Informatics in Medicine Unlocked 9 (2017) 255–263

Contents lists available at ScienceDirect

Informatics in Medicine Unlocked

journal homepage: www.elsevier.com/locate/imu

A comparison of sEMG temporal and spatial information in the analysis of continuous movements

Michela Di Girolamo [a,b,*], Alain Favetto [b], Marco Paleari [b], Nicolò Celadon [b], Paolo Ariano [b]

[a] Department of Applied Science and Technology - DISAT, Politecnico di Torino, C.so Duca degli Abruzzi 24, 10129 Torino, Italy
[b] Center for Sustainable Future Technologies @PoliTo, Fondazione Istituto Italiano di Tecnologia, Corso Trento 21,10129 Torino, Italy

ARTICLE INFO

Keywords:
EMG analysis
Time
Movement discrimination
Continuous movement
Template matching

ABSTRACT

Much effort has recently been devoted to the analysis of continuous movements with the aim of promoting EMG signal acceptance in several fields of application. Moreover, several studies have been performed to optimize the temporal and spatial parameters in order to obtain a robust interpretation of EMG signals. Resulting from these perspectives, the investigation of the contribution of EMG temporal and spatial information has become a relevant aspect for signal interpretation. This paper aims to evaluate the effects of the two types of information on continuous motions analysis. In order to achieve this goal, the spatial and temporal information of EMG signals were separated and applied as input for an offline Template Making and Matching algorithm. Movement recognition was performed testing three different methods. In the first case (the Temporal approach) the RMS time series generated during movements was the only information employed. In the second case (the Spatial approach) the mean RMS amplitude measured on each channel was considered. Finally, in the third case (the Spatio-Temporal approach) a combination of the information from both the previous approaches was applied. The experimental protocol included 14 movements, which were different from each other in the muscular activation and the execution timing. Results show that the recognition of continuous movements cannot disregard the temporal information. Moreover, the temporal patterns seem to be relevant also for distinguishing movements which differ only in the muscular areas they activate.

1. Introduction

A muscle is controlled by a large number of motor neurons, whose axons exit the spinal cord and progressively traverse smaller branches of peripheral nerves until they enter the muscle they control. Because a single action potential in a motor neuron can activate hundreds of muscles fibers, the sum of the resulting currents generates an electrical signal that is readily detectable outside the muscle itself using electrodes on the surface of the overlying skin [1]. Furthermore, when more than minimal force is required, many motor neurons generate an asynchronous barrage of action potentials with overlapping action potentials arising in each muscle unit. The result is a complex pattern of electrical potentials (typically in the order of 100 μV in amplitude) that can be recorded as a surface electromyogram (sEMG) [2].

Despite its complex nature, the EMG signal contains a large amount of information related to limb movements and functionality, so it can be usefully applied as a control signal for prosthesis [3,4] and exoskeletons [5], as a biofeedback in rehabilitation systems [6], or in clinical and sport medicine for gait and posture analysis and diagnosis of neuromotor disorders [7].

Many studies have been performed in order to optimize all the aspects that influence the signal, such as those related to the complex nature of the EMG signal, the practical limitations of data acquisition and the signal processing techniques [8–11].

Important efforts have been devoted in recent years to fill the gap between academia and industry in order to meet important criteria needed to develop ideal devices for the final users (e.g. patients, therapists). One of these criteria is related to proportional control. The design of algorithms able to determine this type of control implies the control of continuous motions [12,13]. Zhang et al. [14] successfully applied a hidden Markov model (HMM) to decode continuous motions of the shoulder and the elbow. Other studies have used neural networks in

Abbreviations: TMM, Template Making and Matching; CCDF, Complementary Cumulative Distribution Function; GCA, Global Classification Accuracy; LCA, Local Classification Accuracy; OP, Output Percentage.

* Corresponding author. Center for Sustainable Future Technologies @PoliTo, Fondazione Istituto Italiano di Tecnologia, Corso Trento 21,10129 Torino, Italy
E-mail addresses: michela.digirolamo@polito.it (M. Di Girolamo), alain.favetto@iit.it (A. Favetto), marco.paleari@iit.it (M. Paleari), nicolo.celadon@iit.it (N. Celadon), paolo.ariano@iit.it (P. Ariano).

https://doi.org/10.1016/j.imu.2017.10.006
Received 14 September 2017; Received in revised form 16 October 2017; Accepted 18 October 2017
Available online 21 October 2017

traditional classification and regression applications, employing a time-domain feature set for finger movements [15] or for forearm and wrist motions [16]. Highly accurate continuous prediction of finger endpoint position during a series of reaches has been obtained with a mixture of Kalman filters [17].

It is well known that the parameters calculated in the time-domain could be very relevant. A variety of time-domain features have been proposed and applied to various motion recognition approaches. Phinyomark et al. [18] recently investigated the performance of sets including 38 time-domain (TD) features, demonstrating their better performances if compared with frequency-domain (FD) features for robust EMG pattern classification. Moreover, a variety of approaches have been studied to determine the temporal parameters in order to obtain the highest motion classification rate.

TD features are mathematical instruments that highlight a specific characteristic of a portion of the signal, called *window*. In literature the temporal information is mainly related to the length of the windows and their overlap. Phinyomark et al. [19] compared eight combinations of window lengths and increments, and demonstrated that the best result in terms of robustness was obtained with a length of 500 ms and an increment of 125 ms when four electrode-pairs were positioned on the forearm. Zardoshti-Kermani et al. [20] experimentally determined that a window length equal to 100 ms is sufficient to classify 5 elbow joint movements using 2 pairs of electrodes. The elbow-joint angle prediction of Triwiyanto et al. [21] shows that a 250 window length yielded the best performance prediction with the same electrode number. Moreover, the relationship between window length and classification accuracy has been investigated in formal studies [22], also considering the aspect of the controllability of a prosthetic device [23]. In fact, the temporal parameters in EMG analysis have to be carefully evaluated in order to reduce the delay and guarantee good controllability in real-time applications [24].

Another fundamental class of parameters which has been widely investigated is related to the spatial information. The spatial information refers to the effect of electrode number, orientation, configuration and geometry on the analysis of sEMG signal. Yanjuan et al. proposed a channel selection method, independent both from EMG features and from classifiers [25]. They tested it on a set including four TD features calculated on a shifting window with a time length of 150 ms and an increment of 100 ms. A high recognition rate was reached with 7 channels on a set of 18 hand motions applying a subject dependent selection method [26]. Five EMG TD features have been calculated on a 250 ms overlapping sliding window and applied to determine the best channels subset [27]. Muceli et al. [28] proposed a method based on the spatial correlation between RMS values, which is robust with respect to the channel configuration. Some recent studies have also investigated the interaction between spatial and temporal information to try to determine the best combination between window length, overlap and number of electrodes in order to obtain the lowest error rate during offline movement recognition [23,29]. Menon et al. [29] have conducted a formal investigation of the relationship between temporal and spatial parameters to find the best combination between window length, overlap and number of electrodes. Performance of temporal parameters have been evaluated for each electrode set and spatial information has been related to the number of electrodes in the electrode set that has been selected from an HD-EMG matrix. Recent focus on the analysis of continuous motions and on the interaction between sEMG temporal and spatial information reveals the importance of quantifying their respective discriminant powers in the analysis of continuous movements.

