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Preliminary Results of Online Classification of Upper Limb Motions from Around-Shoulder Muscle Activities

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Abstract— **Recently, detecting upper-limb motion intention for prosthetic control purpose attracted growing research attention. In most of the studies, recordings of forearm muscle activities were used as the signal sources, from which the intention of wrist and hand motions were detected using pattern recognition technology. However, most daily-life upper limb activities need coordination of the shoulder-arm-hand complex. The disadvantage of relying only on the local information to recognize a whole body coordinated motion is that misrecognition could easily happen, so that steady and reliable continuous motions could not be realized. Moreover, using forearm muscle activities would limit the use of the system for higher level amputation patients. Therefore, in this study we aimed to explore the feasibility of using an online classification algorithm to test the intention detection in real time. Experiments were conducted to record around-shoulder muscle activity using EMG and acceleration sensors. Then, a neural network was trained using these data, and finally tested online in a set of tests. Results showed that, from 5 channels of Electromyogram (EMG) and 4 channels of accelerometers, it is possible to discriminate 3 different grips and 5 reaching direction of arm.**

Keywords- around-shoulder muscle, neural-network, EMG s, accelerometer

INTRODUCTION

Nowadays, different high dexterity robot hands are being developed, therefore, new robust and intuitive intention detection techniques are needed to aid the amputee to take advantage of this dexterity [1]. It has been reported that up to 10 wrist and hand motions could be recognized from 2-3 electromyogram (EMG) channels [2,3]. Other researchers have used non-stationary EMG at the beginning of motion [4] or mechanomyogram (MMG) as the signal source for the motion intention detection [5]. In these studies, motion intention of the wrist and hand were detected using pattern recognition techniques from recordings of forearm muscle activities. However, it is difficult to take into consideration the body coordinated motions from these signals alone; therefore the movement of the artificial limb can be unnatural, if considered as a part of the whole body, and a dynamical coupling between prostheses and their users is not possible. Also, using forearm muscle activities to drive the artificial limb leaves aside the possibility for patients with higher level amputations (e.g. transhumeral amputation) to use the system.

Most daily-life upper limb activities need coordination of the shoulder-arm-hand musculo-skeletal complex. Research in motor control area has shown that during grasping and reaching [6-9], or more sportive motions, such as throwing or catching a ball, the trajectory of the elbow, shoulder and hand are tightly coupled [10]. This coupling is also task and situation dependent, such as reaching and grasping an object in different places and/or in different orientations [11].

Various efforts have been done in order to improve the current intention detection techniques. For example, C. Martelloni, *et al.*, in [12], used a Support Vector Machine based pattern recognition algorithm as an attempt to predict different grips. They were able to discriminate 3 different grips (palmar, lateral or pinch grip), but they included data obtained from the forearm muscles activities of the flexor carpi radialis and extensor carpi radialis. Also, in [13], Xiao Hu, *et al.* compared the performance of a Scalar Autoregresive model with a Multivariate AR modeling for multichannel EMG sensors in order to classify upper arm movements. They were able to classify accurately different arm movements. Although the results are encouraging, they focus the attention on the contribution of the muscles as a whole, and insights on the contribution of individual muscles is lost.

Previous experiments have shown the possibility of using only around-shoulder muscle activities in order to detect different grips and arm motion position [14], but only off-line data analysis was carried out. Therefore, in this study we aimed to explore the feasibility of using an online classification algorithm to test the intention detection in real time. Experiments were conducted to record around-shoulder muscle activity signals by EMG and acceleration sensor. Then, a neural network was trained using these data, and finally tested online in a set of tests.

MATERIAL AND METHOD

A. Subjects

Three male subjects, 23 years old, participated in the experiments. They were informed about the experimental procedures and asked to provide their consent. All subjects were healthy with no known history of neurological abnormalities or musculo-skeletical disorders.

B. *Experimental setup*

Subjects sat comfortably in front of a table and they were asked to move their dominant arm, starting from an assigned position, towards a fixed end-position and then grasp an object. Figure1 shows the different arm end-positions used in the experiment. Each subject was asked to press a button, placed on the table, with their dominant hand in order to mark the start of the motion when released. Then they had to reach and grasp an object with one of 3 grips, as shown in figure 2.

