TOWARDS A HAND GESTURES RECOGNITION USING WEAK AND A SINGLE-CHANNEL SURFACE EMG SIGNALS

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Abstract: *This article presents a method to obtain a myoelectric control system for hand prosthesis with individual fingers, wrist flexion/extension and grasp movements, based on weak surface electromyogram (sEMG) recorded from the forearm, both able-bodied and amputees. This study aims to a reduced-channel scheme (a single sEMG channel) for hand patterns discrimination. A combination of commonly used features in the Frequency Domain (FD) and Time Domain (TD) with the analysis fractal was studied to obtain the best set of features. The results were validated with different classifiers showing the high performance of the method, above 90%.*

Keywords: *EMG, hand prostheses, fractal analysis, pattern recognition, finger control.*

Introduction

The functions to be controlled and the methods in pattern recognition to process the surface Electromyographic (sEMG) signals have been the focus in research about myoelectric prostheses. Most studies focus on recognizing forearm contractions and wrist movements, and the problems with four or more gestures mostly include open/close hand. Some works include individual finger classification [1], but a validation with amputees and experiments in real time are some of the major interest in this research line. Mostly traditional techniques to model sEMG signals are linear and simple. However, actions involving complex tasks like individual finger movements and hand gestures cannot be modeled by linear techniques. Artificial Intelligence techniques and electrodes arrays have also been used to estimate the relative force contraction based on spatial distribution [2]. However, dexterous movements with fingers and wrist would need a precise localization of the electrodes and a calibration for each use [3].

At low-level muscle contraction in processes with similar energy, statistical features are not reliable [4]. Furthermore, there is a non-linear relationship between force and electric activity on the muscles with low levels of contraction. Low-level sEMG signals can be defined as the response of a muscle contraction during a movement realized by its own muscular group with less force as possible. Non-linear properties of sEMG can be estimated by techniques like fractal dimension, entropy or autocorrelation. The use of multichannel sensors can increase the number of hand and fingers commands. However, the addition of new channels increases the complexity and the processing time, being it a drawback for the user. Using only one sEMG channel with satisfactory results can reduce problems during the electrodes fixation and low computational cost. Nevertheless, it is needed to map the sEMG signals related to contraction from different muscles. Instead of the features related to signal amplitude (RMS, WL, MAV) which depend on electrode arrays, other methods based on time-scale like Discrete Wavelet Transform (DWT), Wavelet Package (WPT), or features based on fractals like Higuchi's Fractal Dimension (HFD) or Detrended Fluctuation Analysis (DFA) are being used [5] [4]. DFA is one of the fractal techniques more used, combining advantages from time and frequency domains. Phinyiomark uses DFA to classify low level sEMG signals [5]. Eight gestures were classified with the wrist, hand and forearm using weak upper-limb sEMG signals for five channels. The individual finger movements were not taken into account in their work.

In previous works, we presented the classification of individual finger movements and hand gestures at low contraction level [6]. This paper reports the study of a set of features, both in amputees and non-amputees, towards a reduced number of channels.

Methods:

Subjects – Five able-bodied subjects (AB), two men and three women, aged 23-35, performed the experiments described in this section. In addition, two amputees subjects (AM1, AM2), female aged 35 and male aged 60, respectively, volunteered to participate in this study. Both amputees have trans-radial two-third proximal amputation; A1 of the right forearm and A2 of the left one.

sEMG recording procedure – sEMG data were acquired using bipolar electrodes, manufactured by Touch Bionic. These active electrodes have embedded a pre-amplification and electronic conditioning, with a 60Hz notch filter and a variable gain. The sEMG signals were sampled (1 kHz) via an NI USB-6009 data acquisition system. The skin was previously cleaned with 70% alcohol, and conductive gel was used before attaching the electrodes. Four electrodes were placed on the following muscles: Ch 1 - flexor pollicis longus muscle; CH 2 - flexor digitorum superficialis muscle; Ch 3 - wrist flexors (flexor carpi radialis and flexor carpi ulnaris muscles); Ch 4 - wrist extensors (extensor carpi radialis longus, extensor carpi radialis brevis and extensor carpi ulnaris muscles). Experiments were conducted following the ethical committee approval of the Federal University of Espirito Santo (UFES). The subjects were seated in a chair with both hands on a table and were trained before performing the tasks. For the experiment with amputees, training was performed with bilateral action with both hands.

