating no statistically significant differences). However, it should be mentioned here that Rocket and MiniRocket are based on random initialization of a huge set of kernels without any optimization and for a randomly weighted method to achieve such results without any tweaking is an indicative of the power of the Rocket class of algorithms. On the other hand, the proposed MSWL achieved a classification result of 90.3 and 85.4% on average across all subjects using 3DC and MYO armbands, respectively, outperforming all other individual features extraction methods ($p < 0.1$). The results also show the benefit of merging RMSPHASOR, WLPHASOR and MSWL with MiniRocket which clearly shows the benefit of MSWL (average of 91% on 3DC and 86.2% on MYO) against that of RMSPHASOR (average of 89.7% and 84.9% for 3DC and MYO respectively) and WLPHASOR (average of 89.6% and 84.2% for 3DC and MYO, respectively). Hence, while the concatenation of RMSPHASOR and WLPHASOR with MiniRocket enhanced the average results on both armbands, considering MSWL with MiniRocket still outperformed all other individual and combined feature sets.

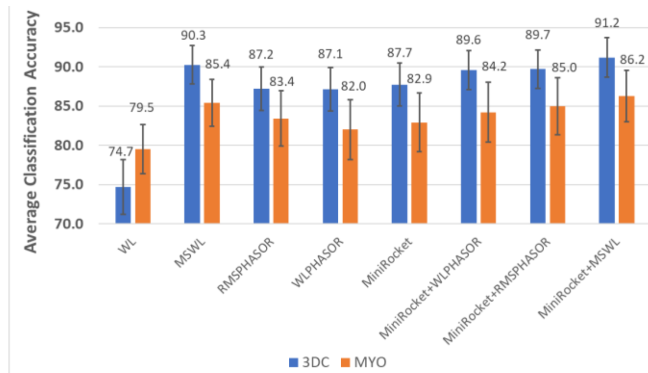

Fig. 3. Average classification results for 3DC and MYO armbands with different methods across all 22 subjects.

While the latest developments of DL based kernel methods can extract features without tweaking the weights of the kernels, like in Rocket methods, it is apparent that light-weight feature engineering methods can still achieve comparable performances, or even better. Our findings, while only demonstrated here on 3DC dataset with 22 subjects and 2 armbands, challenge the narrative of DL methods dominance in Biosignal classification problems. This in turn suggests a reevaluation of the algorithmic focus in EMG pattern recognition, especially when considering the huge computational cost savings offered by the traditional methods against DL models. This suggestion is applicable even with compact representations like MiniRocket, given the huge number of parameters in these models against that in MSWL.

It is understood that the findings might be preliminary, and that testing on more datasets may be required, especially those with a very large sample size. However, it is clear here that developing EMG feature extraction methods focused on synergy extraction, even if in simple form like that of MSWL, is effective in extracting the different movements signatures. Additionally, fusing this concept with long-and-short term temporal components, like that in our earlier development in RMTF [18] can further enhance the results here with an average classification result for RMTF on the 3DC datasets of 92% and 87.2% for 3DC and MYO armbands, respectively [18], while we achieved nearly similar results here with one hand crafted feature engineering concept based on synergistic multi signal waveform length. We argue here that research in this direction should also consider adopting concepts of DL methods and applying these, efficiently, on the light-weight traditional algorithms to have the benefits of both, simplicity of traditional and the power of DL methods. We continue our work in this direction to expand the experiments in our future research.

IV. Conclusion

The findings of this paper urge the research community in EMG pattern recognition to consider reevaluating the direction of research and to move away from sole use of DL methods into a mixture of, traditional and DL, models. Several methods were evaluated including WL, WLPHASOR, RMSPHASOR, MiniRocket, against a proposed method denoted as MSWL that is focused on extracting the synergetic multi-signal waveform length. The justification is clear here as hand movements are a result of action from several muscles rather than individual ones working separately. While methods like Rocket or MiniRocket can capture the spatial relationship between the different EMG channels using the convolution kernels, the traditional methods mostly treat the channels individually when extracting the features. Hence, this paper proposed the MSWL to tackle this limitation using a phasor feature representation of multiple signals jointly. This approach proved effective when testing on the EMG datasets from 22 subjects using two armbands (3DC and MYO) with performance results outperforming WLPHASOR, RMSPHASOR and even MiniRocket. The findings also suggested benefits when concatenating MiniRocket with MSWL which further shines the light on the benefits of the traditional feature engineering approach which should not be yet overlooked, given that MiniRocket was not able to outperform MSWL or the mixture of MiniRocket+MSWL. More research is required in this direction that holds promise for edge implementation of clinically viable EMG-based controllers of prosthetic and miniaturized rehabilitation devices.

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