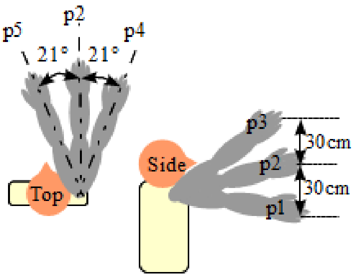

Figure 1. Experimental setup 1: subjects were asked to reach and grasp different placed at five different positions (p1,p2,p3,p4 and p5)

g1: a palmer grip g2: a spherical grip g3: a down side grip

Figure 2. Experimental setup 2: subjects were asked to reach and grasp different objects (g1, g2 and g3) placed at the positions

The objects were placed in order to allow the subjects to perform maximal elbow extension in all five directions (see Figure1). Moreover, the height of the chair was regulated for each subject in order to obtain an elbow's angle of 90° (maintaining the trunk erected). A self-paced speed was allowed for the reaching and grasping tasks. The subjects were asked to reach each object 20 times for every position. Therefore, each subject performed 300 trials (3 objects × 5 positions × 20 repetitions). The subjects could rest for a few seconds between each trial. Also, they were requested not to bend or rotate the trunk in order to prevent translational motions of the shoulder.

C. *Devices*

Signals of muscle activity were recorded at a sampling rate of 400 Hz using LabView (National Instruments) and used for the neural-network training in Matlab. Five EMG sensors and four acceleration sensors were placed on the skin surface, according to [16], and as shown in figure 3.

The EMG sensors were placed in the following muscles:

1. The clavicular part of pectoralis major muscle.
2. Acromial part of deltoid muscle (central fibers).
3. Descending fibers of trapezius muscle.
4. Ascending fibers of trapezius muscle.
5. Teres major muscle.

Also, the acceleration sensors were placed to measure the following muscles activity:

1. Short head of biceps brachii muscle.
2. Long head of triceps brachii muscle.
3. Ascending fivers of trapezius muscle.
4. Infraspinatus muscle and infraspinous fascia.

Disposable solid-gel Ag-AgCl surface electrodes (Biorode SDC-H,GE Yokogawa Medical Systems, Japan) were used for EMG recording.

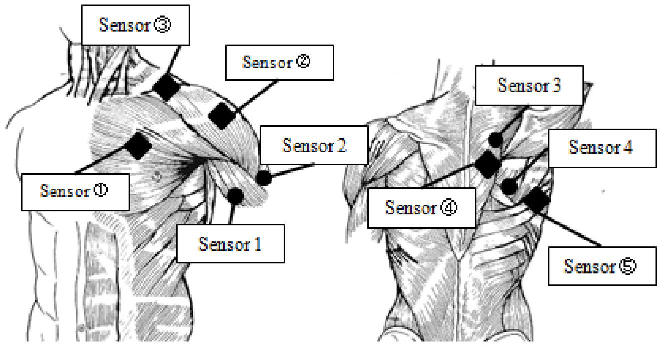

Figure 3. The location of the sensor(□:EMG sensor ●: acceleration sensor)

D. *Feature extraction*

For data classification, three features were employed. The first feature was the mean value (MV), which is expressed by equation (1). The second one was the subtract value (SV), expressed by equation (2) and the third feature was the difference of point values at a certain interval (PV) expressed by equation (3).

$$MV = \frac{1}{T}\sum_{i=0}^{T} P_i \tag{1}$$

$$SV = \sum_{i=1}^{T} \left| P_i - P_{i-1} \right| \tag{2}$$

$$PV = P_T - P_0 \tag{3}$$

T corresponds to the data length the starting point (for this study, T values of 200p, 400p, and 600p were employed). Also, Pi corresponds to the smoothened EMG and acceleration signals.

