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Recognition of Movements Through Dynamic Electromyographic Signals

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***Abstract*—The recognition of movements through electromyographic (EMG) signals is critical for myoelectric control systems. Performance of these systems depend on processing methods and protocols used to extract the EMG signals. The aim of this study is to evaluate the performance of classification of a kinematic recognition system based on dynamic EMG signals. For this, a correlation analysis between dynamic EMG signals and kinematic features of movements is realized, and then, a kinematic recognition system based on dynamic EMG signals is implemented. Dynamic EMG signals from forearm muscles during finger flexion movements were recorded and analyzed by using an amplitude estimator. Linear and no-linear correlations between EMG amplitudes and kinematic features were found. Then, a step of classification based on discriminant analysis was implemented to categorize the finger movements in multiple kinematic states. The accuracy of classifications were 95%, 88%, 81% and 76% for two, three, four and five states respectively, and by using a simple-channel recording and an EMG amplitude estimator. The results of this study demonstrate that it is possible to improve aspects of "intuitiveness" through dynamic EMG evoked by natural and more intuitive movements.**

Keywords—EMG; root mean square; kinematic features; discriminant analysis.

I. INTRODUCTION

Temporal and spectral features extraction from electromyography signal (EMG) is very important in myoelectric control systems [1]. These systems use specific EMG features and converts them into commands for controlling devices. Ideally, it is required that a myoelectric control system be able to control a large number of degrees of freedom by using few recording electrodes. For this, digital processing techniques and EMG acquisition protocols must be optimized and improved. The input features frequently used in a myoelectric control system are extracted from EMG signals evoked by static contraction [2][3]. In these systems, a time to establish a control command is required, thereby exhibiting temporal limitations on information transfer rates. One possible alternative to overcome these limitations is through the use of dynamic EMG.

The dynamic EMG signal refers to EMG signal acquired during a nonisometric and nonisotonic contraction [4]. In a static contraction, i.e. when a muscle performs a constant-force isometric contraction, the EMG signal can be assumed to be one realization of a wide-sense stationary random process [5]. However, when the EMG signal is recorded from the surface of a muscle during varying-force, termed dynamic contraction, (i.e. an exercise where the position of the body segments change), the signal properties may change at a much faster rate because of rapid recruitment and derecruitment of motor units and changes in joint angle. Consequently, the above assumption of stationarity no longer holds in the dynamic phase of a muscle contraction [6].

Analysis techniques for stationary signals are often not appropriate during dynamic contractions. However, many studies have proposed/extrapolated processing techniques for its implementation on dynamic EMG signals [5][7][8][9][10]. In EMG-dynamic signal processing, one must take into account the factors that can introduce mistakes in the data-interpretation process. For instance, EMG amplitude and its frequency content would be related to the continuous changes of force, muscle fiber length, relative position of electrodes and the amount of active muscle fibers during a dynamic task [4][5].

The aim of this work is to assess the performance of classification of a kinematic recognition system based on dynamic EMG signals. Similar studies (such as [11]) have proposed a three states classifier (rest, slow contraction and fast contraction) based on dynamic EMG signals evoked by different speeds of movement of a human elbow. Likewise, Sundaraj [12] implemented a EMG pattern recognition of five status (rest, slow weak contraction, slow strong contraction, fast weak contraction and fast contraction) by using artificial neural network and a classification accuracy of 88% was reported. Our research not only increases the number of states to classify, but also analyze the correlations between dynamic EMG signals and kinematic features of movements. These correlations would optimize the acquisition and processing protocols in myoelectric control systems. Furthermore, the experimental protocols used in [11] and [12] could lead to muscle fatigue, mainly due to the nature of contractions (fast and strong contractions). Here, a experimental protocol based on natural and more intuitive movements is implemented.

Briefly, the organization of the paper is as follows. First, a study of correlation between dynamic EMG signals and kinematic features of movements was realized. Second, a kinematic recognition system based on dynamic EMG signals was implemented.

II. MATERIAL AND METHODS

A. EMG recordings of finger flexors muscles

The EMG signals from finger flexor muscles were registered during dynamic contractions evoked by ring and middle finger flexion movements (right hand). EMG

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recording electrodes were placed on motor point (MP) and out MP (about MP) of Flexor Digitorum Superficialis muscles (muscle subgroups responsible of ring and middle finger movements). The location of two specific flexor muscle MP was established by using electrical stimulation. For this, we used a GRASS S88 stimulator and isolated unit SIU5. The stimuli were square-wave pulses (0.3 ms duration, 40-60 V amplitude, 3 Hz). The reference electrode was placed in forearm backside, while the active electrode was used for to stimulate different places (zones near to MP of interest) (Fig. 1A). The MP was established as the place where electrical stimulation evoked maximum contraction of the flexor muscle subgroup. This muscular contraction level was indirect measured through finger movement by using an accelerometer placed at the fingertip. This procedure was carried out for localization of flexor muscle MPs of ring and middle fingers. Importantly, the electrical stimulation of a MP only evoked the movement of a single finger. The MP locations were realized in sixteen healthy subjects (all male, 25.5 ± 6.8 years old).