The aim of the present work is to investigate the separate contributions of spatial and temporal information and quantitatively evaluate their relevance in the interpretation of the sEMG. With respect to the previously cited works, the present work investigated temporal and spatial information of the EMG signal in a different way. In particular, to assess temporal information, the evolution of the EMG signal provided by each channel was preserved, while the spatial localization of those channels was removed. Moreover, to evaluate spatial information, the mean EMG activity was calculated across time for each channel during movement execution. Thus, the spatial information was represented by the mean RMS signals recorded on different electrodes, while the temporal information was expressed by the behavior of the EMG signal over time through RMS time series. An RMS time series is a series of RMS data points indexed in time order, thus the temporal information, as intended in the present study, is associated to the timing of muscular activation. In particular, it can be supposed that temporal information, may successfully discriminate motions performed with different timings, providing only a small contribution to discerning movements performed with different muscles. Vice-versa, an interpretation based only on space information should behave in the opposite manner.

To this purpose, an offline movement recognition method based on template matching was designed and proposed and its performance was calculated in three different cases. In the first case (the Temporal approach) only the RMS time series generated during movements was employed in the classification. In the second case (the Spatial approach) only the mean RMS amplitude produced on each channel was considered. Finally, in the third case (the Spatio-Temporal approach) a combination of the information from both the previous approaches.

Khushaba et al. [30] have recently proposed a feature extraction framework that aimed to consider both the temporal evolution of the EMG patterns and the spatial coherence. Spatial-Temporal Descriptors (STD) have been calculated with this framework and compared with some well-known EMG feature sets in terms of movement classification performance. The EMG data that has been used to evaluate the framework, has been recorded during isometric movements. In the present work, the concept of using a combination of temporal and spatial information of the EMG signal was extended by performing tests with only one source of information, either temporal or spatial. Furthermore, movements were analyzed during their entire execution and not only during the isometric phase.

Template matching, applied in the present study, is a pattern classification method applied in EMG signal analysis. In 2010 Huang et al. [31] developed a system for handwriting recognition, which was improved in a different study in 2013 [32], based on the smoothed and down-sampled absolute value of sEMG templates. The template matching was performed after Dynamic Time Warping. Another application to handwriting recognition [33] calculated templates using the sEMG compound signal and averaging training epochs. The results obtained by applying template matching to handwriting recognition demonstrated its suitability for this type of purpose. Another application of template matching is the decomposition of sEMG into their constitutive motor unit action potentials with the aim of collecting valuable information about motor unit recruitment and firing rates [34–37]. The template matching approach was selected for the present study due to the possibility of managing input data and explicitly selecting the type of information provided to the classification algorithm.

The experimental protocol included continuous movements [17] which were different in both the muscular activation areas and temporal profiles. By means of the implemented algorithm it was possible to manage the type of information used for discriminating movements without the need to modify the classification criterion, which could influence results according to the method applied. Hence, it is possible to quantify the discriminant power of RMS time series, of muscular activation areas or of a combination of both.

2. Materials and methods

2.1. Experimental setup

The EMG signals were recorded using a portable EMG device (Istituto Italiano di Tecnologia, Morecognition Srl, Turin, Italy). The device integrated an elaboration module where signals were band-pass filtered (bandwidth 10–500 Hz), sampled at 2 kHz and digitally converted (24 bit

A/D converter). The Root Mean Square (RMS) of the digitalized signals was computed using a window of 64 ms and transmitted to a host PC via Bluetooth. The signals were recorded connecting the elaboration module to eight bipolar dry circular electrodes (10 mm diameter, interelectrode distance 20 mm) integrated in a stretchable array. The electrode array covered a circumference that ranged between 17 and 27 cm.

2.2. Experimental protocol

A group of 10 volunteers (seven males and three females) aged between 26 and 35 years participated in the experiment and signed informed consent form. The study was in accordance with the Helsinki Declaration [38] and participant data have been treated according to the Organic Law of Protection of Personal Data.

The electrode array was positioned in correspondence of the 25% of the forearm length measured from the elbow crease, no skin preparation was required. Preliminary experiments showed that the level of crosstalk was acceptable. This electrode configuration allowed the recording of signals from extensor and flexor muscles of the hand (See Fig. 1).

Subjects comfortably sat in front of a PC screen, with their elbow laying on the table, the forearm was perpendicular to the table to guarantee a comfortable rest position with no relevant muscular activity. Furthermore, the rest position allowed the execution of free wrist movements.

The experimental protocol comprised 14 wrist movements and the rest position. Specifically, the protocol included 4 movements (named *single* movements) activating different muscular areas: flexion, extension, supination and pronation. Each of the 4 movements were also performed in 2 temporal variants; in the first one (named *double* movement) the subject performed the same movement twice, returning in the rest position between two motion repetitions, in the second one (named *maintained* movement) the subject had to perform the movement and then maintain an isometric contraction in the target position. Finally, a rotation of the wrist (i.e. a continuous sequence of abduction, flexion, adduction, extension), was included. The wrist rotation was performed as a *single* movement and as a *double* movement (See Table 1).

The experimental protocol was selected to record a heterogeneous dataset about movements which differ both from a spatial and from a temporal point of view. For example, single flexion and single extension induce different activation maps for forearm muscles, but they have similar temporal profiles. On the contrary, single flexion and double flexion, involve the same muscles but the single flexion shows a single peak in the RMS signal, whereas the double flexion induces two peaks. The rotation of the wrist was introduced because its complex patterns involve a specific evolution of the muscular areas on the entire circumference covered by the electrode array over time.

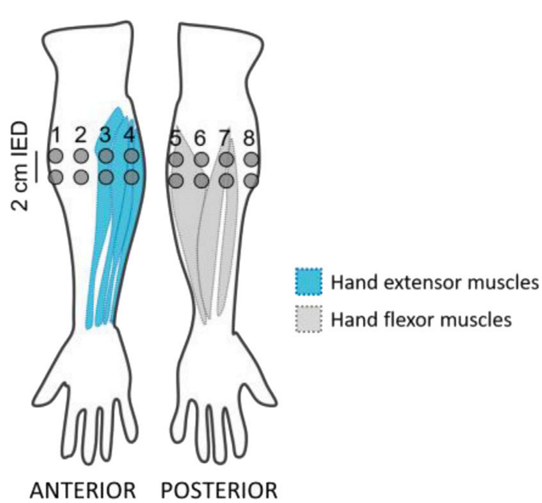


Fig. 1. Scheme of electrode positioning on the forearm with reference to extensor (Anterior view) and flexor (Posterior view) muscles of the hand.

