Shoulder Motion Intention Detection Through Myoelectric Pattern Recognition

Andrea Tigrini[1**], Luca Alberto Pettinari[1], Federica Verdini[1*], Sandro Fioretti[1*], and Alessandro Mengarelli[1*]

[1] Department of Information Engineering, Università Politecnica delle Marche, Ancona, Italy
[*] Member, IEEE
[**] Student Member, IEEE

Abstract—In this study, a motion intention detection (MID) problem from surface electromyographic (sEMG) signals, involving upper limb, was faced through a pattern recognition approach. Linear discriminant analysis (LDA) and multinomial logistic regression (MLR), were used to tackle a multi-class classification for eight healthy subjects. The sEMG signals were segmented with a window centered on movement onset. Different feature sets, engaging time (TD) and frequency (FD) domain, were used to fit the models. Moreover, principal component analysis (PCA) was employed to reduce the whole TD+FD space. In this case, both models performed satisfyingly, reaching mean accuracy of 88.8% (LDA) and 91.8% (MLR). Finally, a heuristic method is proposed to evaluate feature importance. The results here presented support the use of PRC to solve motion intention detection problems, highlighting the possibility to integrate FD features to the commonly used TD ones, as in other myoelectric pattern recognition problems, e.g. hand gesture recognition.

Index Terms—motion intention detection, upper limb, pattern recognition, electromyography (EMG), feature importance.

I. INTRODUCTION

The analysis of surface electromyography (sEMG) plays a fundamental role in kinesiology and represents a valuable information source in controlling neuroprosthetics, triggering assistive devices, or interacting in virtual rehabilitation environments [1]–[3]. This is supported by the high number of works reporting an increasing use of sEMG-based control interfaces, due to an enhancement in the processing techniques that renders the extraction and the use of information fast and reliable [4]. However, the quality and amount of information can differ depending on the degree of complexity that the system, charged with supervising the human-machine interaction, has to handle. As an example, an end-effector rehabilitation robot may require only the muscles onset instant of contraction to deliver assistance when the upper limb motion path is predefined [5]. On the other hand, more refined information from sEMG signals is required when the robot would predict the patient motion intention in terms of direction and final configuration of the arm [6].

The latter problem was commonly faced through machine learning techniques. Indeed, both pattern recognition (classification-based) and proportional (regression-based) control architectures used sEMG derived information, either to predict which class of movement the subject was going to perform or to forecast the evolution of kinematics variables such as shoulder, elbow and wrist angles [6], [7]. However, it should be noted that the patient's degree of impairment can impact on the choice of the assistive control solution. In some cases, they could be weak in certain degrees of freedom (DoF), hence finding the initial trigger of the movement too challenging. In the worst case, patients could not be able to perform a complete path with the upper limb, thus making the kinematic data not suitable for training regression-based architectures [8], [9]. Hence, pattern recognition control (PRC) remains still appealing for eliciting assistive devices for the upper limb such as end-effector robots or exoskeletons [4], [8], [10], [11].

Corresponding author: A. Mengarelli (e-mail: a.mengarelli@staff.univpm.it).

In this context, shoulder motion intention detection (MID) has been relatively less studied under the PRC paradigm. A reason for this could lie on the intrinsic complexity of the shoulder joint, which encompasses a high number of DoF to be decoded [12], [13]. Moreover, in different studies involving the upper limb, PRC architectures were trained using features extracted from static sEMG activation segments (i.e. during isometric muscle contraction) [10], [11], [13]. However, in MID problems a reasonable choice is to consider signal epochs with a time window centered on the movement onset [6], thus capturing a dynamic condition, where the muscles involved in the movement work synergistically and are not fully contracted. This represents a challenge for the PCR scheme development, since transient data tend to be less suited for classification problems, as in hand gesture recognition [14].

Shoulder movements classification was already faced, but considering only sEMG in the static phase of muscle contraction, while the dynamic phase was not explored [13]. In this study, an eight-class shoulder MID problem was treated under the PRC paradigm, only considering the transient phase of myoelectric activity, as it commonly happens in rehabilitation robotics [4], [6], [8].

Hence, the main goal is to assess how EMG feature in time and frequency domain perform over a relatively large-class of shoulder movements. Linear discriminant analysis (LDA) and multinomial logistic regression (MLR) were used as classifiers, since they are widely employed in the practice.