Then, two pairs of bipolar electrodes on MP site and out MP site (about MP) were placed. Each pair of bipolar electrodes was placed in longitudinal alignment to direction of muscle fibers. Inter-electrode distance was 2 cm (Fig. 1B).

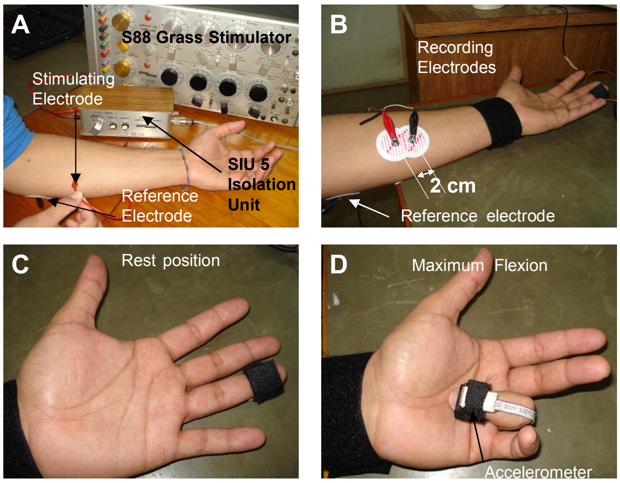

Fig. 1. Recording Set-up. (A) MP location. (B) A pair of electrodes in bipolar configuration for EMG signals acquisition from a flexor muscle subgroup. (C) Rest position of ring finger. (D) Maximum flexion of ring finger. The accelerometer is placed at ring fingertip.

Reference electrode was placed in forearm backside.

Finally, EMG was recorded during voluntary and non-sustained contractions of the extrinsic flexor muscles of ring and middle fingers. EMG was acquired with a BIOPAC system (www.biopac.com): MP30 module, 2 kHz (sample frequency) and 60 dB (amplifier gain). Analog filters were set to obtain 0.05 to 1 kHz of bandwidth. General parameters of acquisition system were set with BSL-Pro software.

B. Monitoring of finger movements

An acceleration sensor ADXL330 (www.analog.com) was used to monitor ring and middle finger movements. The ADXL330 uses a single structure for sensing the *X*, *Y*, and *Z* axes on a single monolithic IC. The operation range is ± 3 g (g = 9.8 m/s^2) and nominal resolution of 0.3 g/V. The acceleration signals were recorded with a bandwidth of 50 Hz (by using a C = 0.10 µF) (see datasheet of ADXL330). The ADXL330 can measure the static acceleration of gravity as well as local acceleration resulting from motion.

The three acceleration signals (*X*, *Y* and *Z* axes) were represented as a vector by using a three-dimensional vector magnitude (3DVM). The 3DVM is a way to sum and normalize the acceleration data from three axes and was obtained as follows:

$$3DVM(i) = \sqrt{accX(i)^2 + accY(i)^2 + accZ(i)^2} \qquad (1)$$

Where, $accX(i)$, $accY(i)$ and $accZ(i)$ are *i-th* samples of the acceleration series recorded in *X*, *Y* and *Z* directions, respectively. First, ADXL330 was placed at the fingertip of ring finger (Fig. 1C and 1D) and measurements were taken during flexion ring finger movements. Then, the ADXL330 was placed at the fingertip of middle finger and the measurements were realized.

The follow procedures were used to synchronize the EMG activity with acceleration signal evoked by finger movements. The acceleration signals were acquire by using a µDAQ-Lite (acquisition board, www.eagledaq.com). Synchronization between EMG and acceleration signals was performed by sending the EMG activity to an analog input of µDAQ-Lite via analog output of the MP30 (Fig. 2A). Thus, EMG activities and acceleration signals were acquired with µDAQ-Lite by using 2 kHz (sample frequency). The acquisition parameters were set with DASYLAB software.

C. Experimental Protocol

Each subject remained seated with the right arm partially extended (angle between the arm and forearm, approx. 120°), and ensuring that the forearm backside remains in contact with the table. The hand palm was maintained extended in a natural and relaxed position before beginning the movements (Fig. 1C).

