Pattern Recognition of Hand Movements with Low Density sEMG for Prosthesis Control Purposes

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***Abstract*—This paper presents a study related to the identification of different hand gestures from EMG signals from forearm muscles, to be used as human machine interface system in a hand prosthesis. The capture of EMG signals was performed with healthy people during different hand gestures related to the fingers flexion -individual and pairs- and flexion / extension and grasp grisp, organized into four categories. The low-level and low-density of sEMG signals was taking into account. Different characteristics were studied based on time and frequency, and were subsequently combined into pairs with fractal analysis, used for low level schemes. The results showed 95.4% higher than recognitions.**

***Index Terms*—sEMG, multifunction myoelectric control system, low level movements, pattern recognition, isometric task.**

I. Introduction

There are already several efforts to uncover the information contained within the surface electromyography signal (sEMG). It has been shown the ability to diagnose muscle disorders and their importance for rehabilitation in people with traumatic amputation of upper and lower limbs. Thus, technological advances have focused on developing Human Computer Interface (HCI), that allows individuals autonomously recover motor skills by controlling devices such as robotic wheelchairs, medical or industrial applications, consumer entertainment, game companies, virtual keyboards, data glove, joysticks control, robotic arms, and within the most important, the development of multifunctional myoelectric prostheses.

The more complex control systems for prostheses the more Degrees of Freedom (DOF), like is the case of the multifunctional hand prosthesis developed by Touch Bionics. It has separate finger movements with the aim to retrieve the amputee a significant variety of motor skills. For the control, it has been used some strategies, such as pattern recognition in sEMG signal for gestures of the hand, fingers and wrist, in normal and amputated people. These patterns are transformed into commands that run the device where adaptability, portability and a better response time are wished. The response cannot have a significant delay in real time in relation to the response expected by the subject, which is less than 300ms.

Thus, one goal to be achieved is to find a suitable set of features extracted from the sEMG signal, based on energy and information complexity methods (amplitude of the EMG signal), prediction model – Auto-Regressive Coefficients (AR) and Cepstral Coefficients (CC) –, Time Dependence (TD), Frequency Domain (FD), Power Spectral Density (PSD), frequency information calculated in the time domain (TFDr), or methods of time-frequency analysis like the Wavelet Transform (WT) and methods of analysis for low level or Fractal Dimension (FD), among the most common (Fig. 1). Thus, when combined decoding with a high degree of accuracy, the intention of the motion generated by the subject can interact with the device, using least amount of information, low computational cost, high sensitivity, specificity and high recognition rate in a short response time.

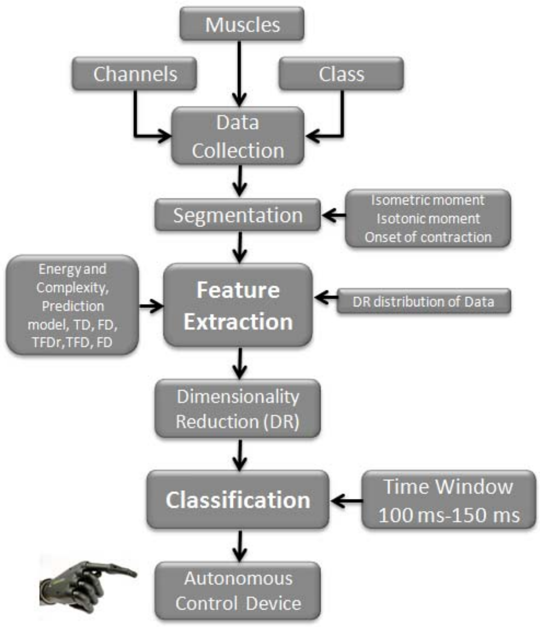

Fig. 1 Myoelectric control system based on pattern recognition.