II. METHODS

A. Dataset presentation and signals segmentation

For this study data from a public available dataset were used [15]. Eight healthy subjects (four males and four females) aged 25 ± 1.8 years were instrumented with eight sEMG probes (sampling frequency 1 kHz) placed over the following muscles: clavicular and sternal heads of pectoralis major, serratus anterior, trapezius descendent, trapezius transversalis, trapezius ascendent, infraspinatus, and latissimus dorsi [13]. Each subject performed eight different upper limb movements mainly involving the shoulder joint in two DoF: shoulder flexion by 45°, 90°, 110° (FL1, FL2, and FL3 respectively); shoulder hyperextension (HY) by −30°; shoulder abduction by 45° and 90° (AB1 and AB2); shoulder elevation by 45° and 90° in a 45° externally rotated plane (EL1 and EL2). Each movement was repeated 10 times.

sEMG signals for all muscles were filtered between 30 and 450 Hz with a fourth order zero-phase band-pass filter [1], [4], [8]. Then, they were segmented for each subject and for each movement repetition by selecting those signal epochs that fall within a MID window of 300 ms, centered on the movement onset, i.e. 150 ms before and after the beginning of movement (Fig. 1) [4], [6]. Thus, a total of 10 (repetitions) × 8 (channels) × 8 (subjects) sEMG trials were available for segmentation, feature extraction and model training.

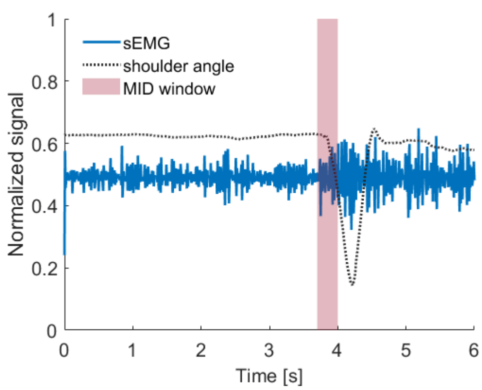

Fig. 1. Example of sEMG signal windowing. The first six seconds of shoulder angle (gray dashed line) and trapezius descendent sEMG signal (blue trace) for subject 1 are reported. Both time-series were range-normalized for a better visualization. The MID window of 300 ms (pale pink box) is centered on the onset of the movement and it highlights the signal epoch taken in this case.

B. Feature extraction and classification

sEMG epochs were sub-segmented into sliding windows of 150 ms with an overlap of 75% (corresponding to a time increment of 37.5 ms) in order to increase the PRC decision density, reducing the global architecture delay [16], [17]. Then, 14 time-domain (TD) and 10 frequency-domain (FD) features were computed on the sliding window for each channel and normalized to have zero mean and unitary variance. Such features were the same proposed in [17], with exception made for the sample entropy, which was replaced by permutation entropy (PermEn) and fuzzy entropy (FuzEn) [2]. Concerning the TD features, note that the auto-regressive (AR) coefficients and EMG histogram (HIST) consist respectively of 4 and 10 values. Thus, a total of 26 different TD features were considered. A single feature vector, using either TD and FD features, had a dimension of $m = (26 + 10) \times 8 = 288$. For the features not directly mentioned above, the same abbreviations reported in [17] were used.

As already mentioned, two models were considered to tackle the eight-class MID classification problem: LDA and MLR. The latter had an L2-regularization term with $C = 1$. Both of them are widely accepted in hand gesture recognition [17], [18] and, in particular, LDA was also employed in upper limb MID problems [8], [10].

Within-subject classification accuracy was evaluated for both classifiers by a five-fold validation method, using four different feature sets. In the first and second case, the classifiers were fit employing TD and FD features and their average accuracy was statistically compared by t-test. Principal component analysis (PCA), retaining 95% of explained variance (PCA95), was applied to the whole feature set (TD+FD) to assess how a common feature reduction technique can impact on both LDA and MLR classifiers [19]. Therefore, a statistical comparison between PCA95 and TD+FD accuracies was performed (t-test). For each comparison significance was set at 5%.

C. Feature importance

Considering the PCA95 feature set, it was interesting to evaluate which features from the TD+FD were more important in defining the PCA components as the new basis to express feature vectors.

By definition, such components form an orthonormal reference frame of the input space. In this case, considering the TD+FD feature set as the initial input space, each PCA component had 288 coordinates: these can be seen as the projection of that component on the original feature axes. The higher the value of such projection, the more is the original feature important to determine the PCA component under consideration. Then, if PCA components altogether have little projection on one of the original feature axis, then this one would be considered less important than other axes for which the overall projection is higher.