Subjects were instructed to perform finger flexion movements at different speed (from slow to faster movements). First, flexion movements had an angular displacement of approximately 180º (from its rest position to maximum flexion position, Fig. 1D). Then, the finger returned to its rest position through an extension movement. Each subject performed at least 120 repetitions of the finger flexion/extension movements. This procedure was carried out for ring and middle fingers. No feedback was provided to the subjects to regulate the position and speeds, but visual validation of the motions was performed by the experimenter. The whole EMG recording setup is shown in Fig. 2.

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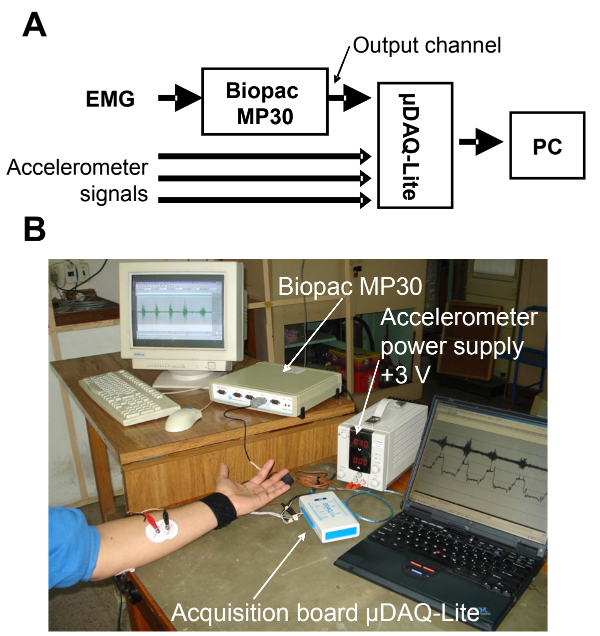

Fig. 2. (A) Connection diagram of experimental Set-up. (B) Equipment used for simultaneous recording of acceleration signals and dynamic EMG.

D. Digital processing

EMG amplitude was analyzed during the flexion phase by using root mean square (RMS). The choice of this amplitude estimator was realized considering previous works [9][13]. RMS is a popular feature in analysis of the EMG signal [14][15]. The mathematical definition of RMS can be expressed as:

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i)^2} \qquad i = 1, 2, \ldots, N \qquad (2)$$

N is number of samples and x_i is the i-sample of EMG signal.

Flexion phase was determined from low-frequency component of 3DVM signal (static acceleration of gravity). For this, high-frequency component of 3DVM was filtered with a Butterworth low-pass filter. Cutoff frequency was established according to maximum average of flexion time (fc = 5 Hz for flexion time of 0.1 sec).

Local acceleration was used to quantify another kinematic feature of fingers movements. For this, low component frequencies were removed by using a 4th order, Butterworth high-pass filter (fc = 5 Hz). Then, the local acceleration amplitudes were estimated with the absolute mean value (AMV) for each finger movement as follow.

$$AMV = \frac{1}{N}\sum_{i=1}^{N}|y_i| \qquad i = 1, 2, \ldots, N \qquad (3)$$

Where y_i is the i-sample of local acceleration serie.

E. Discriminant analysis for classification states

A discriminant analysis was used to categorize finger flexion movements according EMG signal evoked. For this, we have imposed two, three, four and five kinematics states which were pre-established by finger movement measures (flexion time and local acceleration). These states were defined in each subject as follows. First, range value of kinematic features of finger flexion movement was obtained (from slowest to fastest movements). This range was divided in two states (slow movements and fast movements) according to percentiles theory. The same procedure was used to divide the kinematic range of flexion movements in three, four and five states. It is important to highlight that the states were established using only the acceleration signals, while the classification with discriminant analysis only uses the EMG amplitudes.

The basic idea of discriminant analysis is to seek a projection matrix W which projects the original dataset into a new coordinate system where the class separability is maximized by making the between-class scatter (S_b) largest and the within-class scatter (S_w) smallest. S_b and S_w are defined respectively as follows:

$$S_b = \sum_{i=1}^{C} N_i(\mu_i - \mu)(\mu_i - \mu)^T \qquad (4)$$

$$S_w = \sum_{i=1}^{C}\sum_{j=1}^{N_i}(X_i - \mu_i)(X_i - \mu_i)^T \qquad (5)$$

Where C is the number of class, N_i is the number of samples of each class. μ_i is the mean vector for each class, μ is the mean vector for all classes, and X_i denotes the original feature vectors of each class. The optimal matrix W can be obtained by:

$$J(W) = \frac{\det\left(W^T S_b W\right)}{\det\left(W^T S_w W\right)} \qquad (6)$$

The original feature matrix (M x N) is proyected by:

$$y = W^T x \qquad (7)$$

The matrix y stands for the projected feature vectors with R-dimensionality (R ≤ M, R ≤ C-1).

