Does Exerting Grasps Involve a Finite Set of Muscle Patterns? A Study of Intra- and Intersubject Variability of Forearm sEMG Signals in Seven Grasp Types

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***Abstract*— Surface Electromyography (sEMG) signals are widely used as input to control robotic devices, prosthetic limbs, exoskeletons, among other devices, and provide information about someone's intention to perform a particular movement. However, the redundant action of 32 muscles in the forearm and hand means that the neuromotor system can select different combinations of muscular activities to perform the same grasp, and these combinations could differ among subjects, and even among the trials done by the same subject. In this work, 22 healthy subjects performed seven representative grasp types (the most commonly used). sEMG signals were recorded from seven representative forearm spots identified in a previous work. Intra- and intersubject variability are presented by using four sEMG characteristics: muscle activity, zero crossing, enhanced wavelength and enhanced mean absolute value. The results confirmed the presence of both intra- and intersubject variability, which evidences the existence of distinct, yet limited, muscle patterns while executing the same grasp. This work underscores the importance of utilizing diverse combinations of sEMG features or characteristics of various natures, such as time-domain or frequency-domain, and it is the first work to observe the effect of considering different muscular patterns during grasps execution. This approach is applicable for fine-tuning the control settings of current sEMG devices.**

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***Index Terms*— Electromyography, sEMG features, forearm muscles, grasps, muscle coordination, subject variability.**

I. Introduction

SURFACE electromyography (sEMG) is widely used to control different devices. sEMG electrodes are placed on the skin directly over the muscles, having the general advantage of being non-invasive and easy to apply. In clinical practice, robotic devices, such as exoskeletons or gloves, can use sEMG signals to assist patients with certain movements [1], [2], [3], and amputees can use sEMG signals from residual muscles after amputation to actuate hand prostheses [4], [5], [6], [7], [8]. sEMG can also be employed in telerobotics and teleoperation for the remote control of robots/machines by a human operator from a distance [9], [10], [11], [12], [13], [14], [15], [16], [17]. These devices use sEMG signals as input to provide information about the person's intention to perform a particular movement or grasp [18]. The more accurate the information about a person's intention to perform a particular grasp or movement, the better the accuracy of the telerobotics or teleoperation, or the greater the usability of the prosthesis or assistive device [19]. A concerning issue is the intuitiveness of the control of such devices [20], which can be achieved if users do not have to change the way they do the tasks under normal conditions. However, there are several handicaps that hinder this intuitive control [21]: complexity of executing the hand grasp; redundancy of the neuromotor system; the existence of intra- and intersubject variability when doing the same task goal; the many sEMG characteristics that can be used to control different devices [22].

Hand grasp execution is composed mainly of two stages: reach-to-object and the grasp itself [23]. The force needed to close a hand around and grasp an object is determined by grasp stability (the ability to resist external forces), grasp security (resistance to slippery objects), grasp configuration [24], [25], subjects' previous experience [26], as well as by other factors such as fatigue, forearm orientation, time of the day, etc. All these factors impede simulating or mimicking the behavior of a real hand during grasping, hindering intuitive control of devices. To address this problem, the different factors that affect grasp execution should be studied and delimited.

First, grasp configuration, determined by the employed grasp type, has already been extensively studied. Several grasp taxonomies have been reported depending on their purpose [27], [28], such as the 9-type classification applied in [5] to determine the frequency of use of grasps in activities of daily living (ADL). Second, very little is known about the different ways of performing the same grasp based on a subject's previous experience because the solution to this problem is not straightforward. The hand's ability to grasp is possible thanks to the redundant action of 32 muscles in the forearm and hand [29]. This redundancy means that the neuromotor system can select different combinations of muscular activities to perform the same grasp and these combinations could differ among subjects, and even among the trials done by the same subject [30]. Inherent motor abundance means there are multiple solutions for the same task goal [31]. Consequently, the specific role of muscles for performing ADL is still poorly understood. Furthermore, identical movements may have slightly different representations in the muscle domain, which can cause incorrect decoding of user intent and negatively affect the robustness of sEMG devices. A recent work suggests that reducing motor variability could enhance the myolelectric control robustness of robotic devices [31].

In addition, given the large number of muscles that overlap in the forearm [29], it is practically impossible to isolate sEMG signals from one another. Recently, some studies used High Density EMG to control hand prostheses or robotic arms, demonstrating that few numbers of channels are needed for a good accuracy, although highly subject-specific [32]. A primary contributing factor to this outcome is the positioning of the grid or the EMG electrodes with no anatomical localization information of each one [33]. Furthermore, managing a large amount of information from multiple sensors is complex, and many of the obtained signals are highly correlated, as we confirmed in our previous work [34]. To overcome this problem, in that work [34] we identified seven forearm areas, by using five easily identifiable anatomical landmarks, with similar muscle activation patterns that can be used to characterize the muscle activity of the forearm. Thus, studying the inter- and intrasubject variability while performing different grasps could deepen our knowledge of how the forearm muscles from these spots are activated, which may help to improve current assistive prostheses and telerobotic devices.

Finally, there are several sEMG characteristics that can be used to control these devices. Selecting optimal sEMG characteristics, and the best combination between features and channels, are challenging problems for accomplishing satisfactory classification performance [35], [36], [37]. Improving this classification could, in turn, help to improve the identification of someone's intention when performing a movement or grasp [38]. In addition, an increment in sEMG characteristics does not only introduce redundancy into the function vector, but also increases complexity [39]. Muscular activity based on maximal voluntary contraction (MVC) is a popular parameter computed from sEMG signals [40]. Other parameters that are usually considered are characteristics of sEMG waveforms from time or frequency domains. Of the existing characteristics, zero crossing (ZC), wavelength (WL) and mean absolute value (MAV) are those most frequently used for their efficiency and simplicity [41]. Recent works have proposed employing a combination of enhanced parameters, such as enhanced WL (EWL), enhanced MAV (EMAV) and new ZC (NZC) for an efficient sEMG signals classification, and are valuable tools in sEMG pattern recognition [41], [42]. In particular, the results showed that combining EWL and EMAV with other features like WL and ZC obtain the best classification performance. However for a good classification rate, different combinations of four parameters or more are normally necessary, but the classification percentage never reaches 100% [43]. All this may be due to variability among subjects and even repetitions of the same subject and, therefore, to the existence of different patterns when performing the same activity or grasp [44].