Table 1: Motor task performed in the experiments.

Group	Class	Task Name
A	1	Rest state
	2	Little finger movement
	3	Ring Finger movement
	4	Middle Finger movement
	5	Index finger Movement
	6	Thumb finger movement
B	1	Rest state
	7	Wrist flexion
	8	Wrist extension
	9	All fingers flexion
	10	Hand grasp
	11	Pinch grip
	12	All fingers extension

Each muscle activity was performed with five repetitions and maintained 5-6 seconds, followed of a background activity (rest state) of 4-5 seconds to avoid fatigue. Visual and oral cues were presented to perform each repetition for data synchronization. Experiments were repeated three times for the able-bodied volunteers and five times for the amputees on different days, for enhanced generalization capability for performing tasks. Amputees performed more experiments anticipating possible errors and reject data if it is necessary. The sEMG signals were recorded while the participants performed two groups of motor tasks with the hand, described in Table 1. The first one including individual finger flexion and the other one with grasps tasks and wrist flexion/extension. The rest state was included in both groups and was recorded as the first class. The background activity among each repetition was discarded for the analysis.

Signal processing – The sEMG data were pre-processed subtracting the DC level from each signal. The trials were reorganized by concatenating all the same movements. The muscle activity was identified for each repetition extracting the segments corresponding to the isometric contraction on the motor task. It was done by taking two seconds after started the motor tasks, until one second before starting the return to the rest state. An examiner was ensuring that the gesture was started with no more than 1 second after the cue, to avoid potential errors. A windowing function was used to compute the features according with the criteria in [7] where the response expected by the subject would be in no more than 300ms. A sliding window with 250 samples of length (250 ms) and an increment of 125 samples (125 ms) for overlapping was applied for each channel. The duration of the analysis window was chosen to target real-time classification, by minimizing the delay between performed and decoded action. Frequently used time-domain and frequency-domain features presented in [8] were extracted (Table 2). Additionally, the DFA feature based on fractal analysis was computed.

Table 2: Features extracted from sEMG signals.

Domain	No.	Abbr.	Feature
Time Domain	1	RMS	Root mean square
	2	WL	Waveform length
	3	VAR	Variance of EMG
	4	MAV	Mean absolute value
	5	MAV1	Mean absolute value type 1
	6	MAV2	Mean absolute value type 2
	7	SSC	Slope sign change
	8	ZC	Zero crossing
	9	ZC2	Zero crossing
Frequency Domain	10	MNF	Mean frequency
	11	MDF	Median frequency
	12	PKF	Peak frequency
	13	MNP	Mean Power
	14	TTP	Total power
Fractal Dimension	15	DFA	Detrended Fluctuation Analysis

The sequential forward selection (SFS) method was used to analyze the significance of the features in this study and to select an optimal set. It was performed for the two groups of volunteers. To distinguish the different gestures, three classifiers were selected due to their high performance in classification problems and low computational cost: LDA, k-nearest neighbors (KNN) and a multi class SVM. For the multi class SVM, one against one method was implemented. The ANN classifier was repeated 10 times and then averaged in order to obtain generalized results. The classification for the different classes was computed in off-line mode considering the both groups mentioned before. In order to evaluate the classifiers, the error of misclassification was taken into account. A ten-fold cross–validation to validate the system and the classification accuracy was computed as an average accuracy based on the results from cross validation for 10 different training sets. Furthermore, Kappa coefficient purposed by Cohen, which represents the concordance between the targets and the prediction values, was computed.

Experiments – Two different experiments were conducted. The first one, to determine the optimal set of features and to evaluate the combination of the sEMG channels towards a reduced single channel system. The purpose was to explore the different combination of features in relation to the final accuracy in recognition of hand gestures. The SFS method, which selects the most significant feature maximizing the accuracy, was used firstly with all able-bodied volunteers' data together, and later, with each amputee individually. As a result, the optimal configuration was obtained for four, three, two and a single channel, with the best set of features for each case. This process was performed for both groups of gestures in Table 1, using the KNN classifier because of its fast computation. In the second experiment the best sets of features were selected with the other classifiers using a four channel scheme.

