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RESEARCH ARTICLE

Functional Synergies Applied to a Publicly Available Dataset of Hand Grasps Show Evidence of Kinematic-Muscular Synergistic Control

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This work involved human subjects or animals in its research. Approval of all ethical and experimental procedures and protocols was granted by the Ethics Commission of the Canton Valais (Switzerland), and performed in line with the Declaration of Helsinki.

ABSTRACT Hand grasp patterns are the results of complex kinematic-muscular coordination and synergistic control might help reducing the dimensionality of the motor control space at the hand level. Kinematic-muscular synergies combining muscle and kinematic hand grasp data have not been investigated before. This paper provides a novel analysis of kinematic-muscular synergies from kinematic and EMG data of 28 subjects, performing 20 hand grasps. Kinematic-muscular synergies were extracted from combined kinematic and muscle data with the recently introduced Mixed Matrix Factorization (MMF) algorithm. Seven synergies were first extracted from each subject, accounting on average for >75% of the data variation. Then, cluster analysis was used to group synergies across subjects, with the aim of summarizing the coordination patterns available for hand grasps, and investigating relevant aspects of synergies such as inter-individual variability. Twenty-one clusters were needed to group the entire set of synergies extracted from 28 subjects, revealing high inter-individual variability. The number of kinematic-muscular motor modules required to perform the motor tasks is a reduced subset of the degrees of freedom to be coordinated; however, probably due to the variety of tasks, poor constraints and the large number of variables considered, we noted poor inter-individual repeatability. The results generalize the description of muscle and hand kinematics, better clarifying several limits of the field and fostering the development of applications in rehabilitation and assistive robotics.

INDEX TERMS Cluster analysis, cyberglove, hand synergies, kinematic-muscular synergies, kinematics, matrix factorization, myoelectric prostheses, rehabilitation.

I. INTRODUCTION

The use of the hand to grasp and manipulate objects involves the coordination of a multitude of degrees of freedom (DoF) and the exploitation of redundancy and motor abundance [1] both at the kinematic and muscle level. When considering hand grasps, the motion of the hand can be investigated in the kinematic domain, monitoring joint movement, or in the muscle domain, especially for the analysis of the activation patterns at the forearm level. Muscle assessments are often used to evaluate pathological conditions, such as for amputees [2], or to exploit the potential of myoelectric control. While

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finger and hand DoFs are effectively investigated at the kinematic level (for example with sensorized gloves), forearm coordination is usually monitored through muscle activity, for example wearing EMG armbands. Depending on the desired aim, one of the two domains is chosen. Many research studies have focused on the commonly accepted concept that motor modules are the basis of motor control at the neural level [3] and that they may simplify the problem of motor control, reducing the control space required for a variety of motor tasks.

Hand kinematic synergies were applied widely in research, for instance to study human grasps [4], [5], [6] and hand prosthesis control [7]. Many methods allow to achieve dimensionality reduction; the most frequently used method is the Principal Component Analysis (PCA) [4]. Santello et al. [6] recorded 15 joint angles in five subjects while performing of imagined objects grasps, finding that two principal components (PCs, i.e. postural synergies) accounted for more than 80% of the overall variation, while the remaining variation was due to the fine tuning of additional motor control modules. Liu et al. [8] studied postural synergies in ten subjects that were asked to grasp six objects in different relative positions between the human hand and objects, concluding that a reduced number of modules are needed to reproduce the original movement and that synergies are task-dependent. Mason et al. [9] studied five types of reach-to-grasp movements in five subjects, showing that one synergy accounted for more than 97% of the total variance. Jarrassé et al. [10] investigated 15 DoFs in ten subjects grasping nine objects. Four postural synergies were found: the first and second PCs accounted for approximately 90% of the data variation, although pattern refinement can be achieved by adding further PCs. In Patel et al. [11], ten subjects performed twenty-five grasps. While the first few synergies accounted for more than half of the total variation, the remaining variation was distributed across many synergies, indicating that a large set of motor modules is needed to reconstruct the original kinematics. In Thakur et al. [12], eight subjects were asked to perform an unconstrained haptic exploration of fifty objects, in a naturalistic setup. The objects were only explored, few grasping movements were made and the reach and release phases were not considered. Seven synergies encompassed over 90% of the total variance in the hand-grasps and motions, but the results showed that the synergies differ substantially across subjects and tasks. In a recent study, involving a large variety of grasps and number of subjects, Jarque-Bou et al. [4] showed that the number of synergies underlying movement increases when considering a large number of subjects and a large variety of movements involving also the reach and release phases, probably as a consequence of inter-individual variability and multitude of conditions related to hand grasps. This study suggests that the reduction of dimensionality might take place at a lower extent than what was hypothesized before, with an increased number of motor synergies found with respect to previous work.

Despite the kinematic patterns being exploited more often for hand analysis, some studies have investigated the dimensionality reduction problem from the point of view of muscle synergies. The muscle synergy approach is usually based on decomposition algorithms that identify groups of co-activating muscles (synergies) that are coordinated by time-varying activation commands [3]. Another approach is the extraction of time-varying synergies, that are scaled in amplitude and shifted in time [13]. The extracted patterns may be influenced by several factors regarding sEMG, including fatigue, sweating, changes in electrode or arm positioning [14], clinical parameters of the subjects e.g., level of the amputation, phantom limb sensation intensity [15], the BMI [2], other anatomical characteristics of the subjects or training when using myoelectric prostheses [16], as well as signal pre-processing. Few studies to date have addressed these effects and the impact on the resulting muscle synergies. Considering two arrays of sEMG-electrodes, positioned distally and proximally on the forearm, Castellini and Smagt [17] found that the combination of 3 muscle synergies could account for a set of 5 hand grasps, on both sets of the electrodes. The ''main synergy'' represents a ''global, indistinct'' co-activation pattern, while the other two synergies account for dorsal and ventral patterns, respectively. Overduin et al. [18] used the time-varying muscle synergy model [19] to analyze a set of 25 grasps of objects of different shape and size in two monkeys and found that three synergies could explain 71% of the total sEMG variation for proximal muscles, 83% for the wrist and extrinsic hand muscles and 81% of intrinsic muscles. The first of the three synergies was linked to the muscles involved in the reach phase including proximal muscles and distal flexors, the second was characterized by bimodal activation of distal muscles and the third, more related to the transport of the object, featured proximal muscles and distal extensors.