To achieve these objectives, two important aspects must to be taking into account. The first is the collection of less information as possible, decreasing from six to one electromyography channels or using possible combinations. The other, is the low-level sEMG contractions. The signals from one of a selected muscle group contain high-level and low-level sEMG signals for any movement. The low-level

Reference		Channel	Class	Features	Reduction	Classifier	T-Window	Application	Subjects	Recg-Rate
E.C. Orosco, [1]	**2012**	4	5	Biespectrum, DTDF, MEAN, MED, TRIMM	(AM, HM, GM), (AM-D, HM-D, GM-D),	Feedforward NN	128 ms	Robotic arm	5 able-bodied and 1TR (3M-3F)	92% with transitions and 95% without transitions
S. P. Arjunan [3]	**2010**	1 Delsys CH1 2 Delsys CH1,2 4 Delsys	4	RMS, MAV, VAR, WL FD, MFL AMOVA	____	ANN	Off-line	Finger and wrist flexion with low contractions	5 able-bodied and (4M,1F)	90% One channel
M. S. Erkilinc [11]	**2011**	4	5	FFT (Kaiser and Hamming windows)	PCA and SPCA	m- SVM, *one-against-one*	____	Camera with EMG and EEG, hand has joystick	____	81% SPCA
D. Zhang [9]	**2011**	4	6	DBS, DFC Vs AR,TD, PSD	____	SVM BP NN	256 ms(analysis window slides at a 128 ms)	EMG) controlled prosthetic hand	3 TR (2M-1F)	93.1% DFC 91.5% DBS
R Ganesh [12]	**2008**	4 Delsys	3	BSS+RMS	ICA	BPNN	____	Hand gesture (HG)Vs Facial MA (FAM)	5 able-bodied (3M-1F)	100% HG 60% FAM
F. Bitar [13]	**2007**	4	6	CWT	____	SVM	____	Classifying five fingers sEMG for MIDI	1M able-bodied	91%
M. A. Oskoei [10]	**2008**	4	6	Isotonic TD(MAV, WL, ZC, SSC) RMS+AR6	____	SVM kernel(RBF, linear, polynomial, sigmoid) Vs ANN MLP1, ANNMLP2, LDA	200 ms	recognizing hand movement with SVM	11 able-bodied	95% aprox SVM/RBF
J. Chu [6]	**2006**	4 Delsys	9	WP	PCA, non linear mapping by SOFM	MLP	Real time 125 ms moving Window 250ms	Recognition Multifunction Myoelectric Hand	10 able-bodied (6M-4F)	97% PCA+SOFM 97.785%SOFM, PCA: 95.7%
V. P. Singh [7]	**2008**	1 Delsys	4	bi-orthogonal wavelet 3.3.(CWT+ singularities)	2 dimensions clustering	SVM	____	identify very low level finger flexion	4 able-bodied (3M-1F)	94.5%-98.75%
A. Phinyomark [14]	**2012**	1(x5)	7	Low Vs High Level: DFA Vs RMS, WL, MFL and HFL	____	LDA	____	Low level recognition upper-limb movement for HCIs)	20 able-bodied (10M-10F)	62%-90%

Fig. 2 Myoelectric control system based on pattern recognition for 4 channel and 1 channel.

sEMG contraction is related when there is a little movement in the major corresponding muscle group [1].

There is a relationship among the magnitude and the spectral frequency with the force of muscle contraction. However, at low levels of contraction and with complex gestures this relationship is not linear and the signal to noise ratio (SNR) is very poor. Generally, the indicators based on time and frequency information are unreliable at low-level of muscle contraction. For that reason, nonlinear methods have been used to characterize sEMG, as the work reported in [1] where fractal properties of the signal were used to identify small changes in strength of muscle contraction and the location of the active muscles.

Different FD methods have been used in recent studies. The maximum fractal length (MFL) [1], Higuchi's fractal dimension (HFD) and detrended fluctuation analysis (DFA) [2] are three of such methods. The DFA is one of the fractal algorithms most frequently used in EMG classification. Additionally, it has advantages over others time-scale domain methods, based on the selection of a wavelet basis function, i.e., discrete wavelet transform (DWT) and wavelet packet transform (WPT).

In recent works has been obtained patterns of hand gestures of up to 7 different kinds of movements, using a single channel, with success rates ranging from 62% to 90% [1] [2] [3]. This results tends to improve two [4], three [5] or four [6] channels, with accuracy rates of 90%, 95% and 97% respectively, with 10, 6 and 9 kinds of movements. This allows simulating the movement of the prosthesis in a more natural way.