III. RESULTS

Fig. 3 shows the EMG activities evoked by ring finger flexion movements and their corresponding acceleration signals at three different speeds. Low-frequency component of 3VDM signal allowed identifying the finger movement phases: flexion movement, static contraction and extension movement (shaded areas). It is possible to note that time interval of flexion movements is shorter for faster movements; while time interval of static contraction phases shows no significant differences with the movement speed. Furthermore, one can see that amplitude of local acceleration components (Local Acc) increases with the movement speed in flexion phase.

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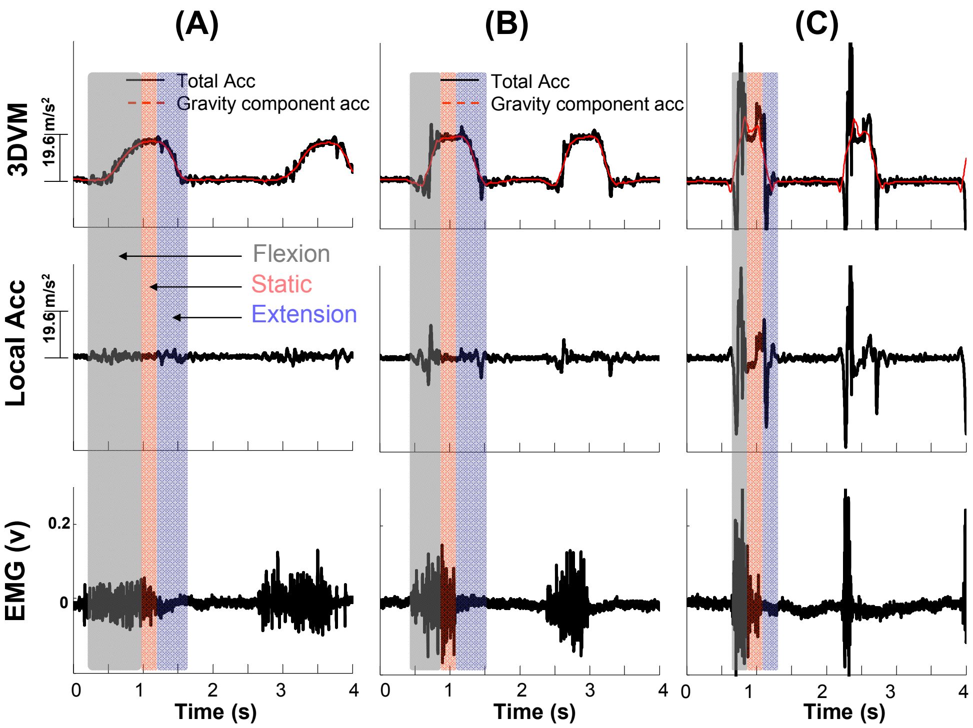

Fig. 3. 3DVM and an EMG evoked by ring finger movements at three different speeds. (A) Slow movements. Each movement consists of three phases: flexion, static and extension phases. 3DVM recording can be considered as the sum of Local Acc plus Gravity component acc (graph at top). The Gravity component acc is the low-frequency component of 3DVM. Thus, Local Acc is Total Acc minus Gravity component acc (middle graph). EMG related to slow movements is shown in bottom graph. (B) Medium movements. (C) Fast movements.