While these studies highlight that hand grasps have been investigated in the framework of muscle and kinematic synergies, a key challenge of using muscle synergies to analyze hand grasps remains unaddressed. This is represented by the impossibility to track all the muscles involved in the grasps, as EMG signals from hand muscles are difficult to acquire due to their small size and anatomical location, which can easily produce cross-talk, and due to encumbrance of probes/wires on the palm of the hand that can prevent a physiological grasp execution. Nevertheless, the reduction of the dimensionality is still a crucial process for the comprehension of the patterns underlying hand use and grasps. On the contrary, the main limitation in using kinematic analysis is that it does not provide a comprehensive overview of muscle activations generating movement, and thus it limits the description to movement output (limiting applications related to electrical stimulation, prosthesis, and rehabilitation). Thus, as muscle and kinematic analysis are interlinked complementary approaches, combining them could allow to shed light on the nature of hand movement control. Despite being clear that different body segments are better analyzed in a specific domain, and despite the potential of the combination of the two approaches, only a few studies have tried to capture the muscle and kinematic relationship in hand grasps in the framework of kinematic and muscle synergies. In fact, a very small number of studies assessed kinematic and muscle patterns together, in order to capture the relationships between the two. One of them is the work of Tagliabue et al. [20] on two-digit grasping. A reduced number of modules (2–3) was needed to explain the largest part of the variation in each grasp and a correlation between muscle and kinematic primitives was suggested, justifying synergy-based analysis in both domains. A multi-modal approach was also suggested in a recent work [21], in which correlations between kinematic and muscular patterns were computed during different grasps. The recent mixed-matrix factorization (MMF) algorithm developed by Scano et al. [22] allows the extraction of synergies from any combination of non-negative signals and unconstrained signals. This algorithm, as the non-negative matrix factorization (NMF) algorithm [23] commonly used for muscle synergy extraction, decomposes signals into synergies and temporal coefficients and allows some of the signals to be also negative. Therefore, when extracting kinematic-muscular synergies, the muscular signals are constrained as non-negative, while the kinematic signals are unconstrained as they may be either positive (joint flexion) or negative (joint extension). As output, the algorithm gives muscle weights (synergies), that can be positive or negative, and non-negative temporal coefficients. Kinematic-muscular synergies directly link the kinematic and muscular domains, allowing a more complete physiological interpretation and providing new insights in the motor control organization. There are several open points in the literature regarding hand grasp multi-modal synergies that can be investigated in more detail. In fact, the intimate link between muscle activations and kinematic coordination was not investigated yet in a comprehensive study and may open new perspectives in the understanding of the coordination patterns at hand level. Also, to define a complete repertoire of hand coordination patterns, analyzing a complete gesture, including pre-shaping, reaching and release, is needed.

In order to contribute to clarifying the mentioned limits of the current scientific literature, the aim of this study was to extract representative kinematic-muscular hand synergies with the MMF algorithm from a publicly available database (NinaPro). The database includes a large number of subjects performing hand movements, and a large number of grasps. The correspondence between the considered hand movements and activities of daily living also fosters the application of the results to improve rehabilitation and assistive robotics. Lastly, the identified motor modules might be employed both in basic studies of motor control, opening new perspectives on the understanding the complexity of coordination of kinematic-muscular patterns, and to evaluate pathological conditions of patients or to control prosthetic devices.

II. METHODS

A brief overview of the main steps of the methods used in this study is reported in Fig. 1.

A. SUBJECTS

The data used in this experiment are from the publicly available NinaPro database [24]. The complete dataset includes over 130 subjects performing up to 53 movements (the number of movements varies slightly between the data sets) while several sensors record the hand movements (e.g. sEMG, force sensors, data gloves, accelerometers, IMUs, eye trackers, . . .). The dataset chosen for this study was Database 2. It includes 40 healthy subjects (28 males, 12 females; 34 right handed, 6 left handed; age 29.9 $\pm$ 3.9 years). Due to possible, occasional noise on some channels, the analyses of this paper focused on the data from 28 selected subjects from NinaPro Database 2, each performing 6 repetitions of 20 hand grasps.

B. ACQUISITION SETUP

The acquisition setup included several sensors, designed to record hand kinematics, kinetics and muscle activity. The sensors were connected to a laptop for data acquisition. Hand kinematics was measured using a 22-sensor CyberGlove II data glove (CyberGlove Systems LLC, www.cyberglovesystems.com). The CyberGlove is a motion capture data glove, instrumented with joint-angle measurements. It uses resistive bend-sensing technology to transform hand and finger motions into real-time digital joint-angle data, achieved through an accurate calibration. Data from the CyberGlove were transmitted over a Bluetooth-tunneled serial port at a sampling frequency slightly lower than 25 Hz. Each data sample was associated with an accurate timestamp using Windows performance counters. The signal was upsampled at 2 kHz to match the sampling frequency of the EMG signal. The acquisition setup is described in detail in Atzori et al. [24], and in Jarque-Bou et al. [4].

The sEMG electrodes were a double differential Delsys Trigno wireless system, measuring the myoelectric signals at 2 kHz with a baseline noise inferior to 750 nV RMS. A total of 12 electrodes were placed over the forearm (8-channel armband), on the flexor carpi ulnaris and extensor carpi ulnaris, biceps and triceps, as shown in previous studies [24], [25]. The set-up is portrayed in Fig. 2.

C. ACQUISITION PROTOCOL

In this paragraph, we briefly present the acquisition protocol. Details are presented in previous papers presenting the publicly available Ninapro datasets [2], [24]. During the experiment, participants were asked to sit at a desktop with the arms relaxed on the table and to repeat a set of movements with their right hand as naturally as possible. The entire experiment included up to 52 movements plus rest, divided into three exercises and selected from the activities of daily living (ADL) and the hand taxonomy literature [26]. In this work, we considered only the set of hand grasps depicted in

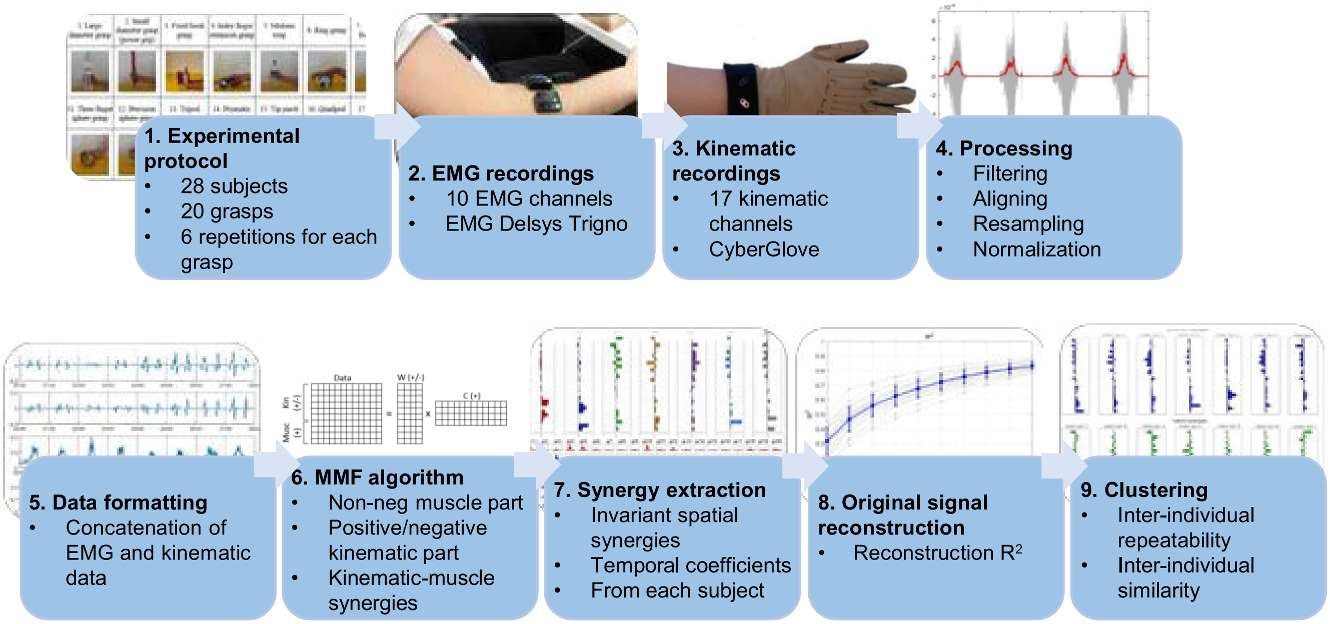

FIGURE 1. Brief overview of the methods of the study. The experimental protocol consisted in executing 6 repetitions for each of 20 considered grasps. We analyzed data from 28 subjects (1). The recorded data were from a 12 channels EMG (2) and a 17 degrees-of-freedom Cyberglove (3). Data from EMG and kinematics were filtered, time-aligned, resampled and normalized (4). Data were concatenated across repetitions (5) to prepare the input for the MMF algorithm (6). Invariant spatial synergies and temporal coefficients were extracted for each subject; spatial synergies from all subjects were then clustered (7). Original multi-modal signals were successfully reconstructed with the set of extracted synergies and the reconstruction R^2 was evaluated (8) and lastly, we defined the inter-individual repeatability and similarity found at kinematic-muscular synergy level (9).