However, there are some ambiguities, which are necessary to solve, such as data redundancy, depending on the selected muscles and the number of channels and clustering features which represent more accurately the performed gesture [2] [7]. Features that offer a real contribution to the separability of the data must to be studied. The sliding window size, which can vary from 50 to 500ms, must be also taken into account, since it affects the acceptable delay for real time implementations, usually below 300ms. Dimensionality reduction, which transforms coordinate multiple vectors should be represented in two dimensional or three dimensional graphics, such as Principal Component Analysis (PCA) [8] among others.

It is also worth to analyze other set of algorithms, as done by Zhang [9]. Zhang has compared the effect caused by the use of Bayesian classifier, neural network and Support Vector Machine (SVM). On the other hand, Oskoei [10] has compared SVM kernels (RBF, linear, polynomial, sigmoid) vs ANNMLP1, ANNMLP2 and LDA, obtaining higher hit rates for SVM-RBF, achieving 95% recognition for six kinds of movements. It has been identified some works that shows the functionality of low-level strategies and low density with the use of four channels and a channel electromyography as shown in Figure 2.

The work performed with 4 channels has a variation of movements to be recognized, since 3 to 9 classes, with characteristics obtained in both time and frequency domain, and combinations thereof. Arjunan [1] has worked with pairs features based on the fractal dimension and some features in the time domain, recognizing four kinds of movements with a single channel and 90% accuracy, using Artificial Neural Network classifier. Oskoei [10] has used features and compared prediction models in combination with Root Mean Square in dynamic tasks to recognize six kinds of movements, finding an accuracy of 95%, using a SVM/RBF classifier.

However, the work presented by J. Chu [6] shows precision rate of 97% for 9 classes of hand movements using four channels, and double reduction, linear nonlinear PCA using self-organizing feature map SOFM, and classifying with Multilayer Perceptron neural network, for real-time implementations with sliding windows of 125 ms and 250 ms. Combinations of features are also selected, based on the performance of Mean Absolute Value (MAV), TD features MAV, WL, ZC, SSC, and set RMS + AR6.

This research aims to evaluate the classification of different hand gestures in healthy people, with 4 electrodes, using sEMG, both individually and together. For this purpose, we implemented a total of 14 features, 8TD, 5FD and 1FD, in order to identify the best combination that represents the patterns associated with each of the classes, using computational intelligence techniques for classification based on fuzzy logic and ANN.

II. METHODS

This research develops an experimental method based on pattern recognition of sEMG signals, at the level of the proximal third of the elbow, in healthy people. The aim is to identify the features that could classify different kinds of gestures of hand and wrist (up to ten gestures), attempting low computational cost and high accuracy, sensitivity and efficiency. The end is the control of a multifunction myoelectric prosthesis using low density and low level.

A. Subjects

Experiments were performed on five healthy adult subjects without amputation, of both sexes, with mean age of 28 years. Subjects were previously assessed by a physiotherapist, including aspects of participant identification and physical examination (inspection, palpation, range of motion and sensitivity). As inclusion criteria the volunteer should not present in their medical history evidence of peripheral neuropathy, central nervous system diseases and restricted mobility. The study was conducted with skilled subjects, using their dominant hand. The volunteers were informed of the objectives and methodology, through oral presentation. After knowing the detailed procedures, they signed the free consent form according to the ethical principles of the Universidade Federal do Espirito Santo (UFES). All procedures were approved by the UFES ethical committee.

B. Instrumentation

A four surface bipolar electrodes set, reusable, manufactured by Touch Bionics, was used, which include embedded pre-amplification and electronic conditioning, with a 60Hz notch filter and a variable gain. The surface EMG signals were sampled (1kHz with four analog inputs channels) and stored to computer via an NI USB-9001 data acquisition device, from National Instruments. A user interface for the acquisition and processing of signals, based on Matlab 7.14, was developed (Dell XPS L502x Notebook / Intel Core i7, 8GB RAM, Windows 7, 64bit).