Hence the aim of this work is twofold: 1) identifying sEMG characteristics of different natures (based on amplitude or frequency) that provide different information to improve the control of current assistive prostheses and telerobotic devices; 2) studying the existence of intra- and intersubject variability of the sEMG characteristics when doing the same task goal, and checking the existence of a limited number of muscle patterns. To do so, four sEMG characteristics (Muscular activity, NZC, EWL, EMAV) were analyzed, as recorded from seven representative forearm spots [34] while performing seven grasp types (most commonly used in ADL). These results will contribute to more effectively use sEMG characteristics to identify the person's intention to perform a particular movement, to more effectively mimic a task and to adjust the control of current sEMG-controlled devices.

II. Methodology

A. Subjects and Tasks

Twenty-two right-handed subjects (12 males, 10 females), averaging 35±9 years old, were selected based on criteria including gender balance in the data, ages between 20 and 65 years, and absence of reported upper limb pathologies. They gave their informed written consent before participating in this study, which was approved by the Ethics Committee of our University (reference number CD/31/2019). Subjects performed seven representative grasps of ADL (Figure 1) based on the grasp taxonomy used in Vergara et al. [45], while recording the muscular activity by means of sEMG: pad-to-pad pinch (PpP); cylindrical grasp (Cyl); lumbrical grasp (Lum); lateral pinch (LatP); oblique palmar grasp (Obl); inter-mediate power-precision grasp (IntPP).

B. sEMG Electrode Placement

A grid was drawn on the forearm using five easily identifiable anatomical landmarks (Figure 2b) while the subjects sat comfortably with their elbow resting on a table (arm-forearm angle of 90°) and the palm of their hand facing the subject. The grid defined 30 different spots that covered the

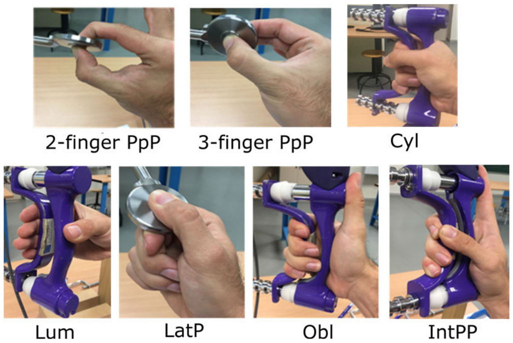

Fig. 1. Grasps performed: 1. 2-finger PpP; 2. 3-finger PpP; 3. Cyl; 4. Lum; 5. LatP; 6. Obl, 7. IntPP.

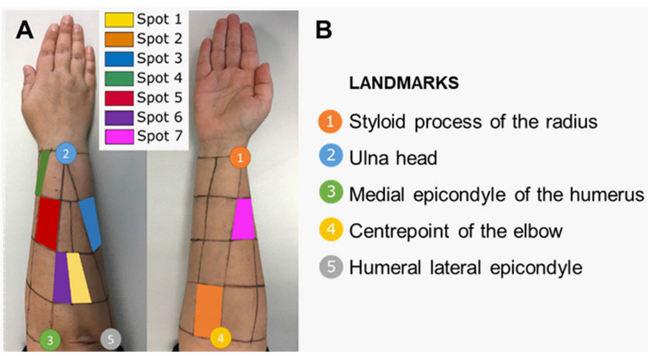

Fig. 2. (a) Grid and spot areas selected for the sEMG recordings. (b) Five anatomical landmarks used to draw the grid.

Fig. 3. Hand grip and pinch dynamometers, sEMG electrode (SX230) and 8-channel sEMG Biometrics Ltd. devices.

entire forearm surface (Figure 2a). Following the SENIAM recommendations [46], electrodes were placed longitudinally in the center of seven of these spots, based on the spot groups obtained in a previous work [34] (Figure 2a): (spot 1) wrist flexion and ulnar deviation; (spot 2) wrist flexion and radial deviation; (spot 3) digit flexion; (spot 4) thumb extension and abduction/adduction; (spot 5) finger extension; (spot 6) wrist extension and ulnar deviation; (spot 7) wrist extension and radial deviation. Before placing electrodes, hair was removed by shaving and skin was cleaned with alcohol.

C. Data Acquisition

Muscle activity was recorded by an 8-channel sEMG Biometrics Ltd. device (Figure 3) at a sampling frequency of 1000 Hz. Integral dry reusable bipolar sEMG Electrodes (SX230) were used, with a gain of 1000, a bandwidth between 20Hz-460Hz and noise below 5μV. Grasp effort was recorded with hand grip and pinch dynamometers (Biometrics Ltd., Figure 3). sEMG electrodes and dynamometer signals were synchronized with the software provided by Biometrics.

D. Experiment Description

For the normalization of the sEMG signals, seven MVC records were measured to each subject: flexion and extension of wrist, flexion and extension of fingers, pronation of forearm, ulnar deviation of wrist and elbow flexion. In the same comfortable posture, all the subjects were asked to exert maximum effort with the muscles of the forearm and hand.