Fig. 3 (i.e. the first 20 movements of the NinaPro exercise B). The subjects were asked to repeat the movements represented in short films that were shown on the screen of a laptop with their right hand and they were asked to focus on mimicking the movements rather than on exerting high forces. Each movement was repeated 6 times in Database 2. Each repetition lasted about 5 s and was separated by the other movements by 3 s of rest. The experiment was approved by the Ethics Commission of the Canton Valais (Switzerland) and were conducted in accordance with the Declaration of Helsinki. Before data acquisition, the subjects were given a thorough written and oral explanation of the experiment itself and were asked to sign an informed consent form.

D. KINEMATIC SIGNAL PRE-PROCESSING

Seventeen kinematic DoF of the Cyberglove were selected: carpometacarpal flexion digit 1 (CMC1f), metacarpophalangeal digit 1 (MCP1), interphalangeal digit 1 (IP1), carpometacarpal abduction digit 1 (CMC1a), metacarpophalangeal flexion digit 2 (MCP2f), proximal interphalangeal digit 2 (PIP2), metacarpophalangeal flexion digit 3 (MCP3f), proximal interphalangeal digit 3 (PIP3), metacarpophalangeal flexion digit 4 (MCP4f), proximal interphalangeal digit 4 (PIP4), metacarpophalangeal abduction digit 4 (MCP4a), metacarpophalangeal flexion digit 5 (MCP5f), proximal interphalangeal digit 5 (PIP5), metacarpophalangeal abduction digit 5 (MCP5a), carpometacarpal flexion digit 5 (CMC5), wrist flexion (WRISTf), wrist abduction (WRISTa). The data analysis was fully performed with MATLAB 2021a with custom-developed software. Joint angles were sampled at 2000 Hz and filtered with a low pass Butterworth filter with a cut-off frequency of 5 Hz. Then, first and second order derivatives were computed to find angular velocities and accelerations. The segmentation procedure was performed according to a threshold on the maximum velocity of all the channels, and allowed to detect movement phases. Tails of 500 ms were used before movement onset and after movement offset in order to capture the full EMG waves. In order to allow the comparison across grasps, the number of time-samples of each movement repetition was rescaled to 100, considering all phases (reaching, grasp and release) and all the grasps. Then, the 6 available repetitions of each grasp from each subject were concatenated. We followed this approach for two reasons. First, to increase reconstruction quality [27]; second, we noted that averaging grasp repetitions might alter or reduce the link between EMG and kinematic time series (especially for differential kinematics). In order to make kinematic data comparable across subjects and to EMG data, we normalized each acceleration waveform to the maximum absolute value found across all the kinematic DoF of all the 20 grasps. In this way, DOFs with a small amplitude are not amplified reflecting the real contribution to the movement and all kinematic data were scaled in an interval of values comprised between -1 and 1.

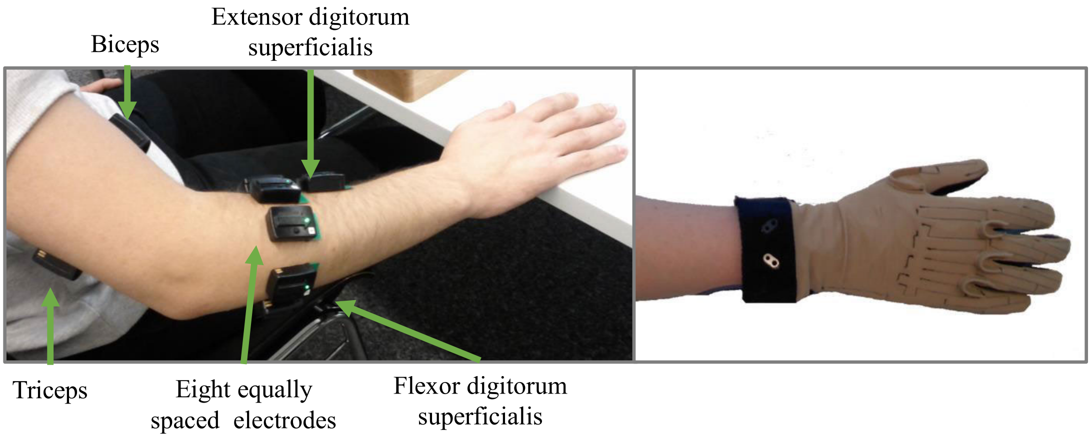

FIGURE 2. The experimental set-up: EMG electrodes placement (left panel) and the Cyberglove used for kinematics acquisition (right panel).

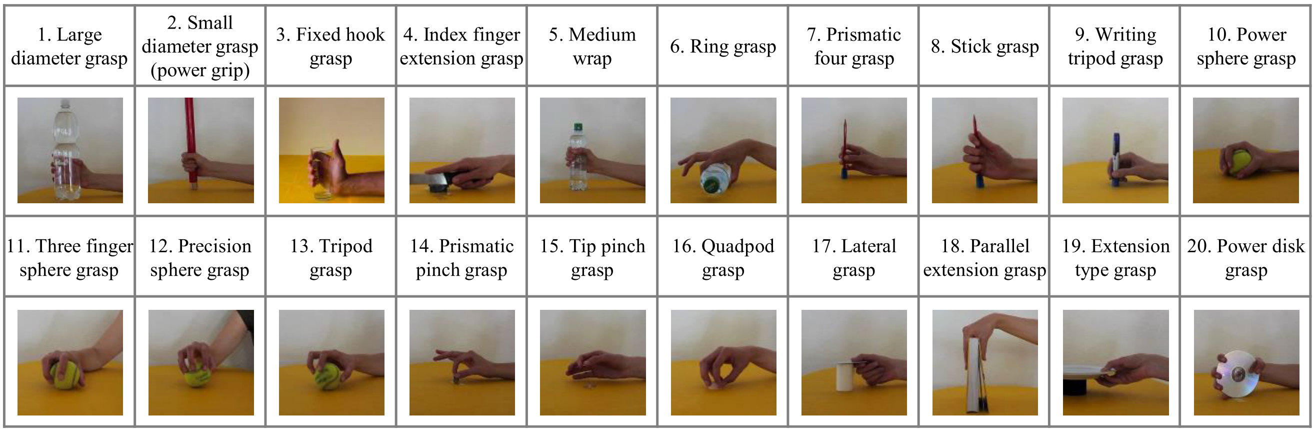

FIGURE 3. The considered hand grasps; each subject repeated each grasp 6 times.

E. EMG SIGNAL PRE-PROCESSING

In this study, EMG signals from 10 muscles were used: flexor digitorum (flex), extensor digitorum (ext), and the eight channels armband (f1: extensor forearm muscle responsible for ulnar deviation, f2: flexor muscle/ulnar deviation, f3: flexor muscle/pronator teres; f4: flexor muscle, f5: flexor muscle/brachioradialis, f6: extensor muscle/supination, f7: extensor muscle/radial deviation, f8: extensor muscle). The EMG signals from the 12 channels were sampled at 2000Hz and were filtered with a high-pass Butterworth filter with a cut-off frequency of 20 Hz, rectified and low-pass filtered with a Butterworth filter with a cut-off frequency of 10 Hz, following the standard procedure for EMG pre-processing in muscle synergy analysis [28]. Then, signals were aligned according to the kinematic segmentation and tails of 500ms were used before movement onset and after movement offset. The delay of EMG data with respect to the kinematics was considered in order to account for the electromechanical delay between the muscular onset and movement production [29]. The resulting envelopes were then resampled at 100 frames per repetition to match kinematic sampling. Lastly, for each subject, each EMG envelope was normalized to the maximum absolute value found for each channel in all the 20 grasps [30]. In this way, the muscle activation reflects the real activity with respect to its maximum activity, and each EMG waveform was scaled in an interval of values comprised between 0 and 1, achieving normalized EMG envelopes.

