On the Decoding of Shoulder Joint Intent of Motion From Transient EMG: Feature Evaluation and Classification

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***Abstract*—Motion intent detection for shoulder actions may allow the early decoding of upper limb motions, thus enhancing the real-time usability of rehabilitative devices and prosthetics. In this study we faced a motion intent detection problem involving four shoulder movements by using transient epochs of surface electromyographic (EMG) signals. Reliability of time and frequency domain features was investigated through clusters separability properties and classification performances. Those features able to provide accuracy greater than 90% were selected and further investigated by a holdout scheme, i.e., decreasing the amount of data for training the learning models (60%, 50%, 40%, and 30%). Key findings of the study are as follows. Firstly, single-feature approach appeared suitable for early decoding shoulder movements, thus supporting reduced recording setup. Time domain features related to the instantaneous variations of signal amplitude produced the best results but frequency domain features showed comparable performances, suggesting no favored domain for feature extraction. Eventually, autoregressive coefficients suffered from a reduced amount of data used for training. Outcomes of this study can support the design of myoelectric control schemes, based on transient EMG data, for driving shoulder joint assistive devices.**

***Index Terms*—Motion intent detection, myoelectric control, human-machine interface, pattern recognition, shoulder joint.**

I. Introduction

In RECENT years, the advances obtained in surface electromyography (EMG) and artificial intelligence permitted to investigate their combined role in many different applications, ranging from medicine to robotics and virtual reality [1], [2], [3], in order to ease the diagnosis of neuromuscular disorders, and to develop neuroprosthetics or trigger assistive devices [1], [4]. This should not be surprising since EMG constitutes a non-invasive source of information for the development of human-machine interfaces with different degrees of complexity [5]. Indeed, the intelligent system supervising the interaction could require only muscle onset information if the upper limb motion was predefined, as in end effector rehabilitation robotics [6]. On the other hand, higher quality information can be mined from EMG signals when the robot has to predict the patient motion intent in terms of direction and final configuration of the arm [7].

The latter problem can be faced through pattern recognition or proportional (regression-based) control architectures [7], [8]. In both cases, EMG signals were pre-processed and used to train models that, in the former case, are able to predict which class of movement the subject is going to perform. In case of proportional control, EMG is used to forecast the time course of joint kinematics [9], [10]. However, regression-based architectures could present issues related to the amount of data needed for training. This aspect is far to be negligible, especially in clinical applications, where few calibration data could be available [9]. A more challenging case can be when patients are not able to follow a predefined path with the upper limb, making unsuitable the use of EMG regression based architectures [11]. Thus, pattern recognition approaches maintain their appeal in order to supervise assistive devices such as end-effector robots or rehabilitation exoskeletons [11], [12], [13], [14], [15].

In this framework, motion intent detection was relatively less studied for the shoulder if compared to other upper extremity joints using a pattern recognition paradigm. A possible reason could be found in the inherent complexity of the shoulder, which embodies a high number of degrees of freedom to be decoded [16], [17]. Indeed, shoulder is composed by four joints and the whole mobility is also enhanced by the translation of the humeral head on the glenoid, with the concurrent activity of a high number of muscles [17]. Further, flexion-extension synergies were also recognized between shoulder and other arm joints, such as elbow, wrist, and fingers [12]. Therefore, the role of the shoulder for upper limb mobility is crucial, since proper hand function cannot be developed without the proximal control of its position in space, being the trajectories of upper limb joints strongly coupled [18], [19]. Indeed, shoulder plays a key role in many upper limb motor tasks, such as reaching or grasping, since it is synergistically engaged by the central nervous system to cooperate with the other proximal joints [20]. For all these

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aspects, decoding the intent of motion for the shoulder joint is valuable for developing assistive technologies that allow a full upper limb functional recovery, incorporating active user information in the trajectory planning [12].

A further important aspect in studies that involved the upper limb regards the feature extraction step. Features were in general computed from static EMG signal epochs, i.e., during sustained muscle contraction [12], [13], [16], as it happens in hand gesture recognition problems [21]. However, when the primary aim is the intent recognition, it is desirable to reduce as much as possible the decision delays [22]. Hence, a plausible choice is to extract features upon signal epochs with a time window centered at the movement onset [7]. This captures a dynamic portion of the myoelectric activity, when muscle are not yet fully contracted. Despite this could challenge the design of pattern recognition schemes, since transient data tend to be less prone to be easily classified [21], the importance of including dynamic data in the design of EMG pattern recognition architectures was already stated [22]. However, shoulder movements classification problem are often taken into account considering only static EMG, excluding transient epochs [16].