After recording MVCs, the subjects were asked to perform seven grasps by considering the order that appears in Figure 1 and following the operator's instructions: with their arm aligned with the trunk and arm-forearm angle of 90°, the subject held a dynamometer to simulate the grasp to be analyzed (Fig. 1) without exerting force on it and then exerting maximum grasping effort (MGE) for 3 seconds while maintaining the posture. To prevent any unnecessary contraction of the muscles not required for the grasp, the subjects were asked to then perform 50% of their MGE: after resting for 3 minutes, subjects, with the help of a screen placed in front of them, were asked to progressively increase their effort for 3 seconds up to 50% of their MGE (50MGE), to maintain it for 3 seconds and to then gradually decrease it until they once again rested. Each 50MGE was repeated 3 times consecutively, with a 3-minute break between repetitions to avoid muscle fatigue. The subjects were able to practice each grasp as many times as necessary before recording and allowing a rest period before grasp recordings. The duration of each trial was controlled. Those tests that exceeded 10 seconds were discarded. Rest intervals, repetitions, and trial duration were arbitrarily decided, based on values previously used in studies conducted by the research group and other works in literature [47] and [48] that use an 1-2 minutes period of rest and 2-5 seconds recordings for maximal forces.

E. Data Analysis

All the statistical analyses were performed using the MATLAB® software.

1) Computed Parameters: First of all, sEMG records during 50MGE were filtered with a 4th-order bandpass filter (25-500 Hz), and waveforms characteristics (NZC, EWL, EMAV) were extracted from each record by considering the 3 seconds during which 50% maximum effort was exerted. The sEMG characteristics were formulated according to [41] and [42] (eq 1 to 3), where x is the sEMG signal (in mV), L is the length of the signal and x_0 is the part of the sEMG signal during which the subjects rested:

$$EWL = \sum_{i=2}^{L} \left|(x_i - x_{i-1})^p\right| \tag{1}$$

$$EMAV = \frac{1}{L}\sum_{i=1}^{L} \left|(x_i)^p\right| \tag{2}$$

$$p = \begin{cases} 0.75, & if\ i \geq 0.2L\ and\ i \leq 0.8L \\ 0.50, & otherwise \end{cases}$$

$$NZC = \begin{cases} 1, & if\ x_i > 0\ and\ x_{i+1} < 0 \\ or & x_i < 0\ and\ x_{i+1} > 0 \\ 0, & otherwise \end{cases} \tag{3}$$

After calculating the sEMG waveform characteristics for all the subjects, grasps, repetitions and spots, and to allow their comparison among the subjects, the characteristics of each spot (k) were normalized between 0 and 1 according to eq(4), where: $charac_k$ refers to every characteristic extracted from each subject (NZC, EWL or EMAV) for each spot; k, max_k and min_k depict the maximum and minimum values for spot k of that characteristic obtained throughout all the grasps for the subject.

$$charac_k^{normalized} = \frac{charac_k - min_k}{max_k - min_k} \tag{4}$$

In order to determine muscle activity, the sEMG records during 50MGE were rectified, filtered by a fourth-order low pass filter at 8 Hz and smoothed by Gaussian smoothing. They were later normalized with the maximal values obtained in any of the seven MVC records measured per subject. Finally for each record, the muscle activity during the 3 seconds allowed for 50% maximum effort was averaged for each spot (A50_EMG henceforth). The data is available at (https://doi.org/10.5281/zenodo.8064019).

2) Global Description: First, Shapiro-Wilk distribution normality test was performed for all the variables, which showed that the distribution deviated from the normal distribution, except for the maximum forces values. Therefore, for an overview of the results, descriptive statistics (median, and range –computed as percentile 95 minus percentile 5) of all the sEMG characteristic values per grasp and spot in the 50MGE records were computed, together with the statistics of the mean and standard deviation force exerted on the dynamometer for the 3 seconds of the MGE records. In addition, a Spearman's correlation analysis among all the sEMG characteristics (EWL, EMAV, NZC and A50_EMG) was performed for all the grasps together. As EWL, EMAV, and A50_EMG were highly correlated (>0.60), for the detailed analysis per grasp, only two characteristics were used: NZC and the one least correlated with it, A50_EMG.

3) Detailed Analysis Per Grasp: The values of the three repetitions of the same grasp for each spot and subject (66 trials per grasp) were used in a clustergram [49] to verify whether the subjects applied different strategies every time they perform the same grasp or not. Intra- and inter-subject errors per grasp (equations 4 and 5) were computed for NZC and A50_EMG, namely X. Let's ${}^{j,s}X_i$ be the i measurement for spot j and subject s, ${}^{j}X_s$ be the mean value of the 3 measurements for spot j and subject s, and ${}^{j}\bar{X}$ be the mean value across the 22 subjects for a given spot and grasp. Then:

- Intrasubject variability: The error due to intrasubject variability is ${}^{j,s}X_i - {}^{j}X_s$. The global RMSE considering all the spots, and subjects is:

$$IntrasubjectError = \sqrt{\frac{\sum_{j,s,i}\left({}^{j,s}X_i - {}^{j}X_s\right)^2}{22 \cdot 7 \cdot 3}} \tag{5}$$

- Intersubject variability: The error due to intersubject variability is ${}^{j}X_s - {}^{j}\bar{X}$.The global RMSE considering all the spots is:

TABLE I

MEAN ACROSS SUBJECTS (μ) AND STANDARD DEVIATION (SD) OF THE MAXIMUM EFFORT PERFORMED DURING EACH GRASP IN KGF

	Grasp						
	2-fingers PpP	3-fingers PpP	Cyl	Lum	LatP	Obl	IntPP
μ	4.9	6.9	32.0	8.8	6.8	22.9	10.9
SD	1.7	1.8	10.4	4.2	1.7	9.6	4.1
SD/ μ	0.35	0.26	0.32	0.47	0.25	0.42	0.38

TABLE II

MEDIAN ACROSS SUBJECTS (P50), RANGE (PERCENTILE 95TH – PERCENTILE 5TH) AND THEIR RATIO FOR A50_EMG PER SPOT AND GRASP. VALUES ARE PRESENTED AS % IN RELATION TO THE MVC