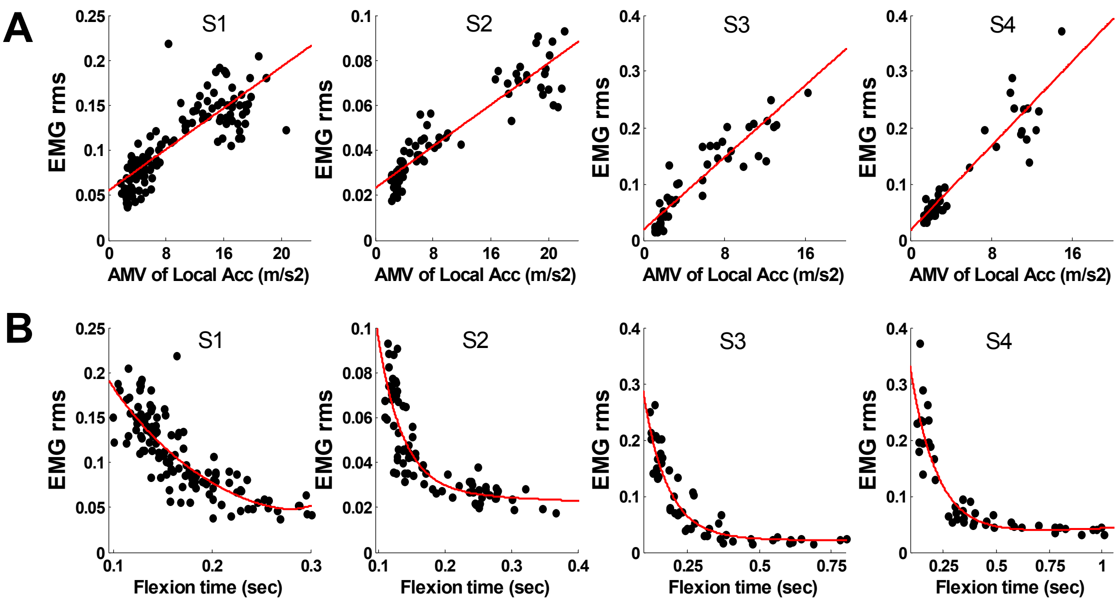

Fig. 4. Fig. 4 Correlation between EMG rms and kinematics features of flexion movements. A) Linear correlation between EMG rms and AMV of Local Acc for four experimental subjects. B) Exponential correlation between EMG rms and Flexion time for four experimental subjects (the same subjects than in A).

Fig. 4 shows the correlation between EMG rms vs kinematic features of flexion movements (AMV of local Acc and Flexion time). These results belonging to four experimental subjects, who executed ring finger flexion movements of right hand at different speeds. It is possible to note that kinematic features ranges of flexion movements differ significantly from one subject to another just like EMG amplitude. A linearly increasing of EMG rms with AMV of local Acc is observed (high values of coefficients of determination, R2) while an exponential decreasing of EMG rms with flexion time is observed. R2 were calculated in both cases, and these are shown in Table 1 and Table 2.

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Goodness of linear fits between EMG rms and AMV of local Acc of ring and middle finger flexion movements were R2 = 0.79 and 0.81 respectively (with recordings electrodes placed on MP of flexor muscles) (Table 1). The R2 coefficients were obtained from an average of 109 and 68 ring and middle finger movements, respectively. R2 values increased when recording electrodes were placed out of MP (0.84 and 0.89, respectively).

Table 2 shows the goodness of exponential fits between EMG rms and flexion time. Averages R2 were 0.79 and 0.84 for ring and middle fingers movements, respectively (with recording electrodes placed on MP). Then, averages R2 were 0.75 and 0.83 with recording electrodes placed out MP. In the latter case it is possible to note that there were no significant changes in R2 values with the recording electrodes position.

Classification errors of discriminant analysis are displayed in Fig. 5. The classes were determined from AMV of local Acc. Then, classification was realized with EMG rms values. Errors have an incremental behavior with number of pre-established classes. Likewise, in most cases, no significant differences were found in the classification of EMG signals with recording electrodes placed on MP and out MP of flexor muscles. A lower error is observed when the recording electrode is placed out MP (error of 33% on MP and 26% out MP) for classification into five classes of ring finger movements.

The confusion matrices for classifications of 2, 3, 4 and 5 classes are shown in Table 3. Here, each column of the matrix represents the instances in a predicted class, while each row represents the instances in an actual class. Thus, the confusion matrix provides detailed information of percentage accuracies obtained in the classification of each group, such as true positives, false negatives, false positives and true negatives [16]. Confusion matrix, referred to as RFFM - On MP (ring finger flexion movement with recording electrodes placed on MP, Table 3A - top left), shows a classification of 90.8% accuracy for Class 1, being misclassified as Class 2 a 5.9% (when these belonging to class 1). Similarly an accuracy of 94% for class 2, and inputs misclassified as Class 1 of 10.5% is observed. Similar results at the classification of ring finger flexion, with the recording electrodes placed out of MP, were observed (matrix lower left - Table 3A). Highest percentages at the classification of middle finger movements with the recording electrodes placed on MP and outside of MP were observed (matrices upper and lower right - Table 3A).

The classification accuracies of three classes (slow, medium and fast flexion movements) with EMG recording electrodes outside MP are higher than on MP (matrices upper and lower left of Table 3B). In all cases, the best classifications are performed for slow and fast movements. For these cases, higher percentages of classification than in two-class classification were obtained.

Overall, percentage accuracies for 4 and 5-classes classifications are higher with recording electrodes out MP (matrices of Tables 3C and 3D).