In this work we aimed to investigate the feasibility of approaching a shoulder motion intent detection problem through myoelectric pattern recognition, transferring part of the hand gesture recognition knowledge regarding EMG feature evaluation and selection [14], [16], [23], [24]. For achieving this goal, we dealt with the shoulder motion intent detection of four types of different movements, i.e., flexion, hyperextension, abduction, and elevation, by relying only on transient data [7], [14], [22]. We investigated multinomial logistic regression and support vector machine models for classification purposes, evaluating features in time and frequency domain. Although time domain features are generally preferred, due to their straightforward computation [11], [14], in this study we explored also possible advantages of using frequency domain features for this specific pattern recognition problem.

We hypothesized that, based on the non-stationary characteristics of transient signal, time domain features would provide higher classification performances with respect to the frequency domain ones, also considering the limited frequency resolution due to the short transient EMG epoch. We further hypothesized that those time domain features computed upon signal differentiation would carry the best information content for transient-based motion identification, since they highlight instantaneous changes in signal time course. In order to test these hypotheses, we firstly evaluated the quality of clusters generated by features in both domains through three different cluster quality indexes [25], [26]. Then, single feature performances were verified through multinomial logistic regression and support vector machine, progressively decreasing the amount of data used for training.

II. Materials and Methods

A. Dataset Presentation and Signal Segmentation

A public available dataset was taken into account [27]. The dataset contains EMG and kinematic data of eight healthy and neurologically intact subjects (four males and four females) aged 25 ± 1.8 years. The subjects were instrumented with EMG electrodes (sampling frequency 1 kHz) to collect the activity of the following muscles: clavicular and sternal heads of pectoralis major, serratus anterior, trapezius descendent, trapezius transversalis, trapezius ascendent, infraspinatus, and latissimus dorsi [16]. Subjects performed eight shoulder movements, each of them ten times. Such movements covered mainly two degrees of freedom: shoulder flexion by 45°, 90°, 110°; hyperextension by −30°; abduction by 45° and 90° and shoulder elevation by 45° and 90° in a 45° externally rotated plane [16]. Since we were interested in detecting the movement intent, we selected the four basic movements, i.e., shoulder flexion by 45°, hyperextension by −30°, abduction by 45°, and elevation by 45°. For each subject, all the EMG signals were band-pass filtered between 30 and 450 Hz with a fourth order zero-phase filter. For each movement repetition, we considered a signal epoch that fell within a window of 300 ms, centered at the movement onset, spanning 150 ms before and after the beginning of the motion (Fig. 1) [7], [14]. Hence, for each subject, 4 (movement classes) × 8 (EMG channels) × 10 (movement repetitions) transient EMG epochs were available for features extraction.

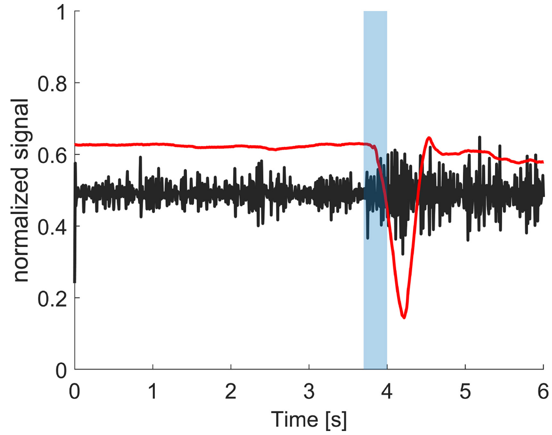

Fig. 1. Shoulder angle (red line) was used for movement onset detection and EMG transient window identification. Transient window was centered on the onset of the movement, lasting 300 ms (blue box).