To define the latter concept, it is reasonable to consider the absolute value of all PCA components, and then make their vector sum. In fact, taking the modulus allows to highlight coordinates with either positive or negative projections, preventing such quantities from canceling out. Therefore, the outcome of these operations is a single vector containing the overall projections. In order to assign to the latter an importance score, each of them is divided by the total sum of all overall projections. This would allow to quantify feature importance as percentage. This heuristic can be better understood in the example shown in Fig. 2.

Considering that the models were trained using a within-subject scheme, feature importances are computed on the PCA95 set for each subject, and then averaged over them. This would yield a vector of dimension 1×288 containing feature importances over the whole dataset. Observe that, if every feature exhibited the same importance, the elements of such vector would be identical, having a value of $100/288 = 0.347\%$. Therefore, it seems reasonable to use such value as an importance threshold T_{imp}, to evaluate whether they are more ($> T_{\mathrm{imp}}$) or less ($\leq T_{\mathrm{imp}}$) relevant.

III. RESULTS

Table 1 reports the mean accuracies over subjects for LDA and MLR classifiers: both provided good classification results except for LDA in TD+FD case, which presented a low accuracy score with a relatively high variance of 12.9%. However, comparing the two classifiers within the same feature set, MLR slightly overcomes LDA. Globally, the better condition was obtained using PCA95 feature set, which raised LDA's mean accuracy to 88.8%, significantly higher than the TD+FD feature set.

Regarding feature importances computed as described in Section II-C, they were averaged over channels in order to obtain mean

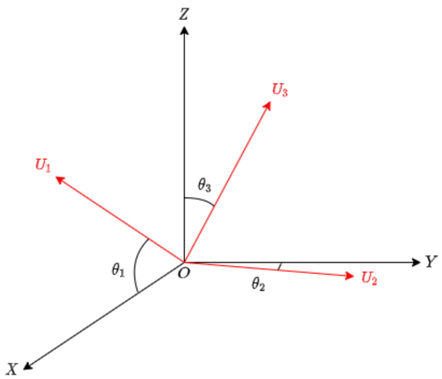

Fig. 2. Assume that $\{\hat{\mathbf{u}}_1, \hat{\mathbf{u}}_2, \hat{\mathbf{u}}_3\}$ are the PCA components of the new reference frame $O - U_1U_2U_3$, starting from the initial reference frame $O - XYZ$ (each axis underlines a feature). In this case, the angles between the original and new reference axes are respectively: $\theta_1 = 45°$, $\theta_2 = 5.06°$ and $\theta_3 = 45.25°$. As such, PCA components with respect to the initial reference frame are $\hat{\mathbf{u}}_1 = (0.71, 0.06, -0.70)$, $\hat{\mathbf{u}}_2 = (0, 0.99, 0.09)$ and $\hat{\mathbf{u}}_3 = (0.71, -0.06, -0.70)$. Applying the heuristic described in Section II-C, the overall projection vector is $(0.35, 0.28, 0.37)$. From this outcome, Y has the least importance in defining PCA components. This is quite intuitive, since 2 out of 3 components project mainly on X and Z axes, making these latter two the more relevant features.

TABLE 1. Table reports the within-subject accuracy in percentage averaged among the eight subjects. † symbol indicates p<0.01.

Classifier	Feature Domain			
	TD	FD	TD+FD	PCA95
LDA	86.9 ± 4.9	82.7 ± 5.0	63.8† ± 12.9	88.8† ± 3.3
MLR	91.8 ± 3.0	87.0 ± 5.3	93.0 ± 3.1	91.8 ± 3.4

feature importances on the core 36 features from the TD+FD set (Fig. 3).

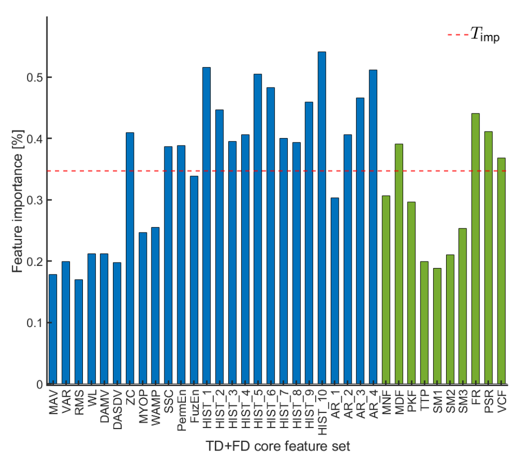

Fig. 3. Feature importance, averaged over channels, for TD (in blue) and FD (in green) features.