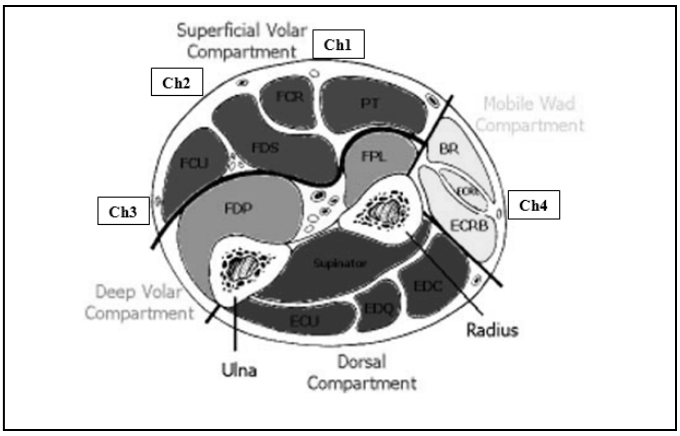

Fig. 3 Vision of a cross section of the forearm with the location of four electrodes identified as Ch1, Ch2, Ch3, Ch4.

C. Skin preparation and electrode placement

In order to reduce the electrical resistance, the skin was previously shaved, cleaned with 70% alcohol, and conductive gel was used before attaching the electrodes. Three channel were recorded from flexor muscles on the surface side of the flying forearm, and one channel was placed on the surface of extensor muscles, on the dorsal side of the forearm, as shown in Fig 2. The reference electrode was placed on the proximal part of the lateral epicondyle, according to standard procedures for recording surface electromyography.

D. Data collection

Subjects were seated comfortably in a chair with the both hands on a table and were trained before performing the tasks. Each experiment was performed with five repetitions of the same task.

TABLE 1. MOTION CLASSES INVOLVED IN THE STUDY.

	Categories	Task	Class Name
	Relax	1	Absolutely relaxed
A	Finger Flexion	2	Little finger movement
		3	Ring Finger movement
		4	Middle Finger movement
		5	Index finger Movement
		6	Thumb finger movement
B	Mix Fingers	7	Little and Ring fingers movement together
		8	Ring and Middle fingers movement together
		9	Little and Index fingers movement together
		10	Index and Middle fingers movement together
C	Flexion / Extension grasp and grisp	11	Wrist flexion
		12	Wrist extension
		13	All fingers movement flexion
		14	Hand grasp
		15	Pinch grip
		16	All fingers movement extension
D	All task with Fingers	1 - 10	Includes the task from 1 to 10

Each repetition begins with the task maintained for approximately five seconds, followed by a rest period to avoid fatigue. The start and the end of the maintained task were indicated visually and verbally. The subjects repeated the experiment during three sessions on different days, for enhanced generalization capability for performing tasks. The tasks were grouped in different categories as shown in Table 1.

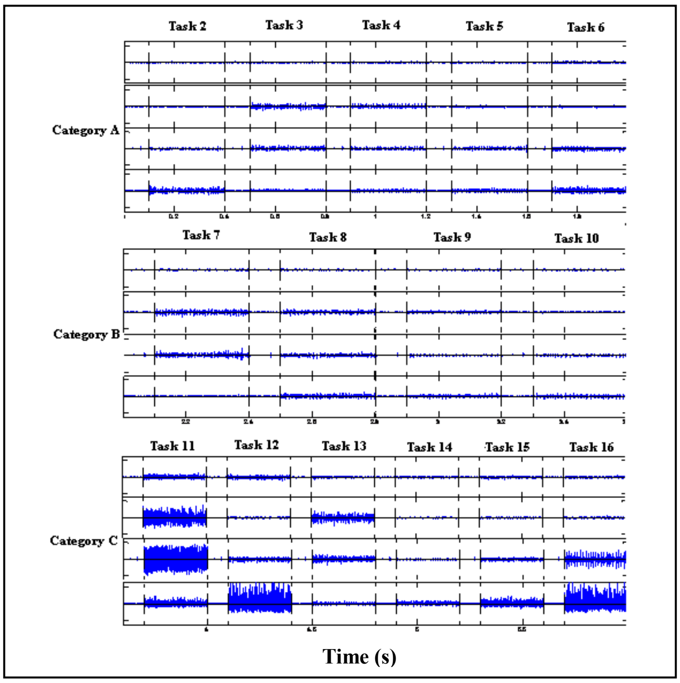

Fig. 4 sEMG signal behavior in the time domain for each motor task to classify by categories A, B and C.