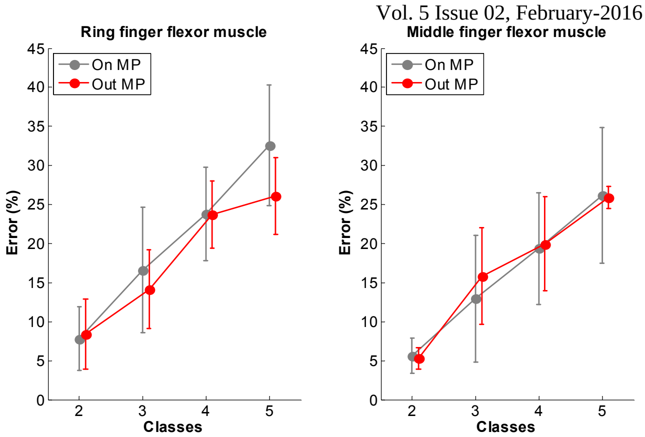

Fig. 5. Classification errors by using dynamic EMG features and discriminant analysis. The mean and standard deviation of sixteen subjects are shown.

IV. DISCUSSION

In this report we show the correlations between dynamic EMG and kinematic features of flexion movements. In flexion phase, EMG amplitude has a strong linear correlation with acceleration motion and an exponential correlation with flexion time. Similar results were observed with other EMG amplitude estimators, such as absolute mean value, difference absolute mean value, variance of EMG and waveform length (data not shown).

Currently, there is much controversy about monitoring of muscle electrical activity on a MP. It is known that if the recording electrodes are placed on the MP, the EMG signal appears as more jagged and with more sharp peaks in the time domain [17]. Here, we have observed that linear correlation, between EMG amplitude versus local acceleration, increases when the recording electrodes are placed outside of MP. This result coincides with comments made by Hermens et al. [17]. However, in practice, a correlation with R2 = 0.79 ± 0.09 (on the MP) could not be significantly different from R2 = 0.84 ± 0.05 (outside of MP). This result allows one to suspect that EMG electrodes placed on MP might not have significant influences on implementation of a myoelectric control based on dynamic EMG.

Many have been the attempts at optimize the processing techniques and acquisition protocols of EMG signals in order to minimize the recording electrodes number, to maximize the amount of gestures to recognize, and to control a larger number of degrees of freedom [1]. Often, efforts have been invested in classification of EMG signals evoked by static contractions [2][3], consequently resulting in temporal limitations on information transfer rates. A recent investigation showed changes in average classification rates due to number of muscle involved. These classification rates were below 90% in all cases. In such investigations, five static hand positions (including a neutral hand position) were classified by using EMG features from five EMG channels [2]. In the present study, percentage accuracies about 75% were obtained using a simple-channel (five classes) and an EMG amplitude estimator. Based on these results one could speculate that the classification could be significantly improved by including others EMG features. Furthermore, the combination of dynamic EMG from different muscle groups would increase the myoelectric control performance.

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TABLE I. GOODNESS OF LINEAR FITS BETWEEN EMG RMS AND AMV OF LOCAL ACC.

	EMG electrodes on MP						**EMG electrodes out MP**					
	Ring finger movements - Local acceleration			**Middle finger movements - Local acceleration**			**Ring finger movements - Local acceleration**			**Middle finger movements - Local acceleration**		
	sse	**R2**	**dfe**	**sse**	**R2**	**dfe**	**sse**	**R2**	**dfe**	**sse**	**R2**	**dfe**
S1	0.07	0.70	127	0.02	0.76	101	0.07	0.79	102	0.03	0.88	83
S2	0.00	0.86	78	0.02	0.85	89	0.02	0.85	75	0.01	0.85	77
S3	0.04	0.86	52	0.01	0.94	54	0.01	0.87	50	0.00	0.91	49
S4	0.02	0.65	58	0.01	0.83	62	0.02	0.81	54	0.05	0.89	57
S5	0.02	0.94	67	0.02	0.88	49	0.01	0.77	56	0.02	0.88	45
S6	0.04	0.85	103	0.01	0.69	81	0.01	0.91	96	0.04	0.87	80
S7	0.01	0.81	96	0.01	0.76	105	0.03	0.87	96	0.00	0.92	54
S8	0.04	0.79	97	0.02	0.78	56	0.06	0.83	80	0.02	0.94	64
S9	0.28	0.83	64	0.04	0.86	60	0.02	0.86	54	0.04	0.87	70
S10	0.06	0.88	149	0.04	0.65	45	0.04	0.87	43	0.03	0.85	61
S11	0.02	0.81	156	0.03	0.81	67	0.03	0.82	84	0.01	0.90	70
S12	0.09	0.73	137	0.03	0.74	68	0.01	0.86	56	0.03	0.80	61
S13	0.01	0.67	161	0.02	0.90	81	0.03	0.88	82	0.06	0.91	40
S14	0.41	0.80	129	0.01	0.84	55	0.01	0.94	44	0.03	0.89	50
S15	0.48	0.84	134	0.01	0.71	66	0.04	0.78	71	0.02	0.89	68
S16	0.73	0.61	138	0.02	0.96	59	0.03	0.80	23	0.03	0.92	46
μ	0.15	**0.79**	109.1	0.02	**0.81**	68.63	0.03	**0.84**	66.63	0.03	**0.89**	60.94
σ	0.21	**0.09**	36.91	0.01	**0.09**	17.92	0.02	**0.05**	22.48	0.02	**0.03**	13.10