IV. DISCUSSION

In this study, a MID problem involving shoulder muscle contractions was assessed through two pattern recognition models commonly employed in myolectric control applications. As it happens in rehabilitation robotics, the design of MID pattern recognition architectures should avail of features vectors extracted from short sEMG signal epochs, which best capture the characteristics of the movement onset [4], [6]. This aspect differs from what was done in other myoelectric PRC schemes, i.e prosthetic control, where models were trained using steady-state sEMG signals [14], [17]. Indeed, MID PRC architectures mirror the necessity of recognizing the intention of the patient, dealing with sEMG transients in muscle contraction rather than steady-state signals from a reached static pose at the end of the movement [4], [6].

Albeit the use of the aforementioned feature sets on transient data might negatively impact on the classification accuracy [13], [14], both LDA and MLR classifiers reported good within-subject accuracies, encouraging the use of such models for solving MID problems [4], [6], [8], [10]. The poor performance observed for LDA using the TD+FD feature set could be explained by a condition where the dimension of the feature space was comparable with the number of training samples, affecting the sample covariance matrix estimation required for the LDA decision boundary computation [20]. This allows to better appreciate the role of PCA95 in boosting the accuracy score for LDA. In fact, the dimensionality reduction permitted to depart from the critical condition mentioned before, improving the well-posedness of the covariance matrix. The latter was supported also by the significantly higher accuracy of the PCA95 over the TD+FD feature set (Table 1).

It is worth noticing that the classifiers here employed represent a common choice when dealing with myoelectric control, in particular for real-time and practical applications, since they are fast to train and offer robust performances also with a limited amount of data [8], [21]. Note that assessing which is the best classifier for this kind of problem is beyond the aim of this study and it would require a fair comparison between a high number of PRC architecture, based on machine learning and deep learning approaches [6], [10], [22].

The problem here analyzed took into account 8 different classes of upper limb movements, and part of them shared the same shoulder DoF. As an example, shoulder flexion was performed for three different final configurations, namely FL1, FL2 and FL3, which were classified with good accuracy although they imply the same class of movements. This suggests that the sEMG epochs windowed at the beginning of the movement contained enough information to discriminate between similar movements. Nevertheless, an opportune selection of the muscles involved in a specific motor task plays a key role [4], [6]. In fact, the subject's motion intention could be viewed as a particular synergistic muscle activation pattern that would emerge only with an adequate number of sEMG probes related to precise muscles. This inevitably poses the attention to the subtle aspect of the experiment design, data collection, and PRC model selection. Furthermore, it should be stressed out that the instant of movement onset is not trivial to be identified in real-time applications [1], while it is easy to pinpoint in post-processing, through kinematic data related to the joints involved in the movement.

Regarding the feature sets employed, TD and FD features separately performed well on both LDA and MLR, although the TD+FD set did not produce a consistent increase in classification accuracy (Table 1). This aligns with the trend observed in literature that prefers the use of TD features for MID, since they are simple and fast to compute [4], [6], [10]. However, by means of the heuristic introduced to compute feature importance, it is possible to see that relevant features came evenly from both TD and FD sets (see Fig. 3). This is confirmed also by the absence of significant differences between TD and FD accuracy for both classifiers (Table 1). In particular, regarding the 10-bins EMG histogram, the relevance of this feature strengthens existing literature [6], encouraging its use and development in future works. Moreover, even if the size of the FD feature space is smaller compared to TD, features like Median Frequency (FD), Frequency Ratio (FR) and Power Spectrum Ratio (PSR) overcame the importance threshold, hence capturing important information that contributed to obtain good classification performances when using the PCA95 feature set. In addition, the use of PCA did not provide a significant loss of accuracy with respect to TD+FD set (Table 1), with the major advantage of a reduced feature space dimensionality [19].

Eventually, an aspect of interest would be exploring feature sets suitable for achieving a good inter-subject operability of PRC models for MID. This could be investigated through deep learning approaches, since they demonstrated high classification performances in myoelectric gesture recognition [23]. However, additional studies are needed to gain insights about using neural network (NN) architectures, such as recurrent or long-short memory NN [22], due to the limited amount of data available during the transient EMG epochs for MID problems.

V. CONCLUSION

In this study the problem of shoulder MID through sEMG data and PRC was faced considering a large number of shoulder movements. The classifiers employed presented good performances in terms of classification accuracy. Moreover, they are particular suitable for application purposes since they are fast and with a limited computational burden, as demonstrated in myoelectric control.

Another important aspect pointed out in the work is the investigation of both TD and FD sEMG features for MID. The use of different domains features for training PRC architectures was commonly faced in hand gesture recognition but not accounted in the field of upper-limb MID, where only TD features were considered. This suggests that approaches used for predicting hand movements can be transferred in the field of MID when one has to deal with transient EMG signal epochs.

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