		Spot						
		1	2	3	4	5	6	7
2-fingers PpP	P50	0.10	0.05	0.06	0.15	0.16	0.20	0.16
	Range	0.16	0.14	0.13	0.42	0.24	0.28	0.18
3-fingers PpP	P50	0.11	0.07	0.09	0.13	0.20	0.26	0.18
	Range	0.19	0.14	0.15	0.38	0.42	0.32	0.27
Cyl	P50	0.31	0.15	0.25	0.26	0.22	0.24	0.33
	Range	0.35	0.18	0.34	0.39	0.33	0.20	0.33
Lum	P50	0.10	0.09	0.09	0.13	0.16	0.13	0.21
	Range	0.16	0.24	0.17	0.31	0.24	0.20	0.20
LatP	P50	0.07	0.05	0.05	0.12	0.15	0.11	0.20
	Range	0.18	0.09	0.10	0.21	0.32	0.18	0.33
Obl	P50	0.24	0.14	0.23	0.19	0.20	0.23	0.31
	Range	0.40	0.19	0.40	0.31	0.28	0.28	0.32
IntPP	P50	0.29	0.10	0.17	0.17	0.21	0.20	0.24
	Range	0.44	0.16	0.30	0.36	0.29	0.42	0.40

$$IntersubjectError = \sqrt{\frac{\sum_{j,s}\left({}^{j}X_s - {}^{j}\bar{X}\right)^2}{22 \cdot 7}} \tag{6}$$

The coordination of each muscle in relation to each grasp is discussed by considering the subjects' variability

III. RESULTS

Global Description: Table I shows the mean (μ) and standard deviation (SD) across the subjects of the maximum force (in kgf) performed during each grasp. The Cyl grasp presents the maximum force, while 2-fingers PpP presents the minimum force, as expected.

Tables II-V show the statistics across subjects for each sEMG characteristic, and per spot and performed grasp. For A50_EMG (Table II), the median values range from 0.05 (spot 2, Lum grasp and LatP) to 0.33 (spot 7, Cyl grasp) of their correspondent MVC. Range values were between 0.28 (spot 2, LatP grasp) and 0.44 (spot 1, IntPP grasp). Spot 2 presents the lowest median values while all the grasps were performed.

NZC (Table III) shows the median values from 0.09 (spot 2, LatP grasp) to 0.90 (spots 3 and 4, LatP), and range value between 0.45 (spot 3, Lum) and 0.99 (spot 6, IntPP grasp).

For EWL (Table IV), the median values ranged from 0.03 (spot 1, LatP) to 0.88 (spot 2, Cyl grasp), and range values between 0.27 (spot 2, LatP grasp) to 0.99 (spots 4 and 6, IntPP).

Finally, EMAV (Table V) had median values from 0.03 (spot 1 and 3, LatP) to 0.88 (spot 3, Cyl grasp), and range values between 0.24 (spot 2, LatP) and 1.00 (spot 7, IntPP).

Table VI shows Spearman's correlation among all the sEMG characteristics. NZC shows the lowest correlation with the other sEMG characteristics ($\leq$ 0.15), while A50_EMG,

TABLE III
MEDIAN ACROSS SUBJECTS (P50), RANGE (PERCENTILE 95TH – PERCENTILE 5TH) AND THEIR RATIO FOR NZC PER SPOT AND GRASP

		Spot						
		1	2	3	4	5	6	7
2-fingers PpP	P50	0.73	0.79	0.72	0.54	0.56	0.55	0.74
	Range	0.57	0.65	0.76	0.84	0.83	0.76	0.64
3-fingers PpP	P50	0.75	0.63	0.35	0.41	0.50	0.63	0.55
	Range	0.49	0.85	0.61	0.58	0.93	0.82	0.74
Cyl	P50	0.29	0.09	0.13	0.21	0.25	0.58	0.26
	Range	0.73	0.51	0.90	0.62	0.67	0.73	0.52
Lum	P50	0.50	0.28	0.16	0.32	0.45	0.63	0.30
	Range	0.91	0.65	0.45	0.83	0.90	0.91	0.68
LatP	P50	0.48	0.64	0.90	0.90	0.55	0.24	0.89
	Range	0.71	0.85	0.60	0.51	0.95	0.87	0.65
Obl	P50	0.35	0.21	0.23	0.24	0.32	0.61	0.32
	Range	0.70	0.62	0.80	0.65	0.88	0.71	0.70
IntPP	P50	0.14	0.35	0.27	0.32	0.49	0.40	0.33
	Range	0.64	0.54	0.51	0.89	0.92	0.99	0.76

TABLE IV
MEDIAN ACROSS SUBJECTS (P50), RANGE (PERCENTILE 95TH – PERCENTILE 5TH) AND THEIR RATIO FOR EWL PER SPOT AND GRASP

		Spot						
		1	2	3	4	5	6	7
2-fingers PpP	P50	0.17	0.17	0.14	0.37	0.28	0.49	0.09
	Range	0.62	0.74	0.49	0.98	0.82	0.79	0.51
3-fingers PpP	P50	0.26	0.37	0.27	0.20	0.45	0.76	0.28
	Range	0.69	0.72	0.48	0.96	0.93	0.77	0.65
Cyl	P50	0.78	0.88	0.87	0.70	0.51	0.69	0.77
	Range	0.51	0.47	0.32	0.73	0.96	0.74	0.63
Lum	P50	0.19	0.32	0.21	0.22	0.14	0.23	0.28
	Range	0.57	0.51	0.46	0.70	0.80	0.67	0.73
LatP	P50	0.03	0.05	0.04	0.25	0.22	0.10	0.39
	Range	0.40	0.27	0.36	0.78	0.87	0.48	0.98
Obl	P50	0.63	0.71	0.66	0.42	0.40	0.58	0.62
	Range	0.91	0.78	0.68	0.87	0.78	0.73	0.80
IntPP	P50	0.71	0.46	0.54	0.44	0.52	0.50	0.38
	Range	0.83	0.60	0.66	0.99	0.93	0.99	0.97

TABLE V
MEDIAN ACROSS SUBJECTS (P50), RANGE (PERCENTILE 95TH – PERCENTILE 5TH) AND THEIR RATIO FOR EMAV PER SPOT AND GRASP