B. Features Extraction and Class Separability Properties

Regarding the feature-set generation, we proceeded extracting time domain and frequency domain features (Table I). The EMG epochs were segmented through a sliding window of 150 ms with an overlap of 75% (time increment of 37.5 ms) in order to increase the pattern recognition decision density [23]. It deserves to be noted that the above mentioned windowing fits the typical requirements for online myoelectric control [28]. The extracted features were those employed in [23]. However, based on our previous results [4], we substituted sample entropy with permutation and fuzzy entropy, since the latter seemed to be higher discriminative than the former in EMG pattern recognition problems. Features were normalized through min-max normalization [24] and then their clustering characteristics were quantified by

TABLE I
FEATURES EXTRACTED FOR BOTH TIME AND FREQUENCY DOMAINS. MORE INFORMATION REGARDING THEIR COMPUTATION CAN BE FOUND IN [4], [24], [29]

Type	Feature Name	Abbreviation
Time Domain features	Mean Absolute Value	MAV
	Variance of EMG	VAR
	Root Mean Square	RMS
	Waveform Length	WL
	Difference Absolute Mean Value	DAMV
	Difference Absolute Standard Deviation Value	DASDV
	Zero Crossing	ZC
	Myopulse Percentage Rate	MYOP
	Willison Amplitude	WAMP
	Slope Sign Change	SSC
	Permutation Entropy	PermEn
	Fuzzy Entropy	FuzEn
	Histogram of EMG, 10-bins	HIST
	Auto-Regressive Coefficients, 4^{th} Order	AR
Frequency Domain features	Mean Frequency	MNF
	Median Frequency	MDF
	Peak Frequency	PKF
	Total Power	TTP
	1^{st} Spectral Moment	SM1
	2^{nd} Spectral Moment	SM2
	3^{rd} Spectral Moment	SM3
	Frequency Ratio	FR
	Power Spectrum Ratio	PSR
	Variance of Central Frequency	VCF

computing three indexes, i.e., the Davies-Bouldin (DB) index, the separability index (SI), and the mean-semi-principal axis (MSA). Computation of each clustering index is reported in the following.

The DB index can be used to quantify the overlapping between clusters, representing a measure of class separability [7], [23]. Following [25], to compute such index we can proceed by defining the cluster similarity measure as:

$$R_{i,j} = \frac{S_i + S_j}{D_{i,j}} \tag{1}$$

where S_i and S_j represent the dispersion of the i_{th} and j_{th} cluster respectively, and D_{ij} is the distance between their mean values [25]. The dispersion of a general cluster k can be computed as the standard deviation of the distance of cluster samples with respect to their cluster center [7]. More formally:

$$S_k = \left\{ \frac{1}{N_k} \sum_{l=1}^{N_k} (x_l - m_k)^T (x_l - m_k) \right\}^{\frac{1}{2}} \tag{2}$$

where N_k is the number of data points (vectors) in the cluster k, x_l is the l^{th} data point in the cluster, while m_k is the cluster centroid. The last term quantifies the distance between two cluster centroids k and p and can be computed through the Euclidean distance:

$$D_{k,p} = \left\{ \left(m_k - m_p\right)^T \left(m_k - m_p\right) \right\}^{\frac{1}{2}} \tag{3}$$

Now, we can define the DB index as the mean of the similarity measures of each cluster with its most similar cluster [7]:

$$\mathrm{DB} = \frac{1}{K} \sum_{i=1}^{K} \max\left(R_{i,j}\right) \quad \text{with} \quad i \neq j \tag{4}$$

Thus, the lower is DB, the greater is the class separability in a given feature space [23]. Although the DB represents a useful metric for myoelectric pattern recognition applications, it provides only a partial description of the data aggregation properties. Indeed, for EMG based human-machine interfaces, additional metrics can be used to assess the separability properties of a feature space and its intra-class variability [26].