Table 1
Movements included in the experimental protocol and labels.

Movement	Label	Variants	Labels
Rest	Re		
Flexion	F	Single, double, maintained	S,D,M
Extension	E	Single, double, maintained	S,D,M
Supination	S	Single, double, maintained	S,D,M
Pronation	P	Single, double, maintained	S,D,M
Rotation	R	Single, double	S,D

A graphical interface (GUI) helped subjects to perform the protocol in the correct way and with the correct timing. The training phase was composed by 10 repetitions of all the movements. The testing phase consisted of 5 repetitions of a randomized sequence of the trained motions; the randomization was applied in order to avoid any adaptation effects. The GUI reproduced sounds in order to indicate timing and duration of the tasks; every repetition of a motion was performed with a predefined timing. Single movements lasted 1.5 s while double and maintained movements lasted 2.25 s. Rest periods were introduced every 10 movements and additionally whenever the subject needed to avoid fatigue. The entire protocol lasted about 40 min.

2.3. Template making and matching (TMM)

Training repetitions were automatically segmented during the template making (training phase); the muscular activity was considered only when the RMS signal of at least 2 channels was higher than a threshold S_{th} equal to the 66° quantile of the signal. The quantile based threshold improved the algorithm robustness to noise and its value was empirically determined for the experimental protocol. By applying the threshold on at least 2 channels it was possible to prevent the segmentation when an inadvertent signal peak was recorded on only one electrode. Whenever the threshold crossing was detected, the signal was segmented for W samples. The optimal value of W equal to 100 samples was empirically determined as the minimum time interval that guaranteed a uniform segmentation (W equal for all the movements), avoiding the overlap between two consecutive tasks. The window length W equal to 100 samples was applied to the entire protocol. The RMS signal on each channel was then normalized with respect to the maximum RMS value measured inside the window. Each template sample was then modelled as a Gaussian variable X of parameters μ and σ using segmented data. Therefore, for each recording channel, each movement was represented as a series of W Gaussian variables.

Fig. 2 (A and B) shows an example template made for channels 3 and 6 respectively. The last row of each figure (orange line on blue background) shows the time series of Gaussian mean values that model the template shape. The average over the training repetitions (*Rep. NR*, $1 \leq NR \leq 10$) results in a smoother signal and some details in waveform are neglected, nevertheless the information about the standard deviation of samples was preserved in order to prevent information losses during the template matching process.

For template matching (testing phase), a similarity measure between the templates and RMS signals recorded was calculated. The normalized RMS signals of the testing dataset were evaluated over a sliding window (the testing window) of length W. To establish the equivalence between the testing window and the motion templates, the probability that every sample of the testing window belonged to each template was computed. To this purpose, for every sample of the testing window, the Complementary Cumulative Distribution Function (CCDF) was calculated with Equation (1).

$$F_X(x) = P(X > x) = \int_x^{+\infty} f_X(t)dt \tag{1}$$

where $f_X(t)$ was the density function of X , X was the Gaussian variable

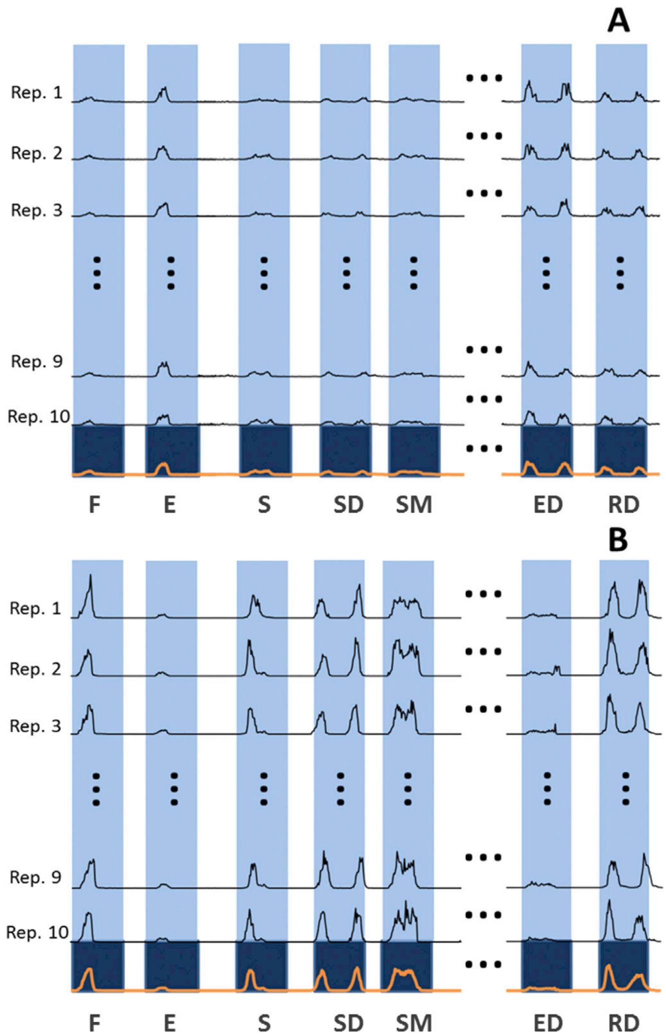


Fig. 2. Examples of template making for 2 channels (3 and 6). Signals were segmented to locate training repetitions, the last row (orange line on blue background) shows the time series obtained averaging over repetitions.

that model a template sample and x was the value of the testing sample. All the Gaussian distributions were normalized to the standard normal ($\mu = 0, \sigma = 1$) to reduce the computational power. CCDF values were then weighted according to the normalized RMS signal amplitude. The linear combination of the CCDF values (global CCDF) of all samples of the testing window was calculated for every movement.

The classification was performed in 2 steps:

1. Rest position vs. all: if the entire signal in the testing window was lower than S_{th}, the window was assigned to the rest position class.
2. Movement classification: windows that were not assigned to the rest position class were analyzed and classified. The testing window was assigned to the template that generated the highest global CCDF. However, if all the global CCDF values were lower than a minimum probability threshold P_{th}, the testing window was rejected and associated to the rest position. The P_{th} threshold, was optimized over the training data of each subject in order to maximize the recognition performance.

Finally, the testing window was shifted by one sample and the new testing window was evaluated on the base of the its global CCDF value. This procedure was repeated until the entire testing dataset was analyzed. Fig. 3 shows the flow chart of the template making and matching process.