Table 3: Summary of results using SFS method for able-bodied and amputees.

	Group A						**Group B**					
Subj.	**Channels** 4 3 2 1	**Features/ Error [%]**					**Channels** 4 3 2 1	**Features/ Error [%]**				
AB	0 1 0 0	**10**	**9**	**2**	**4**	–	0 0 0 1	**5**	**9**	**13**	**15**	**7**
		59.89	49.85	41.71	39.23			58.85	42.33	39.99	38.62	36.84
	1 1 0 0	**10**	**2**	**9**	**1**	**14**	0 1 0 1	**13**	**2**	**4**	**1**	–
		42.19	31.47	24.86	22.69	22.57		28.60	18.96	15.31	15.09	
	0 1 1 1	**14**	**2**	**4**	**3**	–	1 1 0 1	**14**	**2**	**4**	–	–
		24.35	14.08	12.09	12.07			13.44	7.16	5.84		
	1 1 1 1	**14**	**2**	**4**	**3**	–	1 1 1 1	**14**	**2**	**4**	**3**	–
		14.54	8.59	7.20	7.12			7.51	5.00	4.31	4.28	
A1	1 0 0 0	**4**	**9**	**15**	**2**	**12**	0 1 0 0	**11**	**9**	**15**	**7**	–
		39.63	32.99	29.67	27.92	26.90		39.53	32.44	26.50	22.55	
	0 1 0 1	**1**	**2**	**4**	**15**	**14**	0 0 1 1	**10**	**15**	**2**	**14**	**7**
		13.57	11.38	11.04	10.81	9.91		16.21	11.64	10.61	9.80	9.36
	0 1 1 1	**1**	**2**	**7**	**15**	**13**	1 0 1 1	**2**	**15**	**13**	**12**	**7**
		8.95	7.44	6.87	6.58	5.63		11.05	9.07	7.05	6.23	5.99
	1 1 1 1	**1**	**2**	**14**	**7**	–	1 1 1 1	**2**	**6**	**11**	**7**	**15**
		7.15	5.46	5.07	4.62			7.09	5.89	5.65	5.55	4.87
A2	0 0 0 1	**5**	**7**	**2**	**14**	–	1 0 0 0	**1**	**2**	**15**	**4**	**9**
		59.17	47.66	45.29	43.74			46.37	42.08	40.10	38.90	38.78
	1 0 0 1	**5**	**2**	**10**	**4**	**9**	1 0 0 1	**10**	**7**	**2**	**15**	**14**
		44.64	32.34	30.95	30.07	29.80		34.38	24.09	20.83	19.94	18.78
	1 0 1 1	**11**	**9**	**4**	**2**	**10**	1 0 1 1	**13**	**4**	**2**	**7**	**10**
		30.79	22.97	21.49	20.34	20.05		20.12	15.73	12.82	12.70	12.28
	1 1 1 1	**13**	**2**	**4**	**14**	–	1 1 1 1	**10**	**2**	**4**	**7**	**13**
		22.41	18.81	17.39	17.12			14.85	11.89	10.44	10.06	9.17

Results and discussion

The classifier's overall misclassification error for the SFS method is summarized in Table 3. The presence of a channel is indicated by '1' in the combinations showed. For each case of subjects, combinations with four, three, two and a single channel were selected based on the lower percentage error achieved. Feature's numbers (according to the Table 2) corresponding to the channel combinations obtained follow by the error are presented.

For individual finger recognition (group A), the errors were of up to 40% using a single channel for all of cases, with 27% for the amputee A1. For the able-bodied (AB) the results showed a better performance by increasing the number of channels. The results for the amputee A1 were the best in all cases in comparison with A2 and AB, achieving a lower error than 10% with at least two channels. Most of cases, the SFS method achieved the lowest error with no more than 5 features, and for other cases the decrease in error were insignificant including more features. The WL (2) was in all of features combinations for this gestures recognition, followed by MAV (4), included 8 times, and TTP (14), included 7 times out of 12 different combinations. DFA (15) was included in combinations with three or less channels for A1.