The SI index has been employed to quantify the distance between different movement classes [26]. Such metric can be computed as in [26]: given the covariance matrix of class j, namely Σ_j, and the covariance matrix of its most conflicting class, Σ_{Cj}, we can compute Σ as:

$$\Sigma = \frac{\Sigma_j + \Sigma_{Cj}}{2} \tag{5}$$

Then, the SI is obtained as follows:

$$\mathrm{SI} = \frac{1}{K} \sum_{j=1}^{K} \left(\frac{1}{2} \left\{ \left(m_j - m_{Cj}\right)^T \Sigma^{-1} \left(m_j - m_{Cj}\right) \right\}^{\frac{1}{2}} \right) \tag{6}$$

where K indicates the cluster as in the DB formulation, m_j represents the mean of the j^{th} cluster data points and m_{Cj} is the mean of the most conflicting cluster data points with respect to the j^{th} cluster [26]. It deserves to be noticed that the SI metric reflects the distances between classes in the feature space. Hence, the greater is the SI, the better is the mapping of the different movements in the given EMG feature space.

TABLE II
CLUSTERING METRICS AND ACCURACY (ACC) FOR ALL THE CONSIDERED FEATURES. ACCURACY IS PROVIDED AS MEDIAN AND INTERQUARTILE RANGE (IQR). FEATURES THAT PRESENTED A MEDIAN ACCURACY GREATER THAN 90% ARE HIGHLIGHTED IN BOLD. CLUSTERING METRICS ARE COMPUTED AS REPORTED IN SECTION II-B BY EQ. (4) FOR DB, EQ. (6) FOR SI, AND EQ. (7) FOR MSA

Feature Name	DB		SI		MSA		MLR (ACC%)		SVM (ACC%)	
	median	IQR	median	IQR	median	IQR	median	IQR	median	IQR
MAV	2.07	0.57	1.54	0.51	0.78	0.21	90.39	7.29	89.89	5.05
VAR	2.27	0.45	1.38	0.34	0.58	0.27	86.40	17.01	86.27	16.51
RMS	2.05	0.52	1.59	0.47	0.77	0.23	88.06	8.27	85.93	8.43
WL	2.02	0.52	1.72	0.40	0.77	0.28	88.96	5.62	90.73	9.00
DAMV	**2.02**	**0.52**	**1.72**	**0.40**	**0.77**	**0.28**	**91.07**	**6.37**	**92.67**	**7.19**
DASDV	**2.05**	**0.52**	**1.73**	**0.39**	**0.76**	**0.27**	**94.38**	**6.94**	**93.64**	**11.23**
ZC	3.34	0.79	0.97	0.27	1.30	0.11	69.83	13.08	68.18	16.52
MYOP	2.48	0.88	0.78	0.25	0.12	0.02	72.84	18.82	72.04	12.06
WAMP	3.28	2.72	0.56	0.32	0.14	0.01	54.36	17.07	55.58	18.05
SSC	2.87	0.71	1.11	0.39	1.27	0.15	73.34	8.00	71.66	8.85
PermEn	2.92	0.49	1.01	0.35	1.27	0.17	70.69	12.31	69.24	12.20
FuzEn	2.84	0.71	1.10	0.41	1.24	0.10	70.48	18.10	71.36	15.60
HIST	5.70	0.99	3.42	2.17	0.97	0.11	65.11	6.58	64.87	5.21
AR	**3.19**	**0.50**	**3.66**	**0.90**	**0.41**	**0.08**	**92.52**	**8.82**	**91.71**	**9.20**
MNF	2.79	1.13	1.17	0.46	1.20	0.20	69.96	16.31	70.87	17.58
MDF	3.67	1.34	0.92	0.35	1.25	0.35	64.30	22.50	59.50	27.52
PKF	2.84	0.36	1.00	0.21	0.55	0.22	80.91	8.58	80.91	10.58
TTP	**2.27**	**0.48**	**1.39**	**0.34**	**0.58**	**0.27**	**90.33**	**11.39**	**91.27**	**12.72**
SM1	**2.29**	**0.70**	**1.51**	**0.35**	**0.57**	**0.29**	**91.14**	**3.95**	**90.61**	**4.28**
SM2	**2.20**	**0.56**	**1.48**	**0.32**	**0.60**	**0.35**	**90.62**	**4.75**	**91.35**	**4.56**
SM3	2.18	0.80	1.32	0.37	0.66	0.33	86.92	8.46	86.89	7.02
FR	4.56	2.44	0.67	0.27	1.26	0.07	54.69	22.47	53.20	20.38
PSR	4.61	1.24	0.66	0.18	1.33	0.13	46.68	14.92	46.41	15.85
VCF	2.73	0.53	1.25	0.35	1.30	0.14	75.43	7.91	75.43	12.28