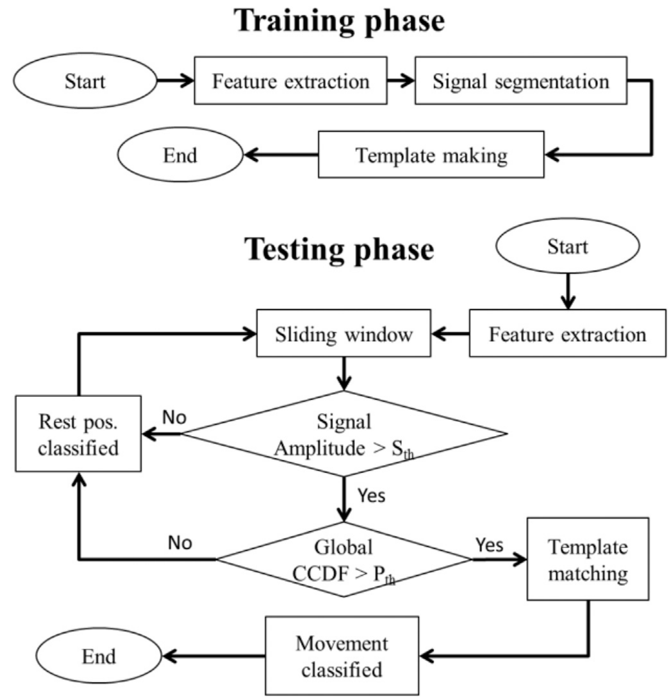


Fig. 3. TMM Work Flow. During the training phase, RMS signals were segmented to identify movement repetitions and define templates. During the testing phase, signals were evaluated over a sliding window of length W. If the amplitude of the window signal was lower that the threshold S_{th} it was classified as Rest position. If it exceeded $S_{th,}$ the linear combination of the Complementary Cumulative Distribution Function (CCDF) of all the window samples was calculated and compared with the threshold P_{th}. If the global CCDF didn't exceed P_{th} the window was classified as Rest Position, otherwise the template matching was performed and the window was classified as the template associated with the highest CCDF.

3. Calculation

3.1. *TMM algorithm implementation*

Since the aim of this work was to separately quantify the discriminant powers of the EMG temporal and spatial information for continuous motions, two different approaches to movement classification were considered and compared: the temporal approach and the spatial approach. Moreover, an additional approach was tested as a combination of both: the spatio-temporal approach. The spatio-temporal approach allowed the validation of the algorithm implemented and an evaluation of performance improvement when signals recorded on different electrodes were associated to RMS time series and vice-versa. Template making and matching was performed as described in Section 2.3, but the data used to build templates and testing windows were different depending on the applied approach.

3.1.1. *Temporal approach*

In this technique the information of muscular activation areas was removed, thus a single signal calculated from all electrodes was applied as the input of the algorithm. Data window were averaged over the 4 channels with the highest average RMS value. The information related to the temporal variation of the RMS value was preserved, while the localization of the electrodes that contributed to the time series was neglected. Every time the segmentation window for template making moved or the testing window for template matching shifted, the selection of active channels was renewed and the averaging process was repeated. Thus, the input signal described the RMS time series generated when a specific movement was performed. Fig. 4 details an example of training signals (red line) and template mean values (blue line) for wrist flexion (Fig. 4A) and extension (Fig. 4B) in the 3 temporal variants. It can be seen that RMS time series for movements performed with the same timings are not distinguishable.

This test was performed in order to analyze the protocol while neglecting the muscles that were involved in the movements and to test the discriminant power of the only temporal information through the RMS time series. It could be expected that this method would completely fail in discriminating movements with same timings (see Fig. 4) even if they differed in the muscles they activated (e.g. single flexion and single extension should induce the same temporal profile on different muscles).

3.1.2. Spatial approach

For this approach, the classification was solely based on spatial localization of muscular activation areas. The temporal information was removed calculating the mean value of the RMS signal samples included in the observation window. A subset of consecutive samples (from 20 samples to 50 samples, according to the movement duration) that exceeded the threshold S_{th} was identified separately for each channel. The RMS mean value of active samples was then calculated. The templates and the testing windows described the level of activation of each channel in terms of mean RMS amplitude for a specific movement. Radar graphs in Fig. 5 represent training signals (red line) and template mean values (blue line) calculated with the spatial approach for wrist flexion and extension. The data length of each spoke is proportional to the normalized RMS amplitude on each channel (radar graph rays). In this case the 3 temporal variants are very similar while movements activating different muscles produce highly different templates.

This test should highlight that it was difficult to distinguish when a movement was performed once, twice or if it was maintained for a long time. On the contrary, this method should discriminate movements performed with different muscles (e.g. flexions from extensions) but confuse when the same motion was performed with different timings (e.g. single flexion vs. double flexion etc.).

3.1.3. Spatio-temporal approach

Considering the information from both the spatial and the temporal approaches, the input of the spatio-temporal approach was a matrix of size $N \cdot W$, where N is the electrodes number equal to 8 and W is the window length equal to 100 samples. Thus, a template was represented by the RMS time series on every channel. This approach was tested to validate the algorithm with a complete set of information and to compare recognition performance when the partial set was applied. The expectation was that this method discriminated both movements where different muscles were involved (i.e. flexion vs. extension vs. supination vs. pronation) and motions with different temporal profiles (e.g. single flexion from double flexion from maintained flexion). Moreover, high accuracy was expected for the recognition of wrist rotation, since this approach should be able to take into consideration both the dynamic spatial pattern, and timings of activation of all the muscles involved in the movement.

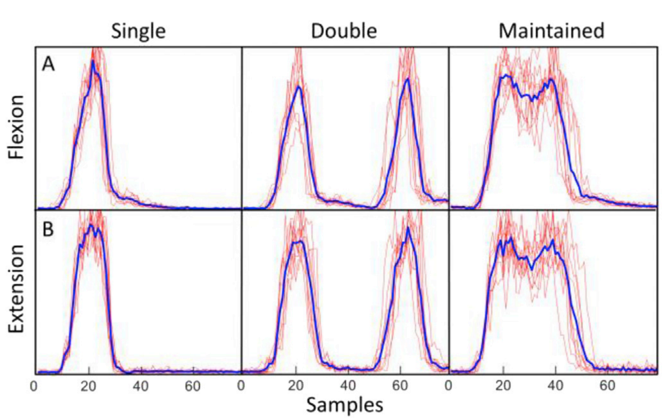


Fig. 4. Examples of templates for wrist flexion (Fig. 4A) and extension (Fig. 4B) in single, double and maintained variants.

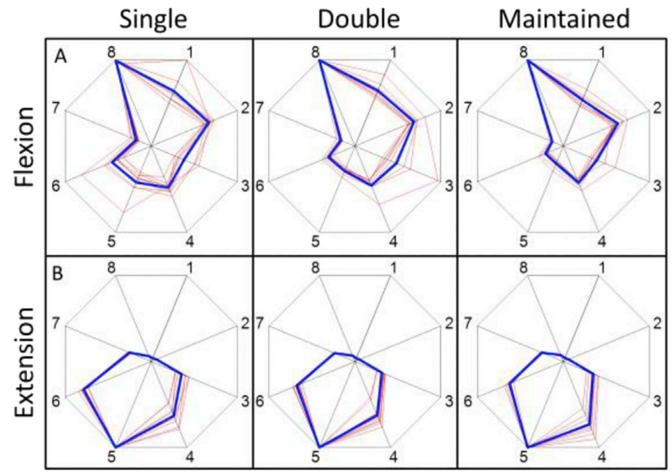


Fig. 5. Radargraphs corresponding to templates for wrist flexion (Fig. 5A) and extension (Fig. 5B) in single, double and maintained variants. Each spoke represents a recording channel and the data length of each spoke is proportional to the normalized RMS amplitude.