		Spot						
		1	2	3	4	5	6	7
2-fingers PpP	P50	0.14	0.10	0.12	0.35	0.24	0.46	0.08
	Range	0.50	0.49	0.39	1.00	0.74	0.75	0.42
3-fingers PpP	P50	0.24	0.31	0.28	0.21	0.47	0.75	0.30
	Range	0.59	0.61	0.56	0.94	0.96	0.81	0.61
Cyl	P50	0.78	0.86	0.88	0.80	0.56	0.68	0.80
	Range	0.50	0.36	0.26	0.65	0.95	0.83	0.54
Lum	P50	0.21	0.29	0.29	0.24	0.19	0.21	0.32
	Range	0.44	0.48	0.46	0.81	0.80	0.61	0.75
LatP	P50	0.03	0.04	0.03	0.17	0.24	0.11	0.28
	Range	0.30	0.24	0.35	0.53	0.85	0.46	0.86
Obl	P50	0.61	0.73	0.72	0.49	0.47	0.57	0.64
	Range	0.89	0.76	0.68	0.84	0.79	0.74	0.81
IntPP	P50	0.72	0.43	0.59	0.49	0.52	0.50	0.42
	Range	0.80	0.69	0.71	0.98	0.92	0.98	1.00

EMAV and EWL were highly correlated (> 0.64). The lowest correlation was observed between NZC and A50_EMG. They were the only characteristics considered in the next analyses.

Intra- and Intersubject Variability: Table VII shows the intra- and intersubject variability of A50_EMG and NZC for each grasp. Regarding intrasubject variability, A50_EMG presented low intrasubject variability (1.5-3.1%), with Cyl showing the highest value and LatP the lowest one. NZC obtained higher intrasubject variability values than A50_EMG (10-13%), which quadrupled variability. Lum was the grasp with the widest variability, while 3-fingers PpP had the narrowest.

Concerning intersubject variability, A50_EMG had values that tripled intrasubject variability (between 6-10%). IntPP obtained the highest value, while Lum and LatP had the lowest ones. NZC also obtained higher intersubject than intrasubject variability values (18-22%), but they were more similar among grasps in this case. IntPP and LatP had the highest values, while Cyl and Obl had the lowest ones.

Detailed Analysis Per Grasp:

TABLE VI
SPEARMAN'S CORRELATION AMONG ALL THE SEMG CHARACTERISTICS

	EWL	EMAV	A50_EMG
NZC	0.18*	0.20*	0.15*
EWL		0.97*	0.64*
EMAV			0.67*

*The correlation is significant at the 0.05 level

TABLE VII
INTRA- AND INTERSUBJECT ERRORS (IN %) COMPUTED FROM THE RMSE

	Intrasubject		Intersubject	
	A50_EMG	NZC	A50_EMG	NZC
2-fingers PpP	2.6	11.1	7.8	19.6
3-fingers PpP	2.1	10.0	9.4	19.7
Cyl	3.1	10.6	8.6	18.6
Lum	2.1	13	6.1	20.3
LatP	1.5	12.5	6.0	21.0
Obl	2.4	12.2	9.0	18.9
IntPP	2.7	12.2	10.0	21.8

A. 2-Fingers Pad-to-Pad Pinch

Figure 4 (A, left) shows the clustergram obtained for each spot area and trial while performing 2-fingers PpP and according to the A50_EMG values. In general, 2-fingers PpP presented less muscle contribution (A50_EMG < 40%). From the column (spots) clustering, three main groups appear: (1) coordination of spots 1 and 6; (2) coordination of spots 2, 3, 4 and 5; (3) spot 7. From the row (trials) clustering, three main groups of trials with different muscle patterns are observed: three subjects' trials were distributed among the three groups, while all the trials of seven subjects were in group 1, with four subjects in group 2 and eight subjects in group 3.

Figure 4 (A, right) shows the clustergram based on NZC values. In this case, 2-fingers PpP had medium values (above 40%). From the column (spots) clustering, three main groups appear: (1) coordination of spots 2 and 3; (2) coordination of spots 4, and 7; (3) spots 1, 5 and 6. From the row (trials) clustering, three main groups of trials with different muscle patterns appear: seven subjects' trials were distributed among the three groups, while all the trials of one subject were in group 1, with eight subjects in group 2 and five subjects in group 3.