The last metric we considered is the MSA, which was introduced to quantify the intra-class variability [26]. Each cluster is modeled as a hyper-ellipsoid in the feature space. Thus, the size of the cluster can be approximated through the singular value decomposition of the data within each cluster and then averaged by the geometric mean of the singular values:

$$\mathrm{MSA} = \frac{1}{K}\sum_{j=1}^{K}\left(\prod_{p=1}^{P} a_{jp}\right)^{\frac{1}{P}} \tag{7}$$

where a_{jp} is the pth singular value of cluster j and P is the dimension of the feature space. The MSA mirrors the agglomeration properties of each cluster and by definition the lower is MSA, the more the clusters are compact.

C. Pattern Recognition Architectures and Classification

Regarding the pattern recognition architectures employed in this study, we selected those that demonstrated to be adequate in myoelectric control problems, i.e., multinomial logistic regression and L1 regularized support vector machine [23], [30]. Then, we performed two different experiments.

1) Experiment 1: In the first experiment, both architectures were trained for each subject and for each same feature, considering all the eight channels. Feature-sets were split in 70% of data for training and 30% for testing. Within-subject classification accuracy obtained in testing was used as a metric for assessing the quality of the feature space [23], [24]. This first experiment was conducted to observe which features better identify the four different shoulder movements.

2) Experiment 2: In the second experiment, we selected those features that presented a mean accuracy among the subjects greater than 90% for both learning models. For such features, we proceeded by training multiple models holding out 40%, 50%, 60%, and 70% of the data for the testing phase. We set this experiment to asses the robustness of the selected features in order to train classifiers when few training data are available. This mirrors cases that occur in real practice, when patients cannot undergo to long lasting trials for the acquisition of training data [7].

For both experiments, hyper-parameter tuning of multinomial logistic regression and support vector machine was performed through Bayesian optimization, employing MATLAB 2020b [1], [23]. Kruskal-Wallis test was used to assess whether differences among the accuracy between holdout conditions, for the same learning model, were statistically significant ($\alpha = 0.05$).

III. RESULTS

A. Experiment 1: Features Clustering Properties

Among the time domain features, we observed good clustering properties in 6 out of 14 features (Table II). However, only DAMV and DASDV overcame the median accuracy threshold (90%) for both pattern recognition models. Although autoregressive coefficients presented greater DB values among the subjects, they revealed good performances, not lower than 91%, consistently with the SI and MSA (Table II).

Regarding the frequency domain features, SM2, SM1, and TTP showed the best clustering properties, presenting the lowest DB and the highest SI values and the best classification accuracy for both learning models (Table II). In particular,