3.2. Evaluation of recognition performance

To evaluate classification performance, the Confusion Matrix (CM) was computed. The CM is a matrix that easily allows the visualization of an algorithm performance. Each column of the matrix represents instances in an actual class (true class), while each row represents instances in a predicted class (output class).

Three parameters were calculated from the CM: the Global Classification Accuracy for all approaches, the Local Classification Accuracy and the Output Percentage only for temporal and spatial approaches.

3.2.1. Global Classification Accuracy (GCA)

The GCA is a CM based measure of the classification performance of an algorithm. It is calculated as the ratio between the sum of instances in the principal diagonal and the sum of all instances. The expectation was that the CM of the spatio-temporal approach had a high GCA. The GCA of the spatio-temporal approach has been calculated in order to validate the TMM algorithm implemented. The temporal and the spatial approaches should have lower GCA values since they are not suitable to recognize respectively, spatial or temporal patterns.

3.2.2. Local Classification Accuracy (LCA)

According to previous considerations, it could be supposed that the spatial and the temporal approaches revealed some classification clusters. Therefore, in the CM calculated for the temporal approach the movements were ordered in the following way: all the single movements, then all the movements repeated twice and finally all the maintained movements. In fact, this approach should fail in discriminating motions that only differed in the muscles activated. In this way, instances of all the movements with the same temporal profile were visualized as consecutive in the CM. On the contrary, the CM computed for the spatial approach was organized depending on the muscles activated: firstly, all flexion movements, then all extension movements et cetera.

The submatrix represented by each cluster was individuated. The LCA was calculated as the GCA of each submatrix. The LCA is a relevant parameter since it allows the quantification of the discriminant power of the type of information expressed by the input data on a specific subset of movements. The LCA was evaluated in comparison with the random guessing. In the case of the temporal approach, the expectation was a homogeneous classification rate of 20% for submatrices including 5 movements (single and double variations) and of 25% for the submatrix including 4 movements (maintained variation). For the spatial approach the expectation was that the recognition and the confusion of single, double and maintained versions of every movement should be homogeneously distributed with a rate of internal confusion comparable to the random guessing; 33% for submatrix of size 3 × 3 (submatrix for all the movements but the rotation) and 50% for the submatrix of size 2 × 2 (submatrix for the rotation).

3.2.3. *Output Percentage (OP)*

The OP was evaluated on the submatrices and calculated in 2 steps. Firstly, the sums of instances in each column of the submatrix (true classes) were calculated and normalized with respect to the number of actual instances pertaining each class. Then, the mean value of the sums was calculated. The OP value allowed the quantification of the correct instances in a specific submatrix. The ideal OP of all the submatrices for both the spatial and temporal approach is 100%. In fact, with the temporal approach the temporal variants should be clearly recognized from each other. On the contrary, the spatial approach should correctly discriminate the movements which generate different activation maps.

To assess the statistically significant difference between the approaches, the Friedman test was applied. If the Friedman test determined the difference, the conditions were compared pairwise using the Wilcoxon signed-rank tests. A level of $p < 0.05$ was selected as the threshold for the statistical significance.

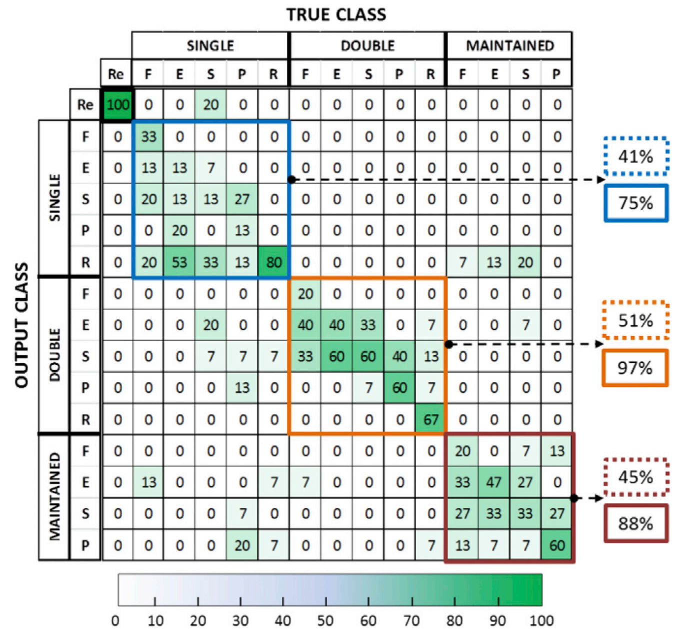
4. Results and discussion

For each approach, the movements in the CMs were ordered to highlight classification clusters (See Section 3.2.2). Different clusters are highlighted with different colors. See Table 1 for labels used in CM.

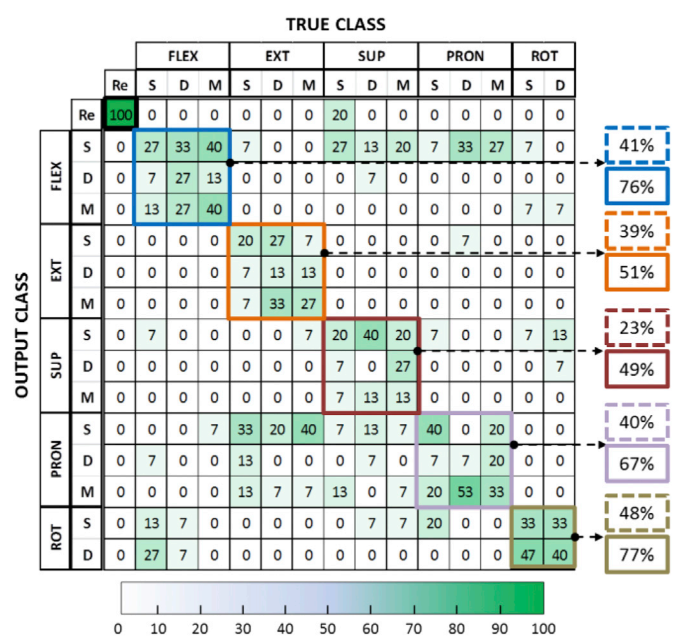
4.1. *Temporal approach*

In the case of the CM for the temporal approach, the movements are grouped according to the temporal profile.