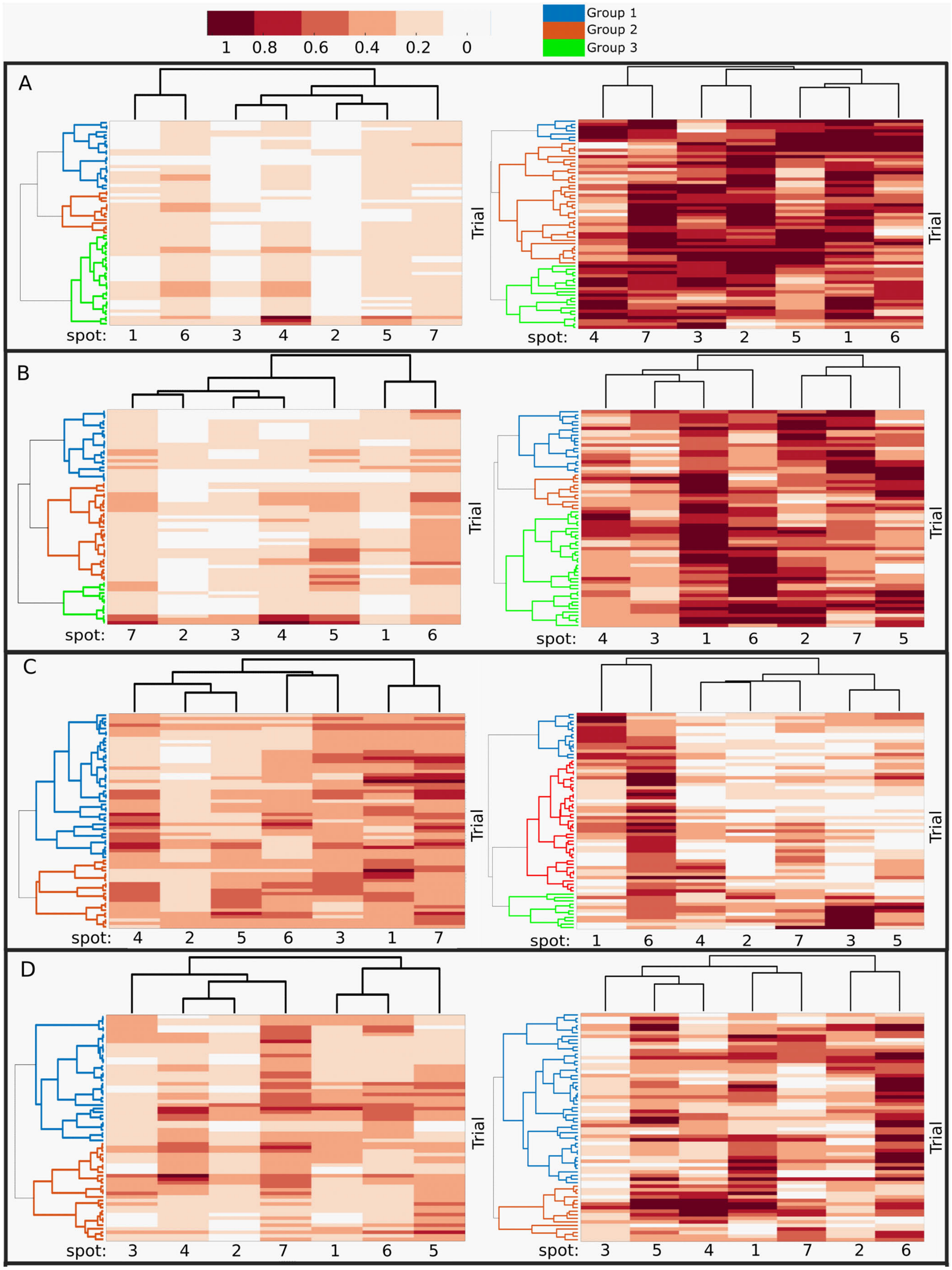

Fig. 4. Clustergrams obtained of each spot area and trial while performing the grasps: (A) 2-finger PpP, (B) 3-fingers PpP, (C) Cyl grasp, (D). Cells are colored according to their A50_EMG value (left) and NZC value (right). Rows represent trials and their clustering depicts group of trials. Columns depict spots and their clustering indicates groups of spots.

B. 3-Fingers Pad-to-Pad Pinch

3-fingers PpP (Figure 4, B left) offered little muscle contribution (A50_EMG values), but it was greater than 2-fingers PpP. Groups of spots: (1) coordination of spots 1 and 6; (2) spots 2, 3, 4 and 7; (3) spot 5. Three main groups of trials were observed: two subjects' trials were distributed among the three groups, while all the trials of seven subjects were in group 1, with nine subjects in group 2 and four subjects in group 3.

Regarding NZC (Figure 4, B right), 3-fingers PpP obtained lower values than 2-fingers PpP. Groups of spots:

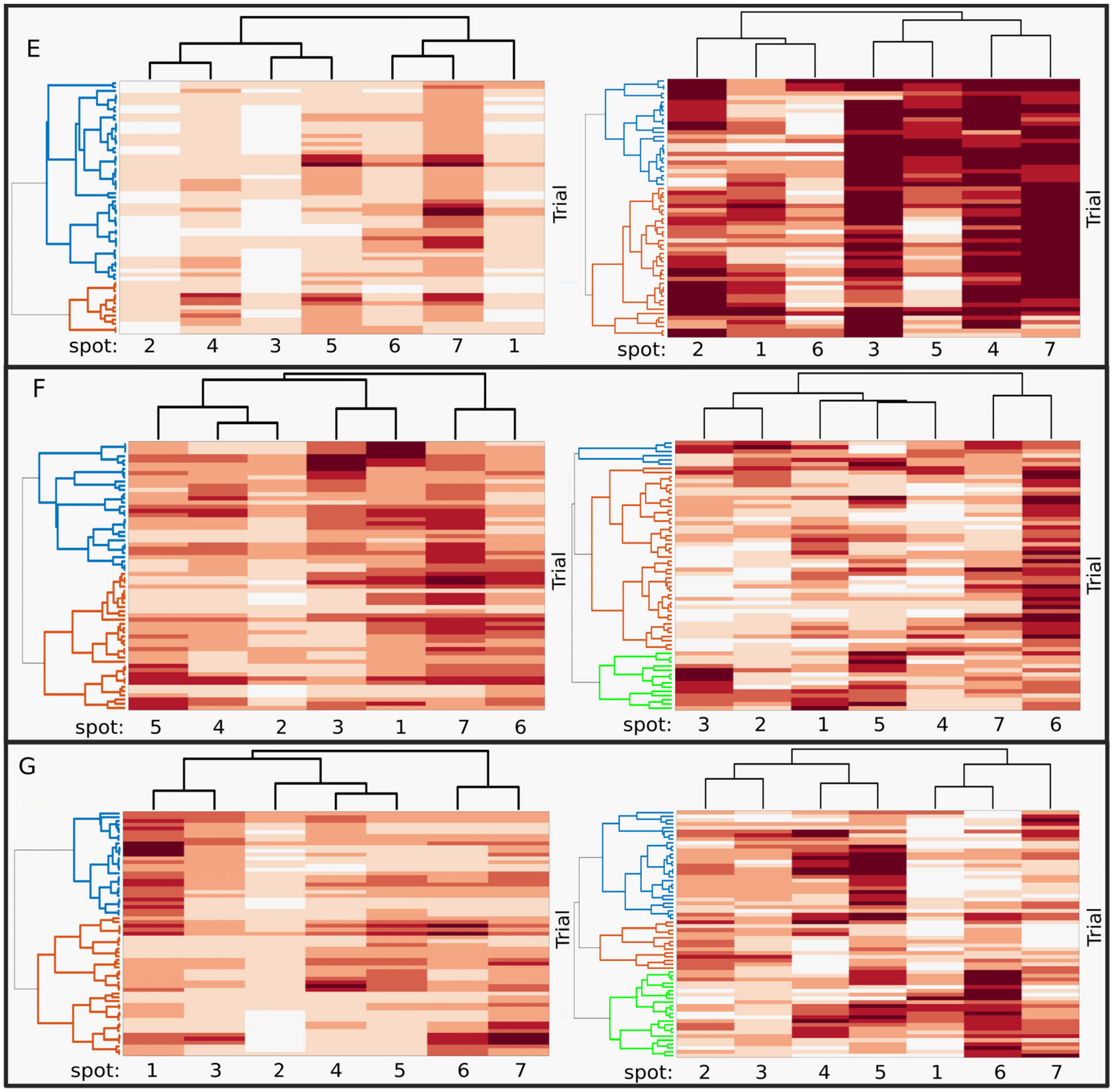

Fig. 5. Clustergrams obtained of each spot area and trial while performing the grasps: (E) LatP, (F) Obl grasp and (G) IntPP grasp. Cells are colored according to their A50_EMG value (left) and NZC value (right). Rows represent trials and their clustering depicts group of trials. Columns depict spots and their clustering indicates groups of spots.

(1) coordination of spots 1, 3, 4, and 6; (2) coordination of spots 2, 5 and 7. Three main groups of trials are observed: seven subjects' trials were distributed among the three groups, while all the trials of four subjects were in group 1, with three subjects in group 2 and seven subjects in group 3.

C. Cylindrical Grasp

The Cyl grasp (Figure 4, C left) offered medium-high muscle contribution from all the spots (above 40%) according to the A50_EMG values. Groups of spots: (1) coordination of spots 1 and 7; (2) spots 2, 4 and 5; (3) spots 3 and 6. Two main groups of trials are observed: only one subject's trials were distributed among the groups, while all the trials of seven subjects were in group 1, with 14 subjects in group 2.

On NZC (Figure 4, C right), the Cyl grasp generally obtained low NZC values (below 40%), except for spot 6 with values over 60%. Groups of spots: (1) coordination of spots 1 and 6; (2) spots 2, 4 and 7; (3) spots 3 and 5. Three main groups of trials: six subjects whose trials were distributed among the groups, while all the trials three subjects were in group 1, with 10 subjects in group 2 and three subjects in group 3.

D. Lumbrical Grasp

Lum grasp (Figure 4, D left) had low A50_EMG values from all the spots (< 40%). Groups of spots: (1) coordination of spots 1 and 6; (2) spots 2, 3, 4 and 7; (3) spot 5. Two main groups of trials are observed: only one subject's trials were distributed among the groups, with all the trials of 12 subjects in group 1 and nine subjects in group 2.

Regarding NZC (Figure 4, D right), the Lum grasp obtained low NZC values (< 40%) except for spots 1, 5 and 6, whose values were generally > 60%. Groups of spots: (1) coordination of spots 2 and 6; (2) spots 1 and 7; (3) spots 3, 4 and 5. Two main groups of trials are observed: three subjects' trials were distributed among the groups, with all the trials of 14 subjects in group 1 and five subjects in group 2.

E. Lateral Pinch

LatP (Figure 5, E left) presented scarce muscle contribution from all the spots (A50_EMG < 40%). The contribution of spot 7 was the greatest. Groups of spots: (1) coordination of spots 1, 6 and 7; (2) spots 3 and 5; (3) spots 2 and 4. Two main groups of trials are observed: two subjects' trials were distributed among the group, with all the trials of 16 subjects in group 1 and four subjects in group 2.

On NZC (Figure 5, E right), LatP generally obtained high NZC values (above 80%), especially in spots 3, 4 and 7. Groups of spots: (1) coordination of spots 1, 2 and 6; (2) spots 3 and 5; (3) spots 4 and 7. Two main groups of trials are observed: six subjects' trials were distributed among the groups, with all the trials of six subjects in group 1 and 10 subjects in group 2.

F. Oblique Palmar Grasp

The muscle contribution of the Obl grasp (Figure 5, F left) was medium from all spots (A50_EMG between 40-50%). Spots 1 and 7 contributed the most. Groups of spots: (1) coordination of spots 6 and 7; (2) spots 1 and 3; (3) spots 2, 4 and 5. Two main groups of trials are observed: only one subject's trials were distributed among the groups, with all the trials of 11 subjects in group 1 and 10 subjects in group 2.

On NZC (Figure 5, F right), the Obl grasp generally had medium NZC values (> 40%). Groups of spots: (1) coordination of spots 2 and 3; (2) spots 1, 4 and 5; (3) spots 6 and 7. Three main groups of trials are observed: four subjects' trials were distributed among the three groups, with all the trials of subjects in group 1, 12 subjects in group 2 and four subjects in group 3.

G. Intermediate Power-Precision Grasp

The muscle contribution of the IntPP grasp (Figure 5, G left) from all the spots was medium (A50_EMG between 40-50%). Spot 1 and 7 contributed the most. From the column clustering, three main clusters of spots are observed: (1) coordination of spots 6 and 7; (2) spots 1 and 3; (3) spots 2, 4 and 5. From the row clustering, two main groups of trials with different behaviors are observed: two subjects' trials were distributed among the groups, with all the trials of eight subjects in group 1 and 12 subjects in group 2.

For NZC (Figure 5, G right), the IntPP grasp generally obtained medium and low NZC values (> 20-40%) and some spots had high values (spots 5 and 6), but not for all the trials. Groups of spots: (1) coordination of spots 2 and 3; (2) spots 4 and 5; (3) spots 1, 6 and 7. Three main groups of trials are observed: six subjects' trials were distributed among the groups, with all the trials of six subjects in group 1, two subjects in group 2 and six subjects in group 3.