F. KINEMATIC-MUSCULAR SYNERGIES

A kinematic-muscular synergy is defined as the coordinated activation of muscles (represented by EMG envelopes) and angular acceleration of articular joints. Despite the non-linearity of the neuromusculoskeletal system, it is reasonable to search for a linear relationship between EMG and acceleration [31], since force is linearly related to acceleration. Moreover, linear models were frequently employed for similar purposes [32]. Following Scano and colleagues [22], our choice was to combine joint accelerations with muscle activities, rather than joint angles or range of motion. For each subject, data from kinematics (angular accelerations from 17 DoF) and EMG (10 channels) were grouped in an aggregated matrix before synergy extraction. For each subject, the kinematic-muscular matrix had dimensionality 27 × 12000. Twenty-seven was the number of kinematic-muscular channels. Instead, for each of the 20 considered grasps, we had 6 time series (repetitions) per grasp, each one 100 samples long. Since the nature of kinematics and EMG signals are different and not directly comparable, apart from the normalization procedure performed in the preprocessing, we employed the MMF algorithm [22]. The peculiarity of the MMF algorithm is that the constrain of non-negativity to the kinematic coefficients is removed (while the EMG data were kept non-negative by definition), allowing the spatial synergies to be negative to account for flexion and extension of joints. The algorithm is based on a gradient descent update rule and decomposes the data $\boldsymbol{x}$ (kinematics and EMG) as a combination of n synergies (i.e., decomposition order):

$$\boldsymbol{x}(t) = \sum\nolimits_{i=1}^{n} \boldsymbol{w}_i c_i(t)$$

where w are the time-invariant weights or spatial synergies and $c(t)$ the corresponding temporal coefficients. w can be either positive or negative for the kinematic part and non-negative for the muscular part, $c(t)$ are constrained to be non-negative. The quality of reconstruction was evaluated with the reconstruction R^2, that is widely used in synergy analysis and quantifies how much of the original signal can be reconstructed [33]. For each decomposition order, the reconstruction R^2, defined as 1 – SSE/SST where SSE is the sum of the squared residuals, SST is the sum of the squared differences with the mean EMG vector [13], was computed. The extraction was repeated 20 times starting from different random initial conditions and the best solution (higher R^2) was chosen as representative of that decomposition order. The algorithm requires to set the parameters μ, that controls the gradient step, and λ, that regularizes the synergy sparseness and the reconstruction accuracy. The parameters μ and λ were chosen empirically and set 0.04 and 3000, respectively. These values allowed to have a good reconstruction accuracy and to minimize cancellations between synergies with weights of opposite sign. The values for μ and λ were determined by generating cancellation and R^2 surfaces, similarly to Scano et al. [22], in order to identify the optimal ranges for μ and λ, by selecting a trade-off between the reduction of cancellations and the R^2 reduction. The result of the extracting procedure were spatial kinematic-muscular synergies. Ten weights representing EMG channels were non-negative, while 17 weights representing kinematic variables could be either positive or negative, depending if a joint was flexed or extended as a result of EMG activity. Thus, each extracted synergy was a vector that contained the weights of each of the 27 original variables in a normalized, dimensionless space where the original data were grouped showing their coordination across physical domains. A schematic description of the MMF algorithm is presented in Fig.4. The mean R^2 across participants was computed and the minimum number of synergies needed for achieving at least 0.75 of the mean R^2 were selected [34]. Extracting the same number of synergies from all the participants allows to compare synergies with similar sparseness.

G. COMPARISON ACROSS SUBJECTS AND IDENTIFICATION OF MEAN KINEMATIC-MUSCULAR SYNERGIES

Following the extraction of kinematic-muscular synergies for each subject, their structure was compared across subjects. The extracted synergies were grouped with a k-means clustering analysis, which is a multivariate technique that allows the classification of elements into groups or clusters, so that each element is very similar to those in its own cluster according to a specific selection criterion. To achieve this, at first the extracted synergies from all the subjects were grouped in a single matrix (dimension: $(Ns \times S) \times N_{dof}$, where $Ns = 28$ is the number of subjects, S is the number of extracted synergies for each subject, $N_{dof} = 27$ is the number of DoF). Then, this matrix was used as input to a k-means clustering procedure. The synergies were grouped into clusters minimizing the sum of the Euclidean distances between each synergy in the cluster and the centroid (mean synergy) of the cluster. The desired number of clusters was identified as the minimum number of clusters needed to avoid more than one synergy from the same subject to belong to the same cluster. This was achieved by increasing the clustering order n_{cl}, repeating k-means clustering 100 times for each n_{cl}, and selecting the best solution for that order. The minimum n_{cl} required to prevent repetitions stopped the algorithm. We then computed the *inter-individual repeatability* related to centroid (mean synergies within each clusters) usage, as in previous work [30], as the number of subjects that used each centroid, to find at what extent synergies are shared across subjects (synergy generalizability), and the *inter-individual similarity* in each cluster, as the cosine angle between all the synergies of the cluster, to measure the robustness of each cluster.

H. SUMMARY OF THE ANALYSIS STEPS

Due to the complexity of the proposed analysis, we report a summary of the main steps.

1) Kinematic-muscular synergy extraction: Extraction of kinematic-muscular synergies from 20 grasps from each of the 28 selected subjects of Ninapro Database 2 (using MMF, reconstructed mean $R^2 > 0.75$). The following analyses were performed:
   - synergy extraction and reconstruction R^2 for different decomposition orders for each subject;
   - selection of the decomposition order for all subjects according to the mean R^2;
2) Synergy clustering: Clustering of the whole dataset of extracted synergies (k-means clustering). The following analyses were performed:
   - identification of the centroids;
   - identification of the inter-individual repeatability of each centroid;

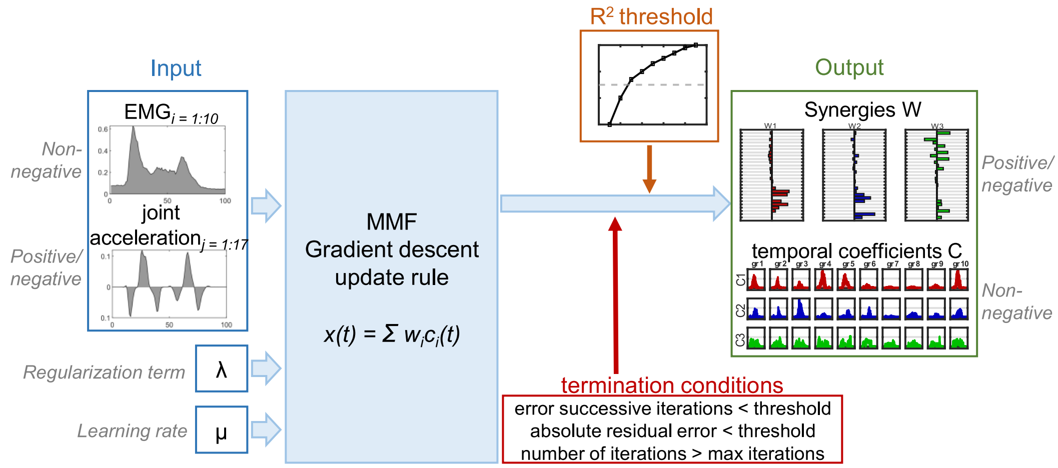

FIGURE 4. The MMF algorithm is based on the gradient descent rule and takes as input the EMG and acceleration data, μ and λ and gives as output kinematic-muscle synergies and the corresponding temporal coefficients. The termination coefficients for the algorithm are: error between two successive iterations reaches the threshold, the absolute residual error reaches the thresholds, or the number of maximum iterations is reached.