CM 1 represents the CM obtained for this approach, the GCA is 44 ± 26%. It can be seen that the mean OP is 87%, it means that misclassifications mostly occurred between movements with the same variations. Moreover, LCA values were calculated: 41% for single movements, 51% for double movements and 45% for maintained movements. The GCA was in line with expectations and revealed that the only temporal patterns were not sufficient to correctly discriminate the set that included movements which differ only in the muscles they activate. Nevertheless, the LCA of the temporal submatrices overtook the expectations. The LCA were about twofold ($\chi^2 = 30$, $p \ll 0.001$) with respect to 20% (single and double variations) and 25% (maintained variation). It suggests that the RMS time series contributed to discriminate movements even when they were performed with similar temporal profiles. In fact, all movements belonging to a temporal cluster, were performed with the same timings, thus they should not be distinguishable if only the RMS time series were considered. Klein Breteler et al. [39] applied Principal Components of the rectified and downsampled EMG to assess EMG temporal waveform generated during 27 American Sign Language (ASL) fingerspelling. They revealed that a particular temporal waveform can be observed for each channel and movement using 8 channels. The temporal patterns of muscle activation have been revealed by Flander et al. [40] for arm movement in three-dimensional space with an analogous procedure based on best covariance values. Thus, the LCA values were in line with previous works that investigated the specificity of EMG temporal patterns when different movements were performed. However, in the present study the concept was applied to a feature time series of the EMG averaged across all the active channels. This suggest



CM 1. Confusion Matrix [%] of the temporal approach, LCA (dashed line) and OP (continuous line) of submatrices grouping movements with similar timings.



CM 2. Confusion Matrix [%] of the spatial approach, LCA (dashed line) and OP (continuous line) of submatrix grouping movements involving same muscular areas.

that a specific temporal waveform in muscular activation could be revealed also when an EMG feature is applied and if the signals are not analyzed on each single channel.

4.2. *Spatial approach*

In the case of the spatial approach, movements are ordered according to activation areas they generate (see CM 2).

The results revealed a mean GCA value of 29 ± 22%. The mean LCA expected was 41.5% and the actual mean value of 38% was few lower, with a minimum of 23% for the supination and a maximum of 48% for the rotation. In fact, the spatial approach showed no statistical differences with random guessing ($\chi^2 = 0.08, p = 0.8$). This approach was inefficient to discriminate movements that differed only from a temporal point of view (e.g. single flexion vs maintained flexion, etc.). Moreover, a mean OP value of 64% was calculated, which was considerably lower than the ideal value of 100%. In fact, it could be observed that the pronation and the maintained pronation, were often wrongly recognized and confused with the 3 temporal variants of the extension, while the flexion was often misclassified as supination and pronation movements. These results suggested that, the selection of the spatial information induced a degree of confusion also between the movements which should be separable for muscular areas they activate. This could be because the movements that have been confused had close activation areas and the only spatial approach was not sufficient to discriminate them in this case. It indicated that the contribution of the temporal information for the recognition of movements of the protocol was not limited to the capability to distinguish temporal variants of the same movement, but also helped to more accurately discriminate different movements with close activation areas.

4.3. Spatio-temporal approach

The confusion matrix related to the spatio-temporal approach was ordered as the latter one (see CM 3).

It can be seen that the matrix is highly diagonal with a GCA of 90 ± 10.5%, this suggests that the algorithm implemented was efficient when applied to the experimental protocol. This result was comparable with the results obtained with the TMM applied to handwriting recognition with a maximum of 6 pair of electrodes positioned on the forearm muscles [33,41]. This approach allowed the discrimination of both the movements that were different for muscles involved and movements that were performed with same muscles but with different timings. Moreover, the wrist rotation (single and double variations) has classification accuracy values comparable with the other movements of the protocol.

Summarizing key results, the CMs obtained for the tested approaches allowed the evaluation of the discriminant powers separately for the spatial and the temporal information. The spatio-temporal approach

TRUE CLASS

OUTPUT CLASS			FLEX			EXT			SUP			PRON			ROT	
		Re	S	D	M	S	D	M	S	D	M	S	D	M	S	D
	Re	100	0	0	0	0	0	0	20	0	0	0	0	0	0	0
FLEX	S	0	80	0	0	0	0	0	0	0	0	0	0	0	0	0
	D	0	7	80	0	0	0	0	0	0	0	0	0	0	0	0
	M	0	0	0	100	0	0	0	0	0	0	0	0	0	0	0
EXT	S	0	0	0	0	73	0	0	0	0	0	0	0	0	0	0
	D	0	0	0	0	0	93	0	0	0	0	0	0	0	0	0
	M	0	0	0	0	0	0	100	0	0	0	0	0	0	0	0
SUP	S	0	0	0	0	0	0	0	73	0	0	0	0	0	13	0
	D	0	0	20	0	0	7	0	0	93	0	0	0	0	0	0
	M	0	0	0	0	0	0	0	7	0	93	0	0	0	0	0
PRON	S	0	7	0	0	27	0	0	0	0	0	93	0	0	0	0
	D	0	0	0	0	0	0	0	0	7	0	7	100	0	0	0
	M	0	0	0	0	0	0	0	0	0	0	0	0	100	7	0
ROT	S	0	7	0	0	0	0	0	0	0	0	0	0	0	73	0
	D	0	0	0	0	0	0	0	0	0	7	0	0	0	7	100

0 10 20 30 40 50 60 70 80 90 100

CM 3. Confusion Matrix [%] of the spatio-temporal approach.

allowed the validation of the algorithm implemented. Moreover, the LCA of the temporal approach on each cluster of movement with the same profile was at least twofold with respect to the random guessing. This revealed that the movements of the protocol performed with similar timings but activating different muscles, had specific RMS temporal patterns which contributed to distinguish one from each other. This was in line with previous studies [39,40] and suggested that the specificity of temporal patterns was also relevant for EMG feature time series regardless the position of the recording electrodes. The statistical difference between the tested approaches was verified ($p \ll 0.01$). Comparing the spatial approach with the spatio-temporal approach, it was shown that the contribution of the time information to the wrist movement recognition was not limited to the discrimination of different temporal profiles, but also allowed a more accurate discrimination between different movements with close activation areas. In fact, the OP values for this approach were 23% higher than the OP calculated with the spatial approach.

These results revealed the efficacy of the present method of separately evaluating the EMG temporal and spatial information of the performed experimental protocol. Moreover, the relevance of the EMG temporal information in the analysis of continuous movements was revealed. The specificity of this type of information went beyond the discrimination of the movements of the protocol performed with different temporal profiles and suggested that temporal patterns were movement-specific even when they were applied to averaged RMS time series.

Findings of the present study are promising and suggest that the EMG temporal information for continuous motions analysis should have a major attention. Several fields of sEMG analysis could take advantage of the improvement of continuous motion decoding.