E. Data analyses

A strategy for pattern recognition, capable of performing real-time processing, was proposed. This initial system includes a pre-processing of digitized information, a feature extraction scheme in TD, FD and FA. Finally, a classifier generates a binary output corresponding to a task recognized. The evaluation and validation of the proposed strategy was performed off-line, after the EMG data were entirely recorded. Despite the system was validated in off-line mode, the time for record raw sEMG signals is according with the criteria reported in others works [6] [15] to be used in a real application.

In the pre-processing stage, the isometric task during the activity was identified from each experiment. For this study, an onset detection task was made, using RMS values of the rectified signal. Subsequently, applying a low pass digital filter with a cutoff frequency of 1 Hz, an envelope is obtained.

Next, a manual procedure is performed by an expert, eliminating the isotonic movements corresponding to the transitions between the resting state and the activity in each case. Finally, the data collection includes only the isometric segments extracted. In fig. 3 a representative sample in the time domain of each one tasks included in the study is shown.

Each record in the data collection is segmented based on a sliding window scheme with overlap. The window includes 200 samples and each 100 samples are displaced. The data of each segment are used to define a sEMG pattern, so that a response is generated every 100ms. The window size is defined taking into account the response time of a myoelectric control system should be less than 300ms, in order to provide a response without any delay perceived by the user or generate frustration [6] [11]. The proposed features in the Table 2 were computed. Each ones of them provide only one dimension per channel. The FD methods, like DFA, are related to the muscle size and complexity while the others features list in the Table 2 are related to the strength of contraction. The combination of several features led to better results [14]. In this study, different set of features were tested, trying to combining the non-linear properties of the fractal methods with the others, including linear properties. Only two dimensional feature vectors were considered in this work to avoid high computational times.

F. Classification

In order to determine the most appropriate set of features to represent the patterns associated with the proposed tasks (see Table 2), a study was conducted to evaluate the classification error, varying according to some criteria: the subject, the capture session and the number of experiment. This study was conducted with all data captured for all subjects, and for each subject individually. Additionally, a study was conducted taking into account the data for each session independently.

Two types of classifiers based on computational intelligence were implemented to obtain comparative results. A multilayer perceptron (MLP) was used as classifier, with a hidden layer with twenty neurons. The architecture was determined by trial and error based on the success rate. 50% of the data were used as training data, 15% for validation and 35% for testing. On the other hand, a Fuzzy Logic (FL) classifier was used like a Fuzzy Inference System (FIS). A Sugeno type FIS was developed to the classification. In both classifiers, the input consists of the feature vector taking into account one or all channels, as appropriate. The output is determined by the number of classes to be distinguished.

TABLE 2. FEATURES INVOLVED IN THE STUDY.

Domain	**Features**	
	Abbreviation	***Feature name***
Time Domain (TD)	MAV	Mean absolute value
	MAV1	Modified mean absolute value type 1
	MAV2	Modified mean absolute value type 2
	VAR	Variance of EMG
	RMS	Root mean square
	WL	Waveform length
	ZC	Zero crossing
	SSC	Slope sign change
Frequency Domain (FD)	MNF	Mean frequency
	MDF	Median frequency
	PKF	Peak frequency
	MNP	Mean Power
	TTP	Total power
Fractal Domain (FD)	DFA	Detrended Fluctuation Analysis

Different classifiers were trained, each one specialized to recognize a set of tasks, selected according to some defined categories (including relax): single finger tasks (2-6); tasks fingers in pairs (7-10), the above two categories (2-10), and tasks associated with wrist movements and gripping objects (11 to 16). Each feature was tested individually, and later, feature combinations in pairs with the better results were used.

III. RESULTS

The features shown in Table 2 were evaluated individually, using each of them as a one dimensional vector like input parameters of the classification system. All data recorded in the database obtained were included in this analysis. Table 3 contains the results for both classifiers implemented, MLP and FL for the four categories. Here, the misclassification is presented for each case and the lowers errors are highlight.

TABLE 3. PERCENTAGE OS MISCLASSIFICATION USING EACH ONES OF FEATURES INDIVIDUALLY.