- identification of the inter-individual similarity in each cluster;
- functional characterization of the mean synergies.

III. RESULTS

A. KINEMATIC-MUSCULAR SYNERGY EXTRACTION

First of all, the output of the kinematic-muscular synergy extraction procedure is shown, by presenting the results from a typical (subject 5). In Fig. 5 (upper panel), time-invariant or spatial kinematic-muscular synergies are portrayed; in Fig. 5 (lower panel), temporal coefficients for each synergy and each grasp are shown. Multiple temporal coefficients graphs are reported since temporal coefficients are repeated for each concatenated repetition of each grasp. Synergies (W) are either positive or negative for the kinematic components and non-negative for the muscular parts. The temporal coefficients (C) are constrained to be non-negative. W1 and W2 can be considered as muscular synergies, since they are characterized by strong muscular activations with small kinematic activity. W1 activates both extensors (f1, f6, f7, f8) and flexors (f2, f3, f5), W2 activates f3, f4, f5 and the extensor digitorum and the flexor digitorum. Since synergies with muscle activations associated with no kinematic activations are recruited in the static holding phase, the temporal coefficients (C1 and C2) show mainly monophasic activity, with the maximum at the half of the movement. Temporal coefficients of synergies with kinematic activity are characterized by more peaks. W3 and W4 are characterized by the flexion of MCP joints and extension of PIP joints of the digits from 2 to 5, while the joints of the thumb are the opposite. In fact, CMC1 flexes and IP1 extends in W3, while CMC1 extends and IP1 flexes in W4. Both W3 and W4 are mainly coupled with the activation of extensor muscles. W5 represents the flexion of almost all the joints, with the activation of extensor muscles and the extensor digitorum. Finally, W6 and W7 represent the extension of the MCP joints, related to the extensor muscles (f8) in W6, and to the radial deviator and the extensor digitorum in W7. In Fig. 6, we show the original signal for joint accelerations and EMG, and the corresponding reconstructed signal achieved with the set of kinematic-muscular synergies and temporal coefficients, for a subset of grasps. EMG signals have smoother shapes and they can be reconstructed better than the accelerations, that are characterized by more peaks. However, most of the variables can be reconstructed adequately and the main patterns can be reproduced. MCP1 and CMC5 show the worst reconstruction, due to the small and noisy activity.

B. NUMBER OF SYNERGIES

In this paragraph, we show the results concerning the data from all the subjects. We begin with the R^2 curve. In Fig. 7, we report the mean and std R^2 computed on the sample of 28 subjects. To achieve at least 0.75 of the mean R^2, seven synergies had to be extracted from each subject.

C. EXTRACTED KINEMATIC-MUSCULAR SYNERGIES

In Fig. 8 and Fig. 9, we report the extracted centroids that were found after applying the k-means algorithm on the whole set of synergies from all subjects. Seven synergies were extracted from each participant. Starting from an overall dataset of 196 synergies from 28 subjects, we found that 21 clusters were needed to group the extracted synergies and guaranteeing that in each cluster included no more than one synergy from the same subject. Then, the centroids were classified in four groups, on the basis of a qualitative assessment aimed at distinguishing the main kinematic patterns, which we summarized in 4 main groups: flexion synergies, extension synergies, hybrid synergies, static grasping synergies.

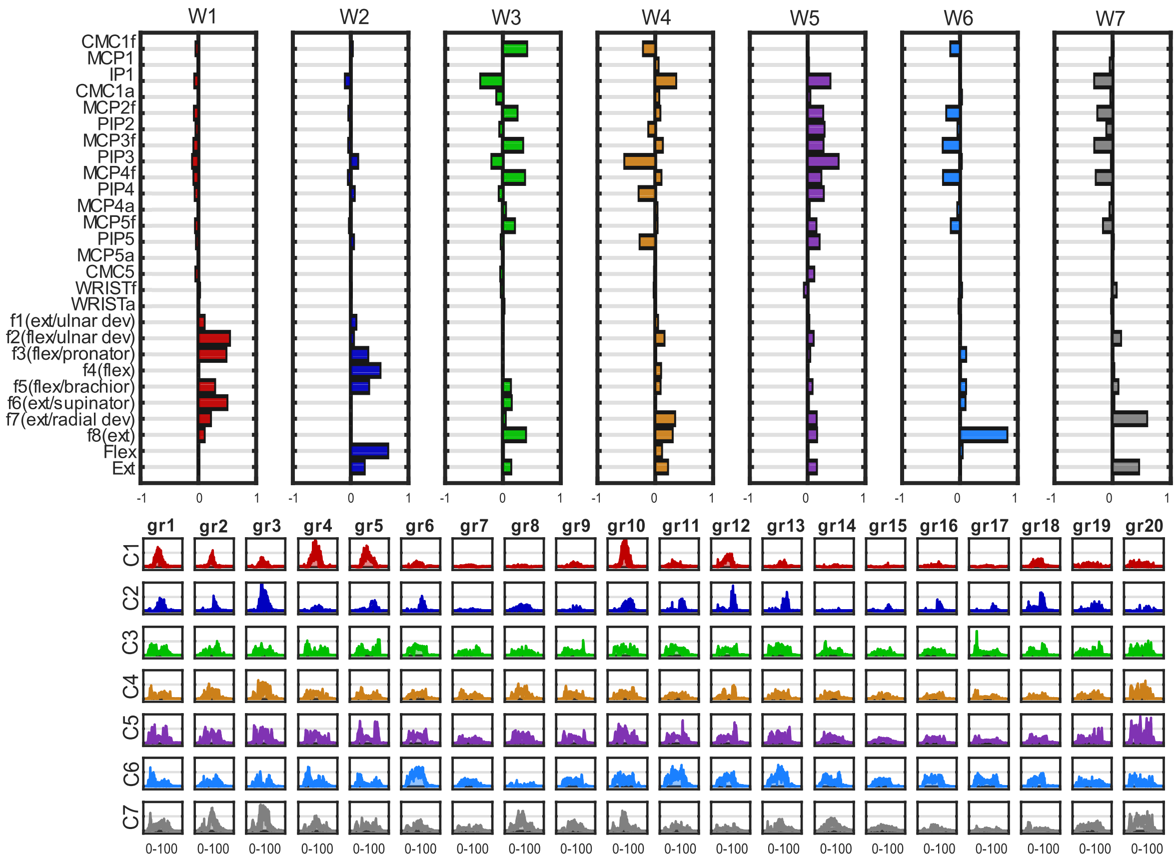

FIGURE 5. Example of spatial kinematic-muscular synergies extracted from the multi-modal data of a subject. In the lower-panel, the temporal coefficients for each synergy and repetition are shown. The portrayed dataset is the full set of extracted synergies and temporal coefficients for subject 5. The complete dataset of kinematic-muscular invariant synergies includes a set of synergies for each of the 28 subjects.

1) FLEXION SYNERGIES

We found three kinematic-muscular synergies characterized by a dominant flexion activity. The first and the second synergies represent the flexion of the digits from 2 to 5 on the MCP joint and on the PIP joint, respectively. The first synergy is mainly coupled with the activation of the extensor muscles, while the second one is coupled with both flexor and extensor muscles. While the MCP and the PIP joints are always flexed synergistically, at the kinematic-muscular level they are extracted separately. The third synergy, instead, is characterized by a general flexion of all the joints, coupled mainly with the extensor muscles.