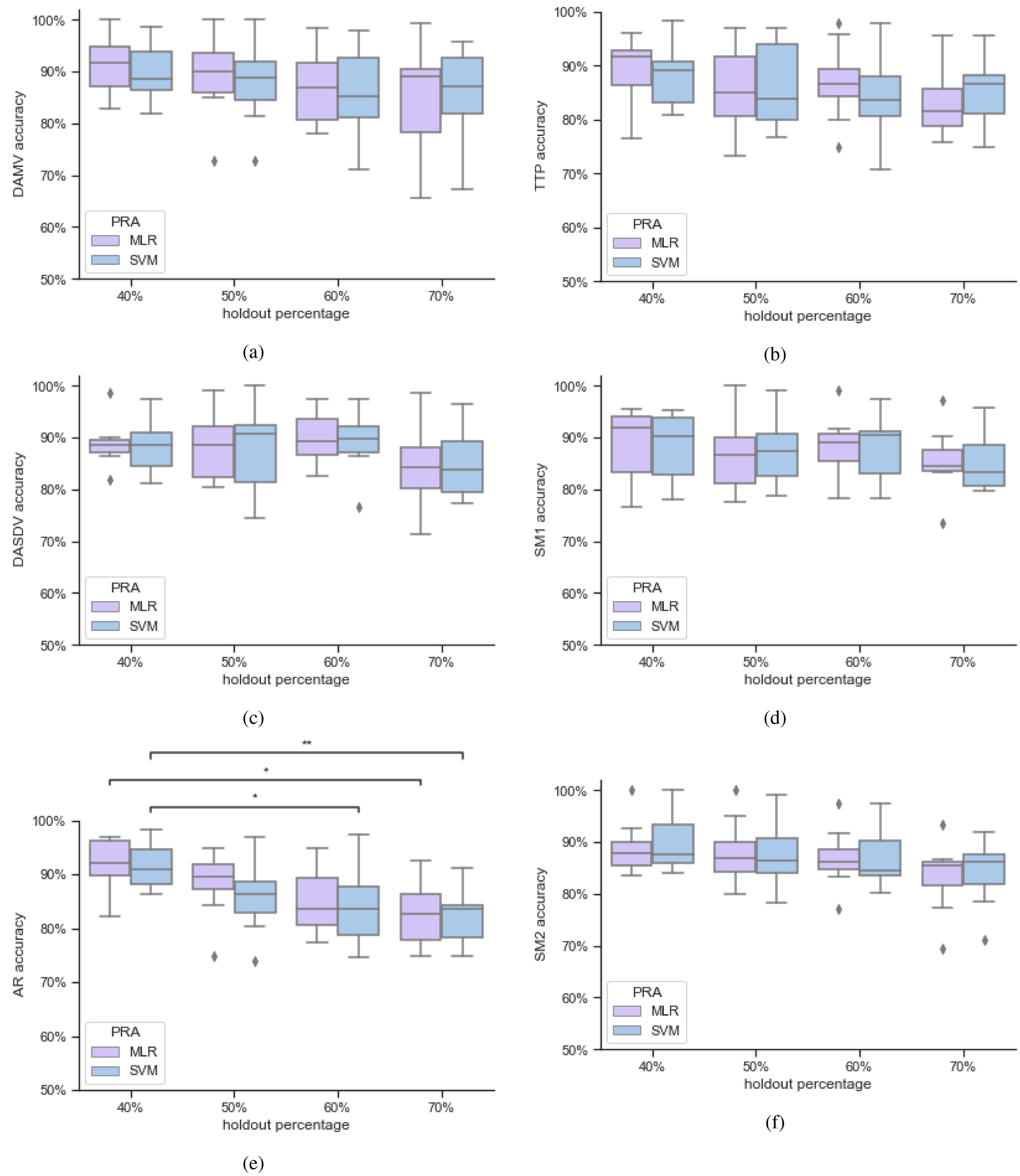

Fig. 2. Classification accuracy as a function of the holdout percentage of data retained for testing for the two pattern recognition architectures (PRA), i.e., multinomial logistic regression (MLR) and support vector machine (SVM). Significant comparison obtained through Kruskal-Wallis are indicated with * (0.01 $<$p$<$ 0.05) and with ** (p$<$ 0.01). A significant drop of accuracy is recognized only for AR coefficients.

SM1 and SM2 presented the two lowest interquartile ranges for the accuracy, also with respect to the time domain features, thus indicating constant classification performances among all the subjects.

B. Experiment 2: Holdout Testing for Single Feature Evaluation

From experiment 1, the best six features were selected: DAMV, DASDV, AR, TTP, SM1, and SM2 (Fig. 2). We did not detect any significant drop of accuracy, neither for time domain nor frequency domain when reducing the amount of data for training (Fig. 2). The only exception was represented by the AR coefficients, for which the accuracy underwent to a significant drop ($p < 0.05$) when the holdout is increased, passing from about 90% to 80% (Fig. 2(e)).

IV. Discussion

In this study we investigated the most suitable features in both time and frequency domain for decoding intent of motion of shoulder joint by using transient EMG data. To this purpose, we applied a two-step procedure: firstly, we considered features clustering properties in order to identify those features that provide the best movement class separability. In the second step, we tested the importance of the information carried out by each feature for developing highly predictive pattern recognition models.

A. Frequency Domain Features

We hypothesized that time domain feature would show superior performances with respect to frequency domain when dealing with transient EMG data. Indeed, features computed in frequency domain are less employed in motion intent problems [7], [11], [14] and time domain features are preferred in such kind of problems due to the reduced computational costs of changing the signal representation domain [24]. As demonstrated for real time applications [14], time domain features allow to reduce the global decision delay of the pattern recognition architectures [23], permitting the entire system to work on line. However, present outcomes showed comparable performances for time and frequency domain in terms of clustering (experiment 1) as well as predictive capabilities (experiment 2). Thus, our first hypothesis has to be rejected and a key finding of this study is that time domain features should not be *a priori* favored over the frequency domain ones when dealing with transient EMG data for recognizing shoulder joint movements.