E. *Method of Analysis*

Due to the EMG and acceleration signals' nonlinearity a back-propagation based neural network (NN) was used for the online-classification. The NN used in this experiment consists of three layers (an input layer, a hidden layer, and an output layer). The input layer consisted of 9 neurons (5 for EMG inputs and 4 for accelerometers). The hidden layer has twice the neuron number as the input layer. And the output layer consisted of three outputs for 3 grips, and five outputs for 5 reaching direction. The Back Propagation algorithm was used to update the weights. The number of learning times was set to 2000. Finally, a leave-one-out method was used for the training and test of the NN.

RESULT

A. Correct Rate of Discrimination

Figure 4 shows the discrimination results obtained from subject A, using SV as feature, when discriminating the reaching direction. The horizontal axis shows the data length, the vertical axis represents the final arm position (refer to figure 1), and the z axis shows the correct discrimination rate in percentage.

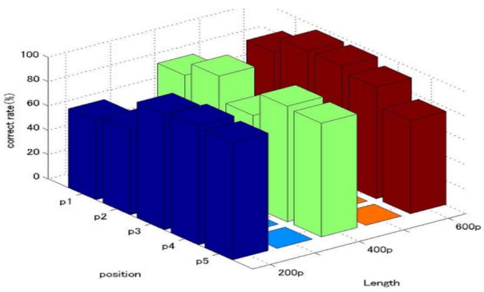

Figure 4. Correct discrimination rate of subject A, using SV as feature

In this case, the highest correct discrimination rate was achieved when using a data length of 600 points. The same result can be observed for the other subjects. Also, for MV feature the highest correct rate discrimination was obtained when using a data length of 600 points, but for the PV feature a data length of 200 points was enough for a good discrimination.

Figure 5 shows the correct discrimination rate average of all the subjects, for different reaching positions. It can be noted that the discrimination rates for position p3 and p4 are higher than the other positions. On the other hand, position p2 had the lowest discrimination rate.

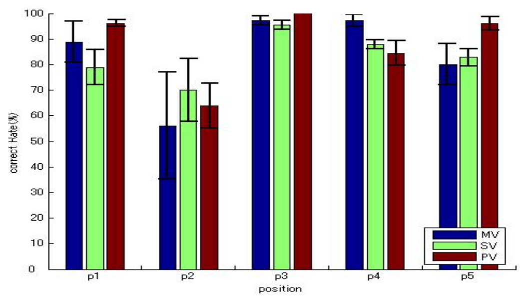

Figure 5. Average correct discrimination rate of all subjects

Figure 6 shows the results obtained from subject A, when discriminating the final grip, using MV as feature. The vertical axis represents the final reaching motion. For this case, the highest correct discrimination rate was obtained for a data length of 600 points. Similar results were obtained for the other subjects. And for the PI feature, a data length of 200 points was enough for a good discrimination.

Figure 7 shows the average correct discrimination rate of all subjects, for different grips. It can be seen that grip g3 had the highest discrimination rate, and g1 the lowest.

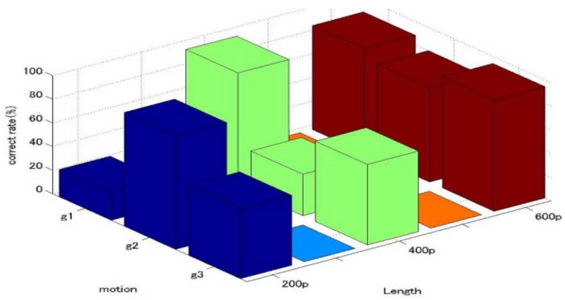

Figure 6. The correct rate of subject A, using MV as feature

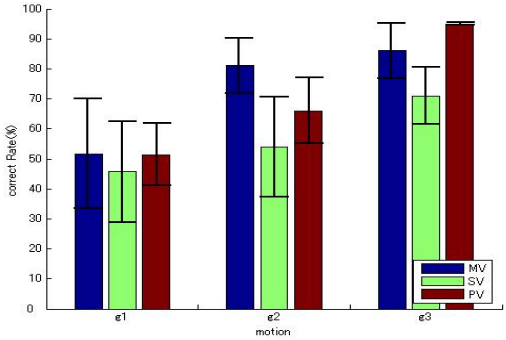

Figure 7. The average correct rate of the higest correct rate of all subjects, using MV, SV and PV as feature.