2) EXTENSION SYNERGIES

Seven synergies were classified as synergies with a dominant extension activity. The first and the seventh synergies represent a general extension of all the fingers, with a great activity also on the joints of the thumb. These two synergies are related to different muscular activations: the first synergy is coupled with extensor muscles and the seventh with both flexor and extensor muscles. The second and the forth synergies regard the extension of MCP joints, with a major activation of the extensor muscles. The third and the sixth synergies showed the extension of all the joints: the third synergy is coupled with the extensor muscles, the sixth mainly with f8. Finally, the fifth synergy is characterized by a great activation of the flexor muscles, coupled with the activation of the thumb and of the third digit.

3) HYBRID SYNERGIES

Seven synergies were classified as hybrid, since both flexion and extension activities were present, but none of the two dominated clearly. Such synergies represent more complex patterns that are found in a mixture of flexion and extension movements. The first and the third synergies are characterized by a strong extension activity of the thumb, related to the extension and flexion of the other joints, respectively. The first synergy is coupled mainly with the extensor muscles and the third with the flexor muscles. The second and the forth synergies show the extension of the PIP joints and flexion of the MCP joints, with almost all muscles activated. The fifth and sixth synergies are, instead, characterized by flexion of the PIP joints and extension of the MCP joints, with a strong activation of extensors in the fifth synergy and extensor and

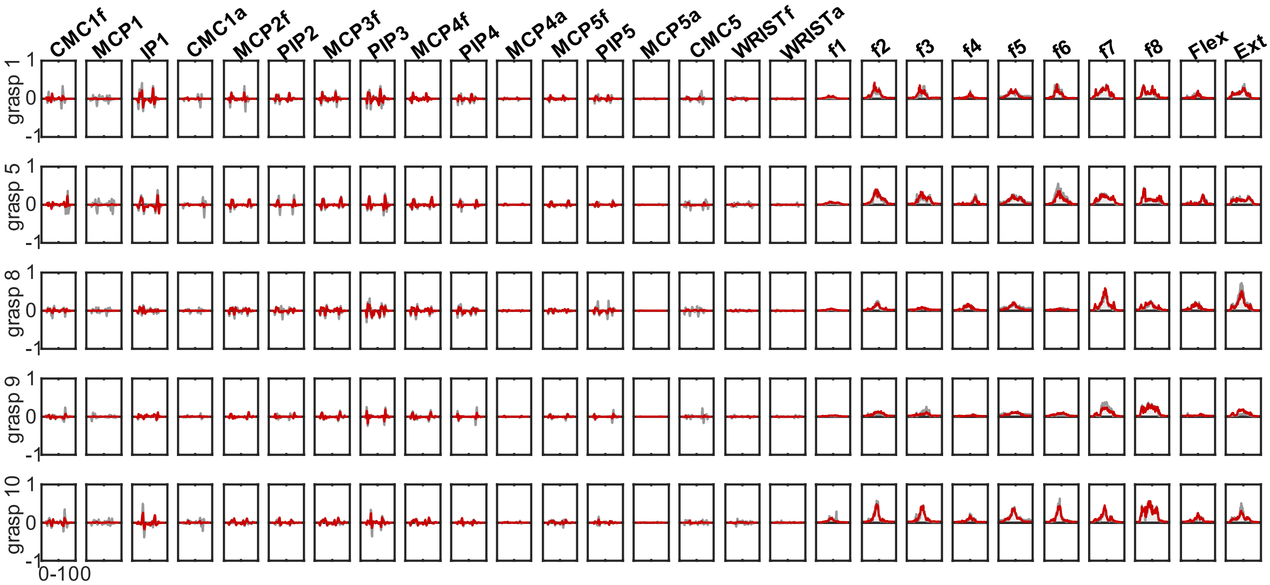

FIGURE 6. Examples of reconstructed kinematic-muscular envelopes (red) and original kinematic-muscular envelopes (light gray area) of the first repetition of subject 5 in a subset of five grasps (1, 5, 8, 9, 10). The reconstruction is achieved by summing the contribution for each spatial synergy, multiplied with its correspondent temporal coefficient. Reconstructing at least 75% of the R^2 with 7 synergies, an adequate matching of the reconstructed signal with respect to the original one was achieved, except for MCP1 and CMC5.

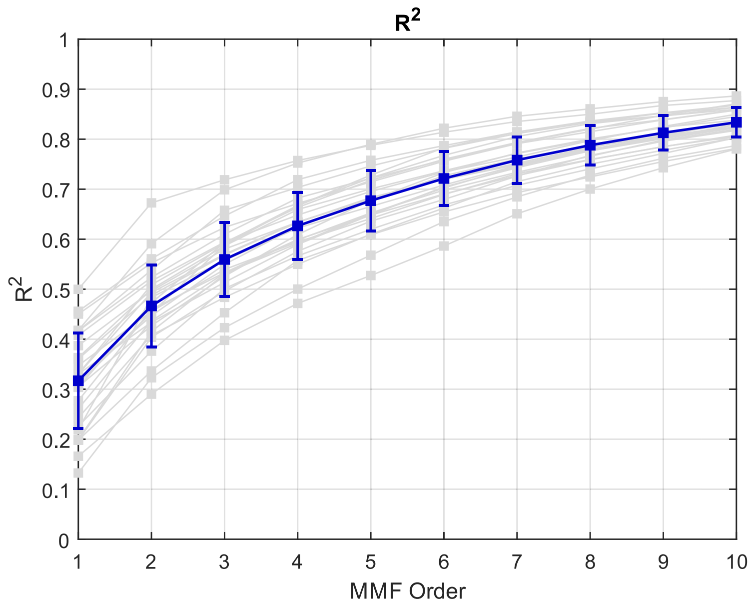

FIGURE 7. Reconstruction R^2. The mean and std of the R^2 is reported in blue, the R^2 of each subject is reported in gray. Only orders 1 to 10 are shown.

deviators in the sixth. The seventh synergy is dominated by the flexion of the thumb, coupled with the activation of the flexor muscles.

4) STATIC GRASPING SYNERGIES

Synergies with almost only muscular activations represent the grasp phase in which only muscles are activated during the grasp and they are characterized by four patterns. The first synergy is characterized by a strong activity of f1 that represents extensor and ulnar deviator muscles; the second one represents the extensor muscles; the third one is characterized by a strong activity of f8 (extensor muscles) and extensor digitorum; the last one represents the activity of brachioradialis, flexor muscles and flexor digitorum.

D. INTER-INDIVIDUAL REPEATABILITY AND SIMILARITY

In Fig. 10, we reported a histogram indicating the number of subjects who share each of the mean multi-modal synergies.