	Classification with Feature Individually							
	A		*B*		*C*		*D*	
	MLP	FL	MLP	FL	MLP	FL	MLP	FL
MAV	33,3	37,5	18,9	13,7	1,0	14,4	74,3	62,9
MAV1	32,2	37,8	**18,5**	13,8	1,8	15,4	74,0	64,5
MAV2	34,3	43,0	25,9	19,0	5,2	21,5	79,2	70,7
VAR	37,4	38,7	22,0	13,0	**0,8**	17,3	78,9	70,8
RMS	35,2	34,6	21,8	10,5	**1,3**	13,7	74,2	64,8
WL	**30,0**	32,6	22,1	**6,1**	**0,5**	14,4	75,7	62,5
ZC	37,8	48,9	29,6	29,0	31,4	37,6	85,7	75,6
SSC	40,6	52,5	28,4	32,9	39,3	43,7	84,1	78,3
MNF	33,7	**30,6**	21,6	8,0	**0,3**	13,2	73,7	63,6
MDF	33,2	32,8	19,8	9,3	**0,3**	12,9	73,6	61,3
PKF	39,4	58,8	29,1	38,9	9,7	27,1	78,8	76,0
MNP	34,2	32,8	19,4	8,0	0,8	12,7	74,2	63,0
TTP	33,3	30,9	21,9	10,1	**0,3**	**12,3**	72,8	61,2
DFA	79,0	82,9	71,1	77,6	79,1	80,0	87,4	87,5

Later, the features with the higher performance were used in pair with the DFA feature as a two dimensional vector like input. The records captured from all subjects were included to validate the classification system and evaluate the inter-subject sEMG patterns relations. The training, validation and testing sets patterns were randomly selected according to the aforementioned. The results are shown in Table 4.

The same study was conducted using the data recorded from each individual session, for each subject. The classification results have higher than 95.4% for all subjects, with 99.3% as the higher rate recognition. Table 5 shows the results for one volunteer.

In most of cases, the pair of features RMS-DFA provided the best information to discriminate the patterns among different set of tasks. On the other hand, the MLP classifier had better results than the FL one, in the most of tests of all categories.

Figure 5 contains two samples representation of the confusion matrix obtained in the classification results for one subject in the category C and D. From this figure, it can be observed that the correct results match to the diagonal matrix, while the others represent the misclassification.

The variability between EMG records from each volunteer in different sessions was also analyzed. For that, the two first sessions data were used to train the classifier, and the last session was used for validation. The sEMG patterns were maintained as repeatable across. the sessions from all patients., with success rate of up to. 98.7%.

TABLE 4. PERCENTAGE OF MISCLASIFICATION USING DFA COMBINED WITH OTHER FEATURES, FOR ALL VOLUNTEERS

	Classification Results							
	A		*B*		*C*		*D*	
	MLP	FL	MLP	FL	MLP	FL	MLP	FL
RMS	**8,1**	**18,2**	**2,9**	**16,4**	**2,4**	17,5	10,5	13,4
WL	9,3	18,4	3,1	17,6	2,7	**15,7**	**9,7**	**12,5**
VAR	13,3	18,3	6,7	16,9	3,5	17,5	15,0	13,2
MAV1	11,2	19,1	13,1	17,4	3,5	17,3	13,9	13,4
SSC	16,8	22,6	11,0	18,5	10,7	24,4	21,9	19,8
ZC	18,7	23,3	15,4	18,9	11,9	24,0	25,2	27,2
PKF	30,1	28,6	26,7	25,6	10,7	24,0	31,1	35,4

TABLE 5. PERCENTAGE OF MISCLASIFICATION USING DFA COMBINED WITH OTHER FEATURES, FOR ONLY ONE VOLUNTEER.

	Classification with pairs of feature							
	A		*B*		*C*		*D*	
	MLP	FL	MLP	FL	MLP	FL	MLP	FL
RMS	1,1	5,5	**0,8**	1,6	**0,7**	**1,1**	**0,7**	1,7
WL	**0,8**	**1,1**	0,9	**1,4**	0,7	1,3	1,0	**1,1**
VAR	4,4	5,7	1,2	2,1	1,1	1,9	1,1	1,9
MAV1	5,4	7,1	1,1	1,9	1,1	1,9	1,2	2,1
SSC	5,1	6,9	9,1	14,9	9,7	16,2	9,6	15,7
ZC	6,4	8,9	8,4	13,7	8,0	13,3	8,2	13,5
PKF	19,3	26,4	5,1	8,4	6,1	9,9	5,6	8,9

Additionally, an analysis was made to identify which channels had the most important information for the process. Each one of the channels were used individually as information and later were used all channels together. When only one channel was used as input information, the misclassification was above 18.7% in all cases, and it was at least 5.8 times bigger that when all channels were used. It is also observed that when using four channels the higher error was 5.1% among all categories.