TABLE II. GOODNESS OF EXPONENTIAL FITS BETWEEN EMG RMS AND FLEXION TIME.

	EMG electrodes on MP						**EMG electrodes out MP**					
	Ring finger movements - Flexion time			**Middle finger movements - Flexion time**			**Ring finger movements - Flexion time**			**Middle finger movements - Flexion time**		
	sse	**R^2**	**dfe**	**sse**	**R^2**	**dfe**	**sse**	**R^2**	**dfe**	**sse**	**R^2**	**dfe**
S1	0.07	0.69	125	0.04	0.65	99	0.13	0.62	100	0.04	0.71	81
S2	0.01	0.74	76	0.02	0.81	87	0.04	0.76	73	0.01	0.70	75
S3	0.04	0.87	50	0.00	0.98	52	0.00	0.96	48	0.05	0.83	41
S4	0.04	0.42	56	0.01	0.95	60	0.05	0.53	52	0.06	0.80	55
S5	0.03	0.91	65	0.02	0.73	47	0.01	0.74	54	0.08	0.83	43
S6	0.02	0.92	101	0.02	0.73	79	0.01	0.93	94	0.04	0.94	78
S7	0.01	0.80	94	0.00	0.81	103	0.02	0.89	94	0.03	0.82	52
S8	0.10	0.79	95	0.04	0.83	54	0.09	0.85	78	0.05	0.75	62
S9	0.22	0.86	62	0.03	0.90	58	0.03	0.76	52	0.03	0.89	68
S10	0.13	0.76	147	0.02	0.82	43	0.03	0.59	41	0.02	0.89	59
S11	0.02	0.82	154	0.03	0.93	65	0.05	0.74	82	0.07	0.83	68
S12	0.07	0.78	135	0.01	0.92	66	0.02	0.74	54	0.06	0.87	59
S13	0.01	0.68	159	0.01	0.59	79	0.02	0.82	80	0.01	0.76	38
S14	0.27	0.87	127	0.03	0.93	53	0.03	0.69	42	0.02	0.89	48
S15	0.24	0.92	132	0.02	0.95	64	0.03	0.63	69	0.06	0.83	66
S16	0.35	0.81	136	0.05	0.92	57	0.04	0.71	21	0.04	0.87	44
μ	0.10	**0.79**	107.13	0.02	**0.84**	66.63	0.04	**0.75**	64.63	0.04	**0.83**	58.56
σ	0.11	**0.12**	36.91	0.01	**0.12**	17.92	0.03	**0.12**	22.48	0.02	**0.07**	13.54

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TABLE III. CONFUSION MATRICES FOR CLASSIFICATION OF TWO, THREE, FOUR AND FIVE CLASSES. REFERENCES: RFFM: RING FINGER FLEXOR MOVEMENT, MFFM: MIDDLE FINGER FLEXOR MOVEMENT, MP: MOTOR POINT.

A

Actual class	RFFM - On MP: Predicted Class 1	2	MFFM - On MP: Predicted Class 1	2
1	90.8	5.9	94.4	5.4
2	10.5	94.1	6.1	94.6

Actual class	RFFM - Out MP: 1	2	RFFM - Out MP: 1	2
1	90.1	6.3	93.3	3.6
2	12.0	94.1	7.7	96.5

B

Actual class	RFFM - On MP: Predicted class 1	2	3	MFFM - On MP: Predicted class 1	2	3
1	85.6	15.1	0.0	96.1	10.7	0.0
2	15.2	74.7	9.6	3.1	77.6	9.7
3	0.3	11.8	91.2	0.0	16.1	90.3