In particular, beyond their clustering proficiency (Table II), the two spectral moments (SM1 and SM2) showed also the lowest inter-quartile range for classification accuracy considering all the six selected features in experiment 2, thus indicating consistent performances among different subjects (Table II). Further, the three selected frequency domain features preserved the same accuracy levels when the amount of data for training is progressively reduced (Fig. 2). This aspect points out that each frequency domain feature encompasses specific information regarding the intent of motion of the shoulder joint, allowing the pattern recognition model to be highly predictive also when less data are used for training and the majority of them are preserved for testing (even more than twice in the 70%-30% holdout scenario).

The holdout evaluation on the importance of the information carried out by the frequency domain features has also key practical implications. Present findings indicate that, by using frequency domain features, the training of reliable pattern recognition models for decoding motion intent requires a limited amount of data. Indeed, few repetitions of the same shoulder movement are needed to be performed by the subject for recording the training set: in the last holdout configuration (70%-30%) only three repetitions of the same shoulder task were used for training the learning models. This aspect is of fundamental importance for practical scenarios, e.g., when dealing with patients affected by diseases disrupting functional capabilities like stroke, who cannot undergo to long data acquisition sessions [7].

As mentioned in the previous, the on-line applicability of myoelectric human-machine interfaces is paramount to spread their usage in actual operating scenarios [2]. In this view, the usage of frequency domain features is generally discouraged since their extraction requires to change the EMG representation domain [29], thus being more computationally demanding with respect to time domain features. However, findings of this study are still valuable also in a real-time usage scenario, since it has been reported that spectral moments can be retrieved directly in time domain, without the need for applying the Fourier transform and thus changing the representation domain, by relying on the Parseval's theorem [29].

All these aspects outline once more the suitability of frequency domain features on transient data. However, for the latter application, feature computation in time domain still remains generally preferred [12], [22]. This can be likely due to the fact that the few data samples within a transient EMG window can lead to unreliable computations of frequency domain features, also due to the rapid change of signal state since, within the transient window, the latter moves from a resting to a bursting phase (ref if possible). Although this aspect merits further investigation, findings of this study showed that frequency domain features extracted from a 150 ms transient window are stable enough to highlight the intention patterns behind the EMG signals, separating synergistic muscle patterns elicited in correspondence of the movement onset. In passing, the window size used in this work for feature extraction was lower with respect to similar studies, e.g., 300 ms or 200 ms [12]. This further supports a key point of this work, i.e., the reliability of frequency domain features for decoding upper limb movement intent from transient EMG.

B. Time Domain Features

For what concerns time domain features, present outcomes indicate that overall they provided the best performances in terms of classification accuracy (Table II). This was an expected result that aligns with existing literature, since, for upper limb movement recognition, time domain descriptors found a widespread employment, also when transient EMG epochs are taken into account [12], [22]. More in detail, we hypothesized that those time domain features computed upon signal differentiation would produce the best classification performances. Our results support this hypothesis: the highest accuracy (Table II) was showed by those features whose computation relies on the discrete differentiation of the EMG signal, i.e., DAMV and DASDV (Table I). The capability of these descriptors in mapping transient data into highly separable classes of movement is reflected also by the high separability index (Table II), matching with previous findings in the field of hand gesture recognition, where architectures trained with the DAMV and DASDV showed high classification results [23], [24].

The importance of the predictive information encompassed by the above mentioned time domain features is confirmed by the holdout evaluation carried on in experiment 2, where DAMV and DASDV alone maintain a stable accuracy of about 90% also when only 30% of data were used for training (Fig. 2). Thus, a key finding of this study is that those time domain features, whose computation is based on the instantaneous variations of EMG signal amplitude, resulted the most suitable for motion intent detection, being able to emphasize the fast EMG changes, that likely represent a characteristic signature of the transient epoch centered at the beginning of the movement.