On other hand, gestures of group B, including grasps and wrist movements, showed a greater difference on increasing the number of channels in relation to the group A. Single channel had 37% of misclassification error for AB subjects, while adding a channel achieved 15% using four attributes in the feature vector. The amputee A1 achieved error below 10% for dual channel, which is a significant result from this study. For A1 subject, errors were similar to subjects AB, as for the three channels case where both group had error below 6%. A2 had the lowest performance, but achieved error below 12% for three and four channels. Similar to the results obtained with gestures of the group A, WL was included to most of features sets, follow by DFA, which was in 7 cases. On the other hand, the sEMG channel related to the thumb flexor (Ch 1) provides relevant information for the separability of the classes for both groups of gestures according to the results. DFA feature was found to be relevant on the selection of features with the study with the subject A1, since it was considered for the cases of three, dual and single channel for the gestures group A, and for all cases with group B.

Based on the above, two sets of features with the most relevant parameters according SFS method results were selected to validate the system. The four set of features, shown in Table 4, were selected taking into account both groups A and B independently. Errors and kappa coefficient were computed for the four aforementioned classifiers. Results are summarized in Table 4. The results indicate that the sEMG signal analysis reported in this work using weak signals can accurately identify individual finger movements, in addition to grasps and hand gestures. ANN had the lowest error in most of the cases, followed by KNN, while LDA had the lower performance. The Kappa coefficient values with values above 0.8 represent an excellent concordance according to the Cohen’s criteria. The subject A1 had a high performance for both gestures groups, with error below 4.8% with features including DFA and an excellent concordance with ANN classification. The subject A2 had the lowest performance, although the error was 16.4% for group A and 10.2% for group B, with ANN, and an excellent concordance according to the Kappa value.

Table 4: Summary of results of classification for able-bodied and amputees.

		Group A								**Group B**							
Features		**WL MAV TTP DFA**				**WL VAR MAV TTP**				**WL MNP TTP DFA**				**WL VAR MAV TTP**			
Sub.		ANN	LDA	SVM	KNN	ANN	LDA	SVM	KNN	ANN	LDA	SVM	KNN	ANN	LDA	SVM	KNN
	Er.	4.7	19.5	5.2	11.3	7.6	30.9	6.8	7.3	4.5	35.2	4.3	11.0	4.3	27.2	3.9	4.2
AB	k	0.5	0.3	0.5	0.4	0.9	0.6	0.9	0.9	0.9	0.6	0.9	0.9	0.9	0.7	1.0	1.0
	Er.	4.5	11.8	6.8	4.6	5.6	11.5	4.8	5.7	4.8	17.8	5.1	4.5	5.8	11.4	5.3	6.8
A1	k	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.8	0.9	0.9	0.9	0.9	0.9	0.9
	Er.	21.3	47.4	20.8	28.7	16.4	41.3	16.6	17.1	15.4	34.2	11.4	16.8	10.2	32.9	7.9	10.6
A2	k	0.8	0.4	0.8	0.7	0.8	0.5	0.8	0.8	0.8	0.6	0.9	0.8	0.9	0.6	0.9	0.9

Conclusion

This study presents results on decoding two groups of hand gestures, the first one including individual finger flexion, and the other one with grasps tasks and wrist flexion/extension. We considered weak sEMG signals during the experiments in order to achieve a suitable and natural control system for the amputees. A study to determine the best set of feature was conducted, for all subjects, to compare the results. Although there were differences in the features obtained for both kinds of volunteers, we show a high performance for all cases. We have shown that a high level of decoding accuracy above 90% can be achieved using an ANN classifier, for both able-bodied an amputees. The results for the amputees were validated independently, due to the difference on the data and performance achieved. This may be related to the time since amputation, which may interfere in the remaining patterns on the muscles in the stump. The reduction of the numbers of channels caused decreased in the accuracy of classification. However, the results are significant considering that the study of information reduction is quite challenging.

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