IV. DISCUSSION

According to the results, the pair of RMS-DFA features led to the best results in most of the categories listed above. WL-DFA showed similar results. These two sets of characteristics are proposed as the most interesting for the future study of sEMG signal analysis for tasks of low-level contraction.

The results showed high recognition performance of different groups of gestures proposed in this study. Better results were obtained during the analysis of the same system with a single subject when using data sets from all volunteers.

However, the levels of recognition obtained in both cases for this study showed that it is possible to relate different sEMG patterns for different hand gestures, for different volunteers, even when the tasks were performed at different times. This makes the system robust to possible variations in the data due to possible changes in the environment, depletion and mindset of each of the subjects in the study.

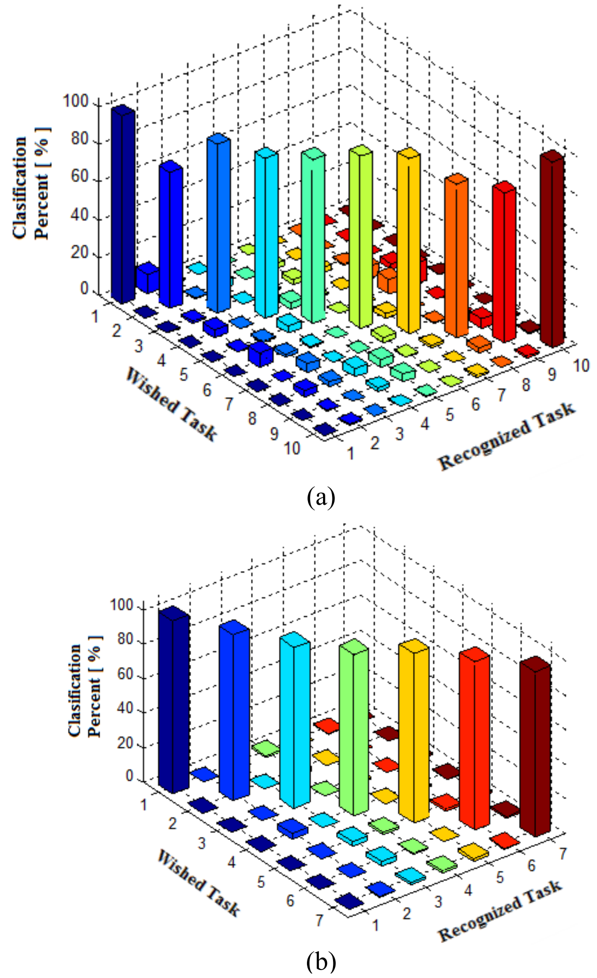

Fig 5. Confusion matrix for one patient, (a) for task category C, (b) for task category D.

V. CONCLUSION

Grouping the different gestures in categories generates a higher level of recognition, so that allowed to recognize up to 10 different tasks with only four channels of information as input. This study could represent an advance in sEMG pattern recognition of low density, with 4 channels of data used, in relation to other works in the literature.

This work with sEMG signals of low-level contraction, for the recognition of different tasks, represents a contribution in the design of hand prosthesis systems penta-digital, requiring less energy from the involuntary amputees to the control of the hand prosthesis. Pairs of features that were selected had the best performance in most of the proposed tasks, making it possible to define a single set of parameters for all classifiers that were trained.

The system proposed in this work entails obtaining a system that can be implemented with an on-line scheme, which will allow the recognition of hand gestures when executed simultaneously by the subject, without any noticeable delay for the user. Subsequently, a new system is expected to obtain a similar recognition level with sEMG signals captured from amputees. Finally, once the complete system is obtained, different studies on cognitive learning for healthy people and amputees can be carried out using a real prosthetic hand.

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