Latest requests in the rehabilitation field include task-oriented (instead of impairment-oriented) therapies and tools to quantitative monitor the recovery progress of patients [42]. This goal demands instruments that enhance information related to the kinematics of the movement and approaches that allow the analysis of muscular patterns. An approach that track the temporal relation between the activation of the muscles involved in the movement could provide an important support to this study. Concerning Sign Language, the EMG signals are recently widely adopted in the field of gesture recognition techniques, often in combination with accelerometers [43,44] and/or gyroscopes [45]. Sign Language gestures are inherently continuous and characterized by specific patterns both in space and time so an approach that contemporary monitor the both aspects appears promising. In sport field, many studies have been performed to correlate muscle coordination and performance. The control of muscle recruiting and related timings has a relevant influence on athlete performance [46] and on the recovery mechanism in case of sport injuries [47].

The spatio-temporal approach proposed in the present study appears suitable for these applications, since it provides an activation map of the muscular areas and information about their evolution during the movement execution.

5. Conclusion

This study provided a TMM algorithm and an experimental protocol with the aim of fully separating the contributions of spatial and temporal information for continuous movement analysis. The proposed algorithm showed congruent results for the three approaches tested and demonstrated the significance of the temporal information of the EMG signal for discriminating continuous movements, both when they only differ in the muscular areas they activate and when they are performed with different timings. Moreover, the results for the spatio-temporal approach could also have relevance in other fields such as rehabilitation, sports and recognition of Sign Language gestures.

Further work will be done to test the algorithm on a more challenging experimental protocol including a set of complex movements. Dynamic Time Warping could be introduced as a preprocessing step to find an optimal alignment between time series and improve results. Finally, the robustness of the method will be tested using other features (e.g. MAV, IEMG, WL, AAC) and other distance measures between the templates and testing sample sequences.

Conflict of interest

None declared.

Funding sources

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Consent

Written informed consent was obtained from the subject for publication of this case report and accompanying images. A copy of the written consent is available for review by the Editor-in-Chief of this journal on request.

References

[1] Kandel ER, Schwartz JH, Jessell TM. Principles of neural science. fourth ed. 2000. New York.

[2] Winters JM, Crago PE, editors. Biomechanics and neural control of posture and movement. first ed. New York: Springer-Verlag; 2000.

[3] Parker P, Englehart K, Hudgins B. Myoelectric signal processing for control of powered limb prostheses. J Electromyogr Kinesiol 2006;16:541–8. https://doi.org/10.1016/j.jelekin.2006.08.006.

[4] Dosen S, Markovic M, Somer K, Graimann B, Farina DEMG. Biofeedback for online predictive control of grasping force in a myoelectric prosthesis. J Neuroeng Rehabil 2015;12:55. https://doi.org/10.1186/s12984-015-0047-z.

[5] Zhang F, Huang H. Decoding movement intent of patient with multiple sclerosis for the powered lower extremity exoskeleton. Proc Annu Int Conf IEEE Eng Med Biol Soc EMBS 2013:4957–60. https://doi.org/10.1109/EMBC.2013.6610660.

[6] Doan-Aslan M, Nakipolu-Yüzer GF, Doan A, Karabay I, Özgirgin N. The effect of electromyographic biofeedback treatment in improving upper extremity functioning of patients with hemiplegic stroke. J Stroke Cerebrovasc Dis 2012;21: 187–92. https://doi.org/10.1016/j.jstrokecerebrovasdis.2010.06.006.

[7] Steele C, editor. Applications of EMG in clinical and sports medicine. Rijeka: InTech; 2011. https://doi.org/10.5772/2349.

[8] Guo Y, Naik GR, Huang S, Abraham A, Nguyen HT. Nonlinear multiscale Maximal Lyapunov Exponent for accurate myoelectric signal classification. Appl Soft Comput J 2015;36:633–40. https://doi.org/10.1016/j.asoc.2015.07.032.

[9] Xie H-B, Huang H, Wu J, Liu L. A comparative study of surface EMG classification by fuzzy relevance vector machine and fuzzy support vector machine. Physiol Meas 2015;36:191–206. https://doi.org/10.1088/0967-3334/36/2/191.

[10] Naik GR, Al-Timemy AH, Nguyen HT. Transradial amputee gesture classification using an optimal number of sEMG sensors: an approach using ICA clustering. IEEE Trans Neural Syst Rehabil Eng 2016;24:837–46. https://doi.org/10.1109/TNSRE.2015.2478138.

[11] Fougner A, Scheme E, Chan ADC, Englehart K, Stavdahl Ø. Resolving the limb position effect in myoelectric pattern recognition. IEEE Trans Neural Syst Rehabil Eng 2011;19:644–51. https://doi.org/10.1109/TNSRE.2011.2163529.

[12] Jiang N, Dosen S, Muller KR, Farina D. Myoelectric control of artificial limbs: is there a need to change Focus? [In the spotlight]. IEEE Signal Process Mag 2012;29: 150–2. https://doi.org/10.1109/msp.2012.2203480.

[13] Farina D, Merletti R, Enoka RM. The extraction of neural strategies from the surface EMG: an update. J Appl Physiol 2014;117:1215–30. https://doi.org/10.1152/japplphysiol.00162.2014.

[14] Zhang Q, Xiong C, Chen W. Continuous motion decoding from EMG using independent component analysis and adaptive model training. In: 2014 36th annu int conf IEEE eng med biol soc; 2014. p. 5068–71. https://doi.org/10.1109/EMBC.2014.6944764.

[15] Pang M, Guo S, Song Z, Zhang S. A surface EMG signals-based real-time continuous recognition for the upper limb multi-motion. In: 2012 IEEE int conf mechatronics autom ICMA, vol. 2012; 2012. p. 1984–9. https://doi.org/10.1109/ICMA.2012.6285126.

[16] Smith RJ, Tenore F, Huberdeau D, Etienne-Cummings R, Thakor NV. Continuous decoding of finger position from surface EMG signals for the control of powered prostheses. In: conf. Proc. IEEE eng. Med. Biol. Soc., Vancouver; 2008. p. 197–200. https://doi.org/10.1109/IEMBS.2008.4649124.

[17] Sachs NA, Corbett EA, Miller LE, Perreault EJ. Continuous movement decoding using a target-dependent model with EMG inputs. In: 2011 annu. Int. Conf. Ieee eng. Med. Biol. Soc., boston; 2011. p. 5432–5.

[18] Phinyomark A, Quaine F, Charbonnier S, Serviere C. EMG feature evaluation for improving myoelectric pattern recognition robustness. Expert Syst Appl 2013:40.

[19] Phinyomark A, Quaine F, Charbonnier S, Serviere C, Tarpin-Bernard F, Laurillau Y. EMG feature evaluation for improving myoelectric pattern recognition robustness. Expert Syst Appl 2013;40:4832–40. https://doi.org/10.1016/j.eswa.2013.02.023.

[20] Zardoshti-kermani M, Wheeler BC, Badie K, Hashemi RM. Feature evaluation for movement control of upper extremity prostheses. IEEE Trans Rehabil Eng 1995;3: 324–33.

[21] Triwiyanto, Wahyunggoro O, Nugroho HA, Herianto. Effect of window length on performance of the elbow-joint angle prediction based on electromyography. J Phys Conf Ser 2017;853:12014. https://doi.org/10.1088/1742-6596/853/1/012014.