Table I, II and III show the mutual discrimination rate values for each reaching direction and grips. For example, in the column p1 of table I, when the subject realized the direction p1, 83.3% of samples were correctly recognized as p1; and 11.7% was misrecognized as p2, 3.3% as p4, and 1.7% as p5.

TABLE I. THE MUTUAL DISCRIMINATION RATE (SUBJECT A)

direction: SV, 600p					
	p1	p2	p3	p4	p5
p1	83.3	1.7	0	0	0
p2	11.7	96.7	3.3	5	8.3
p3	0	0	96.7	3.3	15
p4	3.3	0	0	91.7	0
p5	1.7	1.6	0	0	76.7

grip: MV, 600p			
	g1	g2	g3
g1	88	20	6
g2	0	80	0
g3	12	0	94

TABLE II. THE MUTUAL DISCRIMINATION RATE(SUBJECT B)

direction: SV, 400p					
	p1	p2	p3	p4	p5
p1	90	1.7	0	3.3	3.3
p2	0	48.3	3.3	8.3	1.7
p3	0	8.3	91.7	0	1.7
p4	1.7	13.3	1.7	85	3.3
p5	8.3	28.4	3.3	3.4	90

grip: PV, 400p			
	g1	g2	g3
g1	70	29	6
g2	26	71	0
g3	4	0	94

TABLE III. THE MUTUAL DISCRIMINATION RATE(SUBJECT C)

direction: PV, 400p					
	p1	p2	p3	p4	p5
p1	98.3	1.7	0	1.7	0
p2	1.7	73.3	0	8.3	0
p3	0	0	100	0	0
p4	0	11.7	0	90	0
p5	0	13.3	0	0	100

grip: SV, 600p			
	g1	g2	g3
g1	28	7	18
g2	56	91	28
g3	16	2	54

It is clear from these results that p2 and g1 had the lowest correct recognition rate, but on the other hand, the rest of the positions and grips had very high recognition rates. Figure 8 and 9 shows similar results when comparing between subjects. The high discrimination rate can be noted for all of subjects for most of the tasks except for position p2, where subject B and C had low discrimination rate. Also, for grip g1, subject 3 had very low discrimination rate.

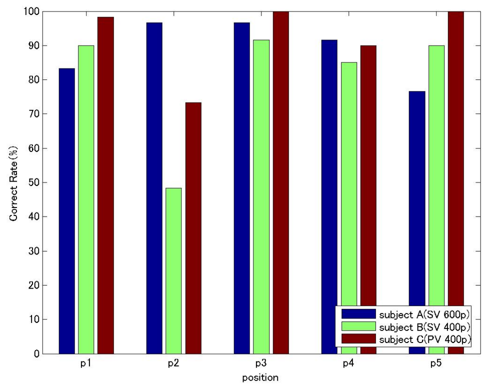

Figure 8. Comparison between subjects : correct discrimination rate of reaching directions

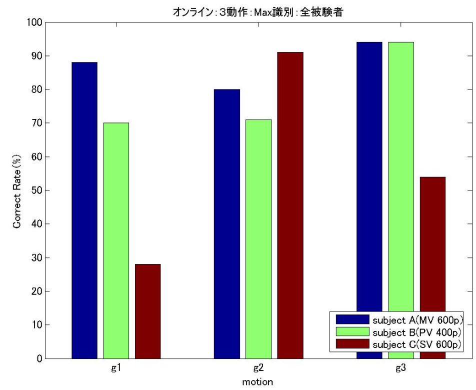

Figure 9. Comparison between subjects: correct discrimination rate of grips

B. Analysis of variance

In order to determine the contribution to the motion discrimination of each sensor channel, a Turkey-Kramer test was performed. Tables 4, 5 and 6 show these results for reaching direction discrimination.