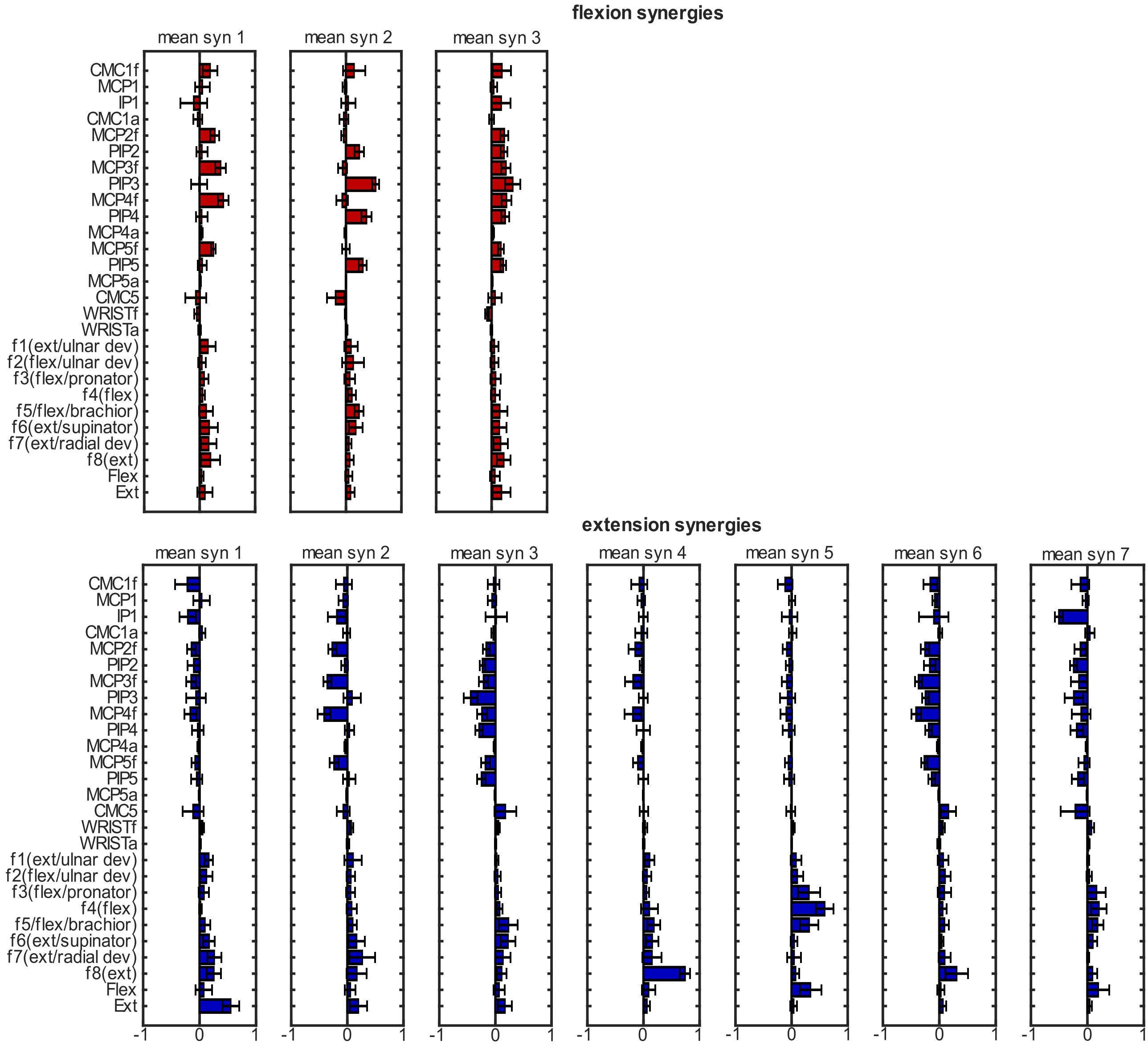

FIGURE 8. Kinematic-muscular synergy clusters (1/2). In the dataset composed of 28 subjects, each one executing 20 grasps, 21 clusters were needed to cluster the extracted synergies without repetitions across subjects. Each cluster is represented by a centroid (mean of the synergies within the cluster) and they were subdivided based on the main kinematic patterns represented: flexion synergies (in red, 3 centroids), extension synergies (in blue, 7 centroids), hybrid synergies (in green, 7 centroids), and static grasping synergies (in orange, 4 centroids).

Interestingly, while some synergies were shared, no synergy was found across all subject and only two mean synergies are shared by more than the half number of subjects.

In Table 1, the inter-individual repeatability and similarity is reported for each centroid. All mean synergies were shared by at least 5 subjects, but no mean synergy was shared across all subjects. The mean number of synergies per cluster was 9.33 (3.85). The mean similarity in each cluster was between 0.64 and 0.78, except for one cluster in which the similarity was lower (0.53). The mean inter-individual similarity was 0.69 (0.06). The average similarity of random chosen pairs of synergies extracted from our dataset was 0.26 (0.22), so consistently lower than the obtained similarities in clusters.

IV. DISCUSSION

A. SUMMARY OF THE MAIN RESULTS

In this paper, we extracted for the first time a set of kinematic-muscular synergies, linking EMG activity to the angular acceleration of hand joints thanks to a newly developed algorithm for synergy extraction (Scano et al., 2022). We found that a reduced set of kinematic-muscular synergies underlie the execution of a large variety of grasps performed by 28 individuals. Seven synergies were extracted from each subject and 21 centroids (mean synergies) were needed to describe the whole dataset of multi-modal synergies. These results suggest that kinematic-muscular synergies can describe a large dataset of grasps with a reduced number