[22] Englehart K, Hudgins B. A robust, real-time control scheme for multifunction myoelectric control. IEEE Trans Biomed Eng 2003;50:848–54. https://doi.org/10.1109/TBME.2003.813539.

[23] Smith LH, Hargrove LJ, Lock BA, Kuiken TA. Determining the optimal window length for pattern recognition-based myoelectric control: balancing the competing effects of classification error and controller delay. IEEE Trans Neural Syst Rehabil Eng 2011;19:186–92. https://doi.org/10.1109/TNSRE.2010.2100828.

[24] Farrell TR, Weir RF. The optimal controller delay for myoelectric prostheses. IEEE Trans Neural Syst Rehabil Eng 2007;15:111–8. https://doi.org/10.1109/TNSRE.2007.891391.

[25] Geng Y, Zhang X, Zhang Y-T, Li G. A novel channel selection method for multiple motion classification using high-density electromyography. Biomed Eng Online 2014;13:102. https://doi.org/10.1186/1475-925X-13-102.

[26] Nagata K, Ando K, Nakano S, Nakajima H, Yamada M, Magatani K. Development of the human interface equipment based on surface EMG employing channel selection method. In: Conf. Proc. IEEE eng. Med. Biol. Soc, vol. 1; 2006. p. 6193–6. https://doi.org/10.1109/IEMBS.2006.260783.

[27] Al-Angari HM, Kanitz G, Tarantino S, Cipriani C. Distance and mutual information methods for EMG feature and channel subset selection for classification of hand movements. Biomed. Signal Process. Control, vol. 27. Elsevier Ltd; 2016. p. 24–31. https://doi.org/10.1016/j.bspc.2016.01.011.

[28] Muceli S, Jiang N, Farina D. Extracting signals robust to electrode number and shift for online simultaneous and proportional myoelectric control by factorization algorithms. IEEE Trans Neural Syst Rehabil Eng 2014;22:623–33. https://doi.org/10.1109/TNSRE.2013.2282898.

[29] Menon R, Di Caterina G, Lakany H, Petropoulakis L, Conway B, Soraghan J. Study on interaction between temporal and spatial information in classification of EMG signals in myoelectric prostheses. IEEE Trans Neural Syst Rehabil Eng 2017;4320. https://doi.org/10.1109/TNSRE.2017.2687761. 1–1.

[30] Khushaba RN, Al-timemy AH, Al-ani A, Al-jumaily A. A framework of temporal - spatial Descriptors based feature extraction for improved myoelectric pattern recognition. IEEE Trans Neural Syst Rehabil Eng 2017. https://doi.org/10.1109/TNSRE.2017.2687520. PP:1–1.

[31] Huang G, Zhang D, Zheng X, Zhu X. An EMG-based handwriting recognition through dynamic time warping. In: Conf proc. Annu int conf IEEE eng med biol soc IEEE eng med biol soc annu conf, vol. 2010; 2010. p. 4902–5. https://doi.org/10.1109/IEMBS.2010.5627246.

[32] Li C, Ma Z, Yao L, Zhang D. Improvements on EMG-based handwriting recognition with DTW algorithm. In: Proc. Annu. Int. Conf. IEEE eng. Med. Biol. Soc. EMBS; 2013. p. 2144–7. https://doi.org/10.1109/EMBC.2013.6609958.

[33] Linderman M, Lebedev MA, Erlichman JS. Recognit Handwrit Electromyogr 2009;4: 2–9. https://doi.org/10.1371/journal.pone.0006791.

[34] Garcia GA, Akazawa K, Okuno R. Decomposition of surface electrode-array electromyogram of biceps brachii muscle in voluntary isometric contraction. IEEE Eng Med Biol 2003;3:2483–6. https://doi.org/10.1109/IEMBS.2003.1280419.

[35] Zhou P, Rymer WZ. MUAP number estimates in surface EMG: template-matching methods and their performance boundaries. Ann Biomed Eng 2004;32:1007–15. https://doi.org/10.1023/B: ABME.0000032463.26331.b3.

[36] Okuno R, Nishitani R, Akazawa K. Interactive decomposition of MU with multi-channel template-matching of surface EMG. Biomed. Eng. In: IEEE EMBS asian-pacific conf., 2003; 2003. p. 226–7.

[37] Doulah ABMSU, Member S, Fattah SA, Zhu W, Member S, Ahmad MO. Wavelet domain feature extraction scheme based on dominant motor unit action potential of EMG signal for neuromuscular disease classification. IEEE Trans Biomed Circuits Syst 2014;8:155–64. https://doi.org/10.1109/TBCAS.2014.2309252.

[38] Saif M. World Medical Association Declaration of Helsinki: ethical principles for medical research involving human subjects. 2000.

[39] Klein Breteler MD, Simura KJ, Flanders M. Timing of muscle activation in a hand movement sequence. Cereb Cortex 2007;17:803–15. https://doi.org/10.1093/cercor/bhk033.

[40] Flanders M. Temporal patterns of muscle activation for arm movements in three-dimensional space. J Neurosci 1991;11:2680–93.

[41] Huang G, Zhang D, Zheng X, Zhu X. An EMG-based handwriting recognition through dynamic time warping. In: Conf. Proc. Annu. Int. Conf. IEEE eng. Med. Biol. Soc. IEEE eng. Med. Biol. Soc; 2010. p. 4902–5. https://doi.org/10.1109/IEMBS.2010.5627246.

[42] Timmermans A a a, Seelen H a M, Willmann RD, Kingma H. Technology-assisted training of arm-hand skills in stroke: concepts on reacquisition of motor control and therapist guidelines for rehabilitation technology design. J Neuroeng Rehabil 2009; 6:1. https://doi.org/10.1186/1743-0003-6-1.

[43] Cheng J, Chen X, Liu A, Peng H. A novel phonology- and radical-coded Chinese sign language recognition framework using accelerometer and surface electromyography sensors. Sensors Switz 2015;15:23303–24. https://doi.org/10.3390/s150923303.

[44] Kim J, Wagner J, Rehm M, André E. Bi-channel sensor fusion for automatic sign language recognition. In: 2008 8th IEEE int. Conf. Autom. Face gesture recognition, FG, vol. 2008; 2008. https://doi.org/10.1109/AFGR.2008.4813341.

[45] Wei S, Chen X, Yang X, Cao S, Zhang X. A Component-Based Vocabulary-Extensible sign language gesture recognition framework. Sensors Switz 2016:16. https://doi.org/10.3390/s16040556.

[46] Chapman AR, Vicenzino B, Blanch P, Hodges PW. Leg muscle recruitment during cycling is less developed in triathletes than cyclists despite matched cycling training loads. Exp Brain Res 2007;181:503–18. https://doi.org/10.1007/s00221-007-0949-5.

[47] Britton W, Redmond C. Psychology of sport injury. first ed. 2017.