TABLE IV. COMPARISON OF SENSORS CONTRIBUTION TO POSITION DISCRIMINATION FOR SUBJECT B, USING SV AS FEATURE (DATA LENGHT OF 600 POINTS)

subject A	EMG				Acceleration				
positions	1	2	3	…	Z	X	Y	Z	Total
p1/p2	○	×	×	…	○	○	○	○	12
p1.p3	○	○	○	…	○	×	○	○	13
p1/p4	○	○	×	…	○	○	○	○	14
p1/p5	○	×	○	…	○	×	○	×	13
p2/p3	○	○	○	…	○	○	×	×	9
p2/p4	×	○	○	…	○	×	○	×	11
p2/p5	○	○	×	…	○	○	○	○	13
p3/p4	○	○	○	…	×	○	○	×	13
p3/p5	○	○	×	…	○	×	○	○	12
p4/p5	○	○	○	…	○	○	○	○	16

pi/pj means the discrimination between pi and pj

○significant difference × no significant difference

TABLE V. COMPARISON OF SENSORS CONTRIBUTION TO POSITION DISCRIMINATION FOR SUBJECT A, USING SV AS FEATURE (DATA LENGHT OF 400 POINTS)

subject B	EMG				Acceleration				
positions	1	2	3	…	Z	X	Y	Z	total
p1/p2	×	×	×	…	○	○	○	○	13
p1.p3	○	○	○	…	○	○	○	○	17
p1/p4	×	○	○	…	○	○	○	○	14
p1/p5	×	×	×	…	○	○	○	○	13
p2/p3	○	○	○	…	○	×	×	×	9
p2/p4	×	○	○	…	○	×	×	×	10
p2/p5	×	×	×	…	○	○	○	○	9
p3/p4	×	×	○	…	○	×	×	×	9
p3/p5	×	○	○	…	○	○	×	○	12
p4/p5	×	○	×	…	×	○	×	○	12

pi/pj means the discrimination between pi and pj

○significant difference × no significant difference

TABLE VI. COMPARISON OF SENSORS CONTRIBUTION TO POSITION DISCRIMINATION FOR SUBJECT C, USING PV AS FEATURE (DATA LENGHT OF 400 POINTS)

subject C	EMG				acceleration				
positions	1	2	3	…	Z	X	Y	Z	total
p1/p2	×	×	○	…	×	○	×	○	10
p1/p3	×	○	○	…	○	○	○	×	15
p1/p4	×	×	○	…	○	○	○	○	13
p1/p5	×	○	○	…	○	○	○	×	14
p2/p3	×	○	○	…	○	○	○	○	13
p2/p4	×	×	×	…	○	○	○	○	10
p2/p5	○	×	○	…	○	×	○	○	13
p3/p4	×	○	○	…	○	○	○	○	14
p3/p5	×	○	○	…	○	○	○	×	15
p4/p5	×	○	×	…	○	○	○	○	13

pi/pj means the discrimination between pi and pj

○significant difference × no significant difference

It can be observed that when discriminating reaching direction p2, only few sensors contributed to the classification process, therefore it was more difficult to be discriminated correctly.

Table 7, 8 and 9 shows the contribution of each sensor channel to the motion discrimination for the different grips.

TABLE VII. COMPARISON OF SENSORS CONTRIBUTION TO GRIP DISCRIMINATION FOR SUBJECT A, USING MV AS FEATURE (DATA LENGHT OF 600 POINTS)

subject A	EMG				acceleration				
Motions	1	2	3	…	Z	X	Y	Z	total
g1/g2	×	×	×	…	○	×	×	○	8
g1/g3	×	○	×	…	×	×	×	×	7
g2/g3	×	○	○	…	○	×	×	○	11
total	0	2	1	…	2	0	0	2	

pi/pj means the discrimination between pi and pj

○significant difference × no significant difference

TABLE VIII. COMPARISON OF SENSORS CONTRIBUTION TO GRIP DISCRIMINATION FOR SUBJECT B, USING PV AS FEATURE (DATA LENGHT OF 600 POINTS)