Actual class	RFFM - Out MP: 1	2	3	MFFM - Out MP: 1	2	3
1	86.3	15.2	0.0	91.6	19.6	0.0
2	13.8	79.0	7.7	7.0	73.9	11.4
3	0.0	8.1	93.6	0.0	10.3	88.5

C

Actual class	RFFM - On MP: Predicted class 1	2	3	4	MFFM - On MP: Predicted class 1	2	3	4
1	80.9	15.8	0.9	0.0	85.7	11.2	0.0	0.0
2	22.6	67.5	15.1	0.8	15.8	77.3	11.1	0.0
3	1.3	17.7	72.7	18.5	2.0	12.3	72.0	8.3
4	0.0	0.8	12.3	84.6	0.0	0.0	23.0	90.9

Actual class	RFFM - Out MP: 1	2	3	4	MFFM - Out MP: 1	2	3	4
1	84.9	21.6	0.0	0.0	87.8	15.6	0.0	0.0
2	12.8	66.0	12.9	1.3	11.6	75.7	7.4	0.0
3	0.5	23.2	73.9	16.5	0.0	10.5	73.3	8.8
4	0.0	1.0	15.1	86.0	0.0	0.0	28.7	87.8

D

Actual class	RFFM - On MP: Predicted class 1	2	3	4	5	MFFM - On MP: Predicted class 1	2	3	4	5
1	76.6	18.0	1.8	0.2	0.0	78.9	15.6	0.0	0.0	0.0
2	27.6	55.5	23.0	3.1	0.0	33.7	68.1	22.7	0.0	0.0
3	1.5	24.8	62.4	11.2	1.3	0.0	14.3	63.5	39.6	0.9
4	0.4	2.3	21.1	66.0	28.1	0.0	2.4	19.9	70.6	7.4
5	0.0	0.0	3.3	19.7	77.8	0.0	0.0	1.8	10.3	92.7

Actual class	RFFM - Out MP: 1	2	3	4	5	MFFM - Out MP: 1	2	3	4	5
1	82.0	14.4	5.6	0.0	0.0	83.0	9.5	0.0	0.0	0.0
2	20.5	68.9	18.9	6.0	0.0	20.7	61.3	26.4	0.0	0.0
3	0.8	15.2	71.8	13.6	1.7	0.0	45.6	67.2	21.4	2.4
4	0.0	2.5	8.6	69.7	16.6	0.0	0.0	11.6	74.8	1.6
5	0.0	0.0	1.3	19.0	82.0	0.0	0.0	5.6	29.2	93.9

Classification errors achieved in this report are in some cases higher than those found by [2][3] and many others [18][19][20][21]. However, all these involve isometric contractions in their experimental protocols. Isometric contractions are still used as information source due to its higher signal amplitude, lower sensitivity to load variation and without motion artifact. A myoelectric control system based on isometric contractions is not intuitive, especially for subjects who have the limb with a diminished strength. Here, we have proposed the dynamic EMG as information source for myoelectric control. Importantly, the experimental subjects who participated in of this investigation had no any previous training, and finger movements were made in the most natural way possible. Thus, one might suspect that subjects with the ability to vary the kinetics features of finger flexion movements (with previous training) could reach high levels of control by setting multiple states.

Moreover, one could use the extensor muscles of the forearm (which is very feasible) and improve / increase the control performance. This possibility significantly would increase the degrees of freedom that could be controlled. Finally, the multiple possibilities that can provide a myoelectric control based on dynamic EMG still must be studied, and technical feasibility aspects must be taken into account. Even so, it has been demonstrated that a myoelectric control based on dynamic EMG may be feasible, repeatable and accurate.

V. CONCLUSIONS

In this study is observed that dynamic EMG amplitude presents a linear correlation with local acceleration of flexion movements, and an exponential correlation with flexion time. Furthermore, these correlation levels change slightly when the recording electrodes are placed on MP of flexor muscles. In view to myoelectric control implementations, we propose to classify kinematic states via dynamic EMG amplitude. The accuracy of classifications were 95%, 88%, 81% and 76% for two, three, four and five states respectively, and using a simple-channel recording and an EMG amplitude estimator.

The performance of a myoelectric control system is based on the optimization of three important aspects of controllability: the accuracy of movement selection, the intuitiveness of actuating control, and the response time of the control system. This study seeks to improve aspects of "intuitiveness" through dynamic EMG evoked by natural and intuitive movements.

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ETHICAL APPROVAL

All the subjects in this study signed a consent form of the experiments after being informed that the data acquired from them would be used for research purposes only. This study was approved by the Ethics Committee of National University of Tucumán.

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