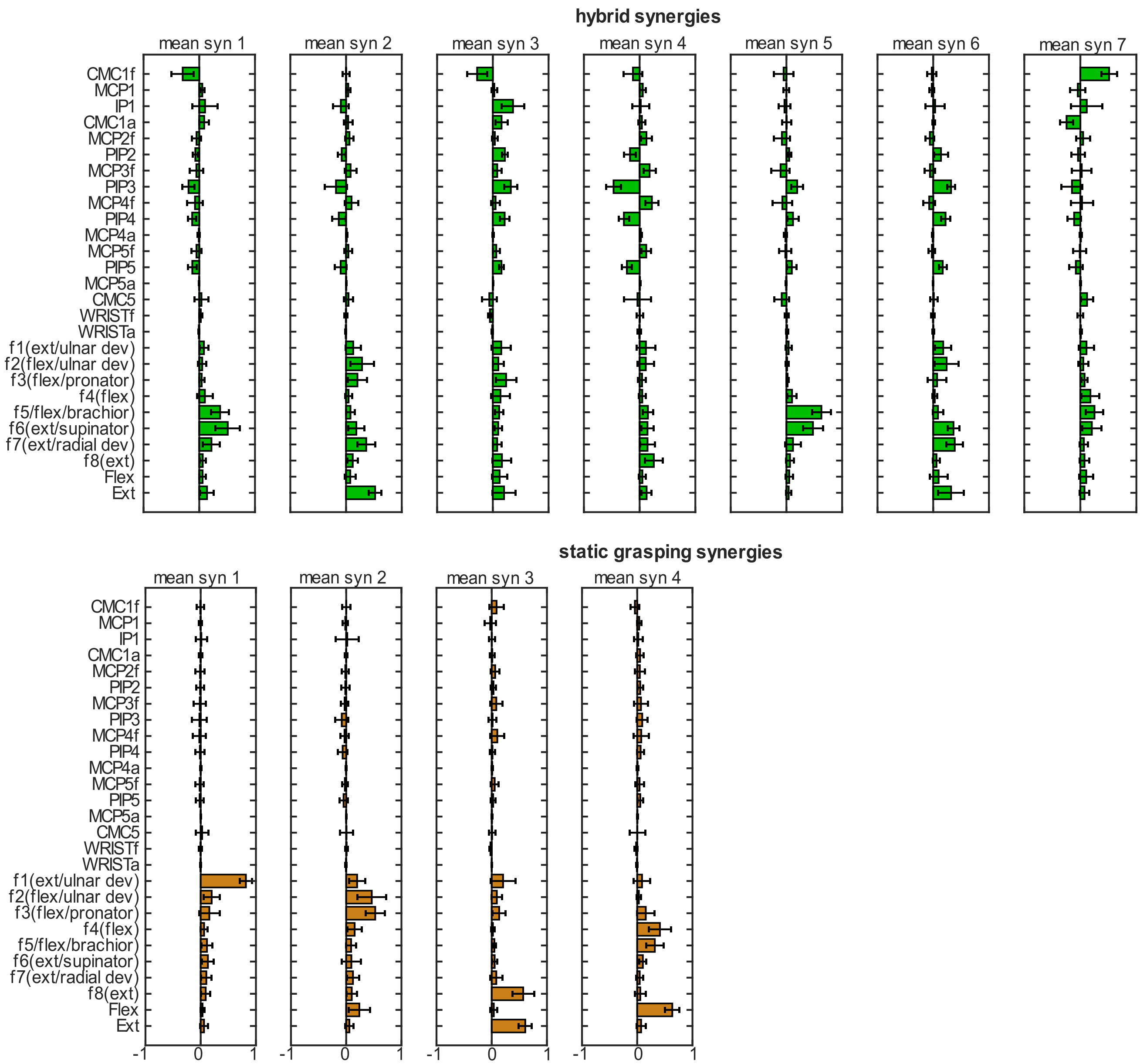

FIGURE 9. Kinematic-muscular synergy clusters (2/2). In the dataset composed of 28 subjects, each one executing 20 grasps, 21 clusters were needed to cluster the extracted synergies without repetitions across subjects. Each cluster is represented by a centroid (mean of the synergies within the cluster) and they were subdivided based on the main kinematic patterns represented: flexion synergies (in red, 3 centroids), extension synergies (in blue, 7 centroids), hybrid synergies (in green, 7 centroids), and static grasping synergies (in orange, 4 centroids).

of modules; however, they have a limited inter-individual repeatability.

B. MODULAR ORGANIZATION OF KINEMATIC-MUSCULAR SYNERGIES

Whether the human central nervous system exploits a modular organization for the simplification of the motor control problem is widely debated. In this context, the muscle synergy approach represents the current state of the art for the analysis of the modular organization of the neuro-motor system. The analysis of hand and forearm behavior in refined movements as grasps is particularly meaningful, since it is naturally connected to a wide variety of movements related to activities of daily living, exploiting abundancy at both the kinematic and muscle level [1]. This scenario requires the exploration of a large variety of conditions and thus is suitable for muscle synergy analysis.

We found that 7 kinematic-muscular synergies reconstructed reasonably well EMGs and kinematics for all subjects, supporting the hypothesis of modularity. However, we observed a large inter-individual variability in synergy structure. Thus, in this experimental scenario, while it is believable, or even likely that motor control is organized

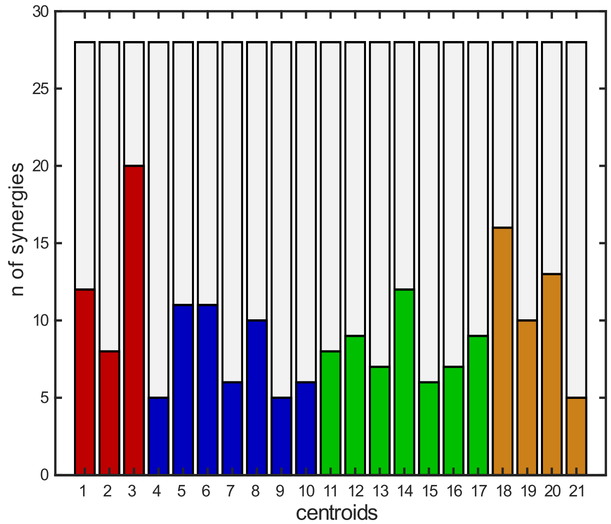

FIGURE 10. For each of the mean centroids (n = 21), the histogram shows the number of subjects that share the same kinematic-muscular synergy. Groups are highlighted by different colors: flexion synergies in red, extension synergies in blue, hybrid synergies in green and grasping synergies in orange.

TABLE 1. Number of synergies in each cluster (inter-individual repeatability), and the mean inter-individual similarity of synergies in each cluster.

	Syn 1	Syn 2	Syn 3	Syn 4	Syn 5	Syn 6	Syn 7
Inter-individual repeatability							
Flexion	12	8	20				
Extension	5	11	11	6	10	5	6
Hybrid	8	9	7	12	6	7	9
Grasping	16	10	13	5			
Inter-individual similarity							
Flexion	0.64 (0.13)	0.75 (0.08)	0.74 (0.08)				
Extension	0.66 (0.12)	0.66 (0.13)	0.75 (0.09)	0.74 (0.08)	0.71 (0.14)	0.75 (0.11)	0.66 (0.11)
Hybrid	0.65 (0.18)	0.67 (0.10)	0.64 (0.11)	0.66 (0.15)	0.70 (0.08)	0.67 (0.10)	0.53 (0.16)
Grasping	0.78 (0.11)	0.74 (0.10)	0.64 (0.17)	0.76 (0.07)			

in synergies, we cannot conclude that the same synergies are used by all individuals when considering daily life movements along with their natural variability. According to our study, it emerges that, when examining hand coordination through kinematic-muscular synergies, the control space has a higher dimensionality and less consistency across individuals than previously reported. This result is in partial disagreement with the findings of previous studies that instead are in general supporting low-dimensional and consistent upper-limb synergies [13], [18], even though such models were muscular-only; however, the testing conditions and the examined domains are different in respect to the one of our study and are not directly comparable. Higher modularity with respect to previous literature was already found on hand and wrist movements by Jarque-Bou et al. [4], in which a high number of kinematic synergies was needed to reconstruct a dataset including large number of grasps and subjects.

C. ANALYSIS OF VARIABILITY

In this work, we addressed the variability of muscle synergies focusing on the *inter-individual variability*. We found that only two modules were shared by more than half of the participants. The large amount of inter-individual variability found in our results may be due to several factors. First, the experimental protocol proposed in this study was based on structured reach-to-grasp gestures, involving several movement phases (reach, pre-shaping, grasp, release, going back). It was already observed in a recent kinematic analysis performed on the Ninapro dataset that this might be a factor leading to increased number of extracted modules [4]. Moreover, it was also recently shown that naturalistic experimental conditions with limited constrains may lead to higher variability of the extracted modules with respect to more constrained experiments [30]. One may observe that different modules were found because strong movement constrains were not imposed; however, in real life and scenarios, tasks are never constrained in pre-determined paths and thus this experimental condition is realistic. In these kind of movements, high variability of muscle synergies was found also in synergies extracted from the different acquisition sessions of the same subject, demonstrating that there is a natural variability in human movements and, therefore, this leads to a high variability between subjects [35]. The moderated experimental variability is thus resembling real use cases. In fact, differently from many previous articles where only postural synergies are studied [6], [8], the data refer not only to the postural synergies for grasping, but also include the pre-shaping, object grasping, and release movement phases, with a relative freedom given to subjects as in a natural context. It is thus understandable that inter-individual repeatability is lower than in previous studies, as dynamic features are investigated, emphasizing also the agonistic and antagonistic roles of muscles that may need more synergies to be explained. The wider intra-individual repeatability found could also indicate the existence of different strategies to perform the same grasp based on both subjects' previous experience and the anatomical differences between subjects as shown in previous work [36]. Kinematic-muscular analysis may help in quantifying the different strategies adopted for each grasp, and these characteristics could be used to better discriminate the distinct grasps. Thus, our findings seem to suggest more complex patterns for hand coordination and agree with recent work and with neurophysiological evidences. First, extending synergistic analysis on a large number of subjects, grasps and repetitions, Jarque-Bou et al. [4], already demonstrated that ''more synergies'' where needed to describe hand motion. Secondly, recent work also observed that the complex mechanisms for hand control cannot be reduced