Additional discussion is deserved by the AR feature (Table I). These coefficients found a widespread employment for myoelectric pattern recognition and this is confirmed by their remarkable clustering capabilities (Table II). However, the AR resulted the only feature, among those selected for experiment 2, with a significant drop in the classification performances (Fig. 2), pointing out that the AR feature is poorly insightful for the models to be predictive. A possible explanation can be found considering that the modelling of a timeseries with an autoregressive model requires a certain degree of stationarity in the data [31], which lacks for a transient EMG window where muscular activity moves from a resting to a contraction phase. Hence, our findings indicate that AR feature may not be suitable for myoelectric pattern recognition using transient data. However, this aspect deserves to be further investigated by a direct comparison between AR identification of transient and static EMG signal epochs.

C. Additional Points and Limitations

It is worth noticing that in this study attention was devoted to proposing solutions suitable for a rapid technological transfer toward the design of myoelectric interfaces. Hence, in view of a technical applicability of our results, remarkable findings can be listed as follows. Firstly, we relied on pattern recognition architectures, i.e., multinomial logistic regression and support vector machine, that can be easily implemented in micro-controllers [32], without requiring the high computational burden typically needed in practical contexts [33], [34].

Secondly, our results showed that a single feature approach is reliable enough to obtain high and stable classification accuracy (Fig. 2), thus allowing to reduce the computational burden needed for extracting large feature sets. Therefore, a multi-channel EMG probes setup emerges a viable solution for real-time motion intent detection on shoulder joint, avoiding the use of more cumbersome setup, as high-density EMG [28]. Finally, although the holdout procedure was valuable for evaluating the feature importance for the model to be predictive, it showed also that the proposed solutions need few data for calibrating reliable motion intent pattern recognition.

It deserves to be highlighted that the absence of a real-time testing of the proposed methodological approach, that was instead developed and evaluated off-line only, represents a limitation of the present work that deserves to be faced, since the pattern recognition solutions should be employed for actual prosthetic upper limb control design. Although in this study we considered four movement tasks only, this represents a first attempt aimed at establishing appropriate methods and solutions for shoulder motion intent detection. Hence, we decided to limit the inherent complexity of this joint by focusing on four functional movements potentially useful for controlling prosthetic limbs [35], [36] or assistive rehabilitation devices [12], [14], [16]. However, a more comprehensive evaluation involving the full range of motion of the shoulder still remains an open issue to be addressed.

Regarding the applicability of present results, it deserves to be pointed out that here we dealt with intact subjects, whose myoelectric patterns were not corrupted by neuromuscular impairments. Even if a reduction in the classification performances may be expected in pathological subjects [7], [11], myoelectric activity was successfully used for decoding upper limb intent of motion in robotic aided rehabilitation [11], [12]. In this context, the decoding of single degree of freedom movements, as done in this study, showed quite stable performances in healthy and impaired individuals [11], [14]. Further, even on impaired subjects, EMG data resulted able to improve the detection of the motion intent, with respect to using other sources of information alone [12]. However, additional analyses are required for assessing the applicability of present findings to impaired patients [11].

Eventually, in this study we considered only EMG signal for intent detection of the shoulder but the use of load cell and inertial data, in conjunction with myoelectric signal, has been yet reported [12], [37], [38], [39] and thus fusing information coming from other sensors can represent a viable solution for improving the overall performances of the proposed architecture [40].

V. Conclusion

Time domain features, based on EMG signal differentiation, showed the best performances in terms of classification accuracy, indicating their suitability in emphasizing the fast variations within a transient epoch of EMG signal. However, spectral moments proved to be a viable alternative, also in terms of clustering capabilities, although less used for transient myoelectric pattern recognition. Hence, no favored domain can be suggested for feature extraction when dealing with shoulder joint intent of motion recognition. The selected features and learning models proved to be reliable also when the amount of data used for training is progressively reduced, thus outlining their value for the model prediction. In this context, the only exception were the autoregressive coefficients, that suffered from reduced performances when few data are used for training. Finally, outcomes of this study suggest that a sparse spatial covering of muscular activity, without the need for computing large feature sets, can be a proper solution for movement intent detection. This provides advantages in terms of computational burden, particularly important when the decision epoch is small by necessity.

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