IV. Discussion

In this work, forearm sEMG signals during grasp performance were studied by analyzing four sEMG parameters (EMAV, EWL, A50_EMG and NZC) of seven representative forearm areas to bridge two gaps that may help to improve current assistive, prostheses and telerobotic devices: 1) sEMG characteristics of different natures (based on amplitude or frequency) can provide different and useful information; 2) the existence of intra- and intersubject variability of sEMG characteristics when performing the same task goal, which can confirm the existence of a limited number of muscle patterns.

A. Relation Among sEMG Characteristics

For the first gap, EMAV and EWL are highly correlated (0.96) and they also correlate highly with A50_EMG (> 0.75). On the contrary, NZC is poorly correlated (<0.3) with the other sEMG parameters. Therefore, EMAV, EWL and A50_EMG seem to provide the same information in terms of muscle contribution patterns, while NZC may provide different relevant information. These results are consistent with previous works [38], [39], where the highest rate classification scores tended to combine amplitude-based sEMG characteristics (i.e. EMAV or EWL) with frequency-based sEMG characteristics (i.e. NZC or slope change sign). The results found herein can provide insights into one of the reasons why the combination of sEMG characteristics of different natures leads to greater classification success, which is a novel contribution that can bring about an improvement in current control systems.

B. Inter- and Intrasubject Variability

Regarding the second goal, A50_EMG and NZC presented different levels of inter- and intrasubject variability.

Muscle activity (A50_EMG) presented very low intrasubject variability compared to intersubject variability. This means that, in general, the subjects performed each grasp in the same way during the different attempts. Intersubject variability could confirm the existence of different muscular patterns. On the contrary, the inter- and intrasubject variability of NZC, independently of the performed grasp, were of the same order of magnitude.

Then, the differences in NZC values from the various repetitions by the same subject could be as large as those from distinct subjects. However, all the trials of a vast number of subjects are in the same cluster group. These facts bring to light the possibility of using these sEMG characteristics to classify sEMG signals to provide sufficient information about a person's intention to perform a particular movement.

The wider intersubject variability suggests the existence of different strategies, but limited in number, to perform the same grasp based on subjects' specificity (age, profession, specific skills, anatomical structure, etc.). This fact means that if we could quantify the different strategies observed per grasp, these characteristics could be used to better discriminate the distinct grasps. The results are consistent with a recent study [44] where muscular and kinematic patterns during the execution of different grasps were examined. It was found that with 7 kinematic-muscular synergies, a reasonable reconstruction of

EMGs and kinematics for all subjects was achieved, albeit with a long inter-individual variability: only 2 synergies were shared by more than half of the participants. This implies that, for a good classification rate, the distinct muscular patterns according to each subject's previous experience should be considered. It confirms the need to study in-depth what these patterns are in order to adjust the control of these sEMG-controlled devices. In addition, a combination of several parameters is needed to provide us with different information, such as NZC and muscle activity. Hence, these findings could be relevant to enhancing the control of prosthetic limbs, exoskeletons, rehabilitation devices, and telerobotics. This improvement could involve customizing the controls of these devices by utilizing a finite number of patterns, for instance or using other parameters for the control, not only the level of activation.

C. Muscle Coordination

The results show a different synergistic functioning of muscles, some of which are shared among grasps and depend on the sEMG characteristic. For muscle activity, some patterns are observed during all the grasps: 1) coordination between wrist flexors and extensors, which could stabilize wrists while performing precision grasps during which the thumb points upward; 2) coordination of thumb muscles with FCR for contributing and assisting thumb abduction movements. Other patterns are grasp-specific: while performing precision grasps, finger flexors are more coordinated with finger extensor. During power grasps, finger flexors are more coordinated with wrist muscles. For NZC, there is no clear shared pattern among grasps. However, wrist flexors and extensors share different patterns with one another depending on the grasp being performed. Likewise, finger flexors and extensors (including thumb) seem to also share different patterns depending on the grasp being performed.

The results suggest that focusing on the coordination between spots can provide us with an idea of the grasp to be performed more than the specific value of each spot. In other words, by controlling the synergistic functioning of the forearm muscles, it would be possible to determine the type of grasp that a user is performing and, therefore, to more effectively mimic this real behavior. Therefore, the various patterns identified in this study could validate the importance of considering them to enhance the control of current sEMG devices.

The work has certain limitations. Firstly, the results are drawn from healthy subjects, while most of these technologies are intended for individuals with medical conditions or injuries. Secondly, our focus on static postures, where the upper arm remains fixed in a specific orientation, might impact certain wrist muscles. Thus, further studies would be essential to investigate similar behaviors observed in this study under dynamic conditions and in patients.

V. Conclusion

We analyzed the contribution of seven forearm spots while performing some grasp types representative of ADL. In muscle activity terms, we observed how the different subjects applied distinct strategies to execute the same grasp. These strategies appear to be influenced by the individual's experience, which highlights mainly the presence of intersubject variability. However, other sEMG characteristics, such as NZC (New Zero Crossing), did not exhibit distinct strategies based on the subjects. Table VIII summarizes the spots more robust against this variability, meaning those spots that are highly activated but also activated similarly among subjects. These results highlight the need to use different combinations of sEMG features or characteristics of distinct natures (time or frequency), and not only those based on signal amplitude to discriminate among grasps due to intra- and intersubject variability, among other factors.

TABLE VIII
Summarization of the Results. The Spot/Spots More Robust Against Intra and Inter-Subject Variability (Selected as the Spots With the Highest Ratio p50/Range)

	A50_EMG	NZC
2-fingers PpP	7	1, 2, 7
3-fingers PpP	6	1
Cyl	6,7	6
Lum	7	6
LatP	6,7	3,4,7
Obl	6,7	6
IntPP	5	2

In addition, our findings support the hypothesis of a limited number of muscular patterns that could improve current sEMG devices. Further studies should aim to investigate and describe these patterns in detail by determining whether sEMG characteristics can effectively differentiate several grasp types.

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