subject B	EMG				acceleration				
Motions	1	2	3	…	Z	X	Y	Z	total
g1/g2	×	×	×	…	○	×	○	○	7
g1/g3	×	○	×	…	×	×	×	○	7
g2/g3	×	○	×	…	○	×	○	○	13
total	0	2	0	…	2	0	2	3	

pi/pj means the discrimination between pi and pj

○significant difference × no significant difference

TABLE IX. COMPARISON OF SENSORS CONTRIBUTION TO GRIP DISCRIMINATION FOR SUBJECT C, USING SV AS FEATURE (DATA LENGHT OF 600 POINTS)

subject A	EMG				acceleration				
Motions	1	2	3	…	Z	X	Y	Z	total
g1/g2	○	○	○	…	○	×	×	×	6
g1/g3	○	○	×	…	○	×	×	○	9
g2/g3	○	×	○	…	×	×	○	×	8
Total	0	2	1	…	2	0	0	2	

pi/pj means the discrimination between pi and pj

○significant difference × no significant difference

It can be noticed from these tables that few sensors contributed for the classification of grip g1, therefore it was harder to discriminate this grip correctly.

DISCUSSION

In order to take full advantage of the many degrees of freedom in current light-weighted dexterous prosthetic hands, research effort are requiered to improve the motion intention detection algorithms available nowadays. The new algorithms have to take into account the whole body dynamics to aid the amputee to realize natural and intuitive manipulation of the prosthesis. To this date, different data mining methods have been used to extract and predict information from EMG sensors, among wich neural networks are the most commonly used [1-3, 12-16]. In [18], R. Ashan et al. made a review on the different types of classifiers used until 2009 for EMG extraction for Human Computer Interaction applications. They conclude that the use of neural networks dominates for these applications, but point out also the advantages of other methods. Moreover, in [13], a statistical approach was used in order to model the arm motions. In this case a multivariate analysis of the EMG information approach was used in order to take advantage of the correlation of the EMG activities when making arm movements. The results of these studies show that it is possible to extract arm dynamics information from activities of the proximal muscles, but unlike the present study, all of them processed the data off-line, thus, the real time performance of the classifier is not taken into account.

The results of this study shows that it is possible to recognize different arm positions and grips in a dynamical way using online processing. As seen from the results, the discrimination rate for most of the motions was high. The lowest discrimination rate was observed in reaching direction p2, which is reaching an object at the center. In this case, there aren't any distictive components like in the other motions (for example reaching up or to the sides). Also, as expected, the subject variability is very high. This can be due to sensor position or subject's individual muscle strenght. Despite this difference, by inspecting different features, different directions and grips can be correctly discriminated. Certanily, more subjects are needed to be tested to determine stadistically the performance of the system.

Another point that has to be taken into account, is that the NN was trained only off-line, which can leave many important features of the motions out. This is why, currently an on-line training scheme is being developed in order to improve the detection rates, despite of individual differences. Furthermore, the recognition delay has to be further improved, as for now it is about 1s, which is too slow to use in any real life application. Finally, the experiment setting used for this study had many constrains in order to reduce external perturbances to the system and facilitate preliminary analysis, but for future tests the experiment setting has to be adapted to more realistic situations. Therefore we should take in consideration the influece of other variables (e.g. motion of the torso, variability of reaching position, etc.) that are easily found in daily living situations.

These preliminary findings set the base to developed a system able to achieve a dynamical coupling between the person and the machine because, by taking in account the whole body dynamics, it will allow more natural and intuitive manipulation of the robot hand.

CONCLUSION AND FUTURE DIRECTION

This study shows that it is possible to distinguish, dynamically, different grips and arm direction from only around-shoulder muscle activities using an online classifier. Therefore, by using EMG and acceleration sensors, different features can be detected from the muscle activities, and high recognition rates can be obtained despite of subject's individual differences.

More tests, with different subjects, are currently being realized, to obtain more robust data. Also, an on-line training of the NN is being implemented to adjust differences in the reaching motion of each user in order to improve even further the recognition rates. Finally, how to improve the detection delay is being investigated and the experiment setting is being adapted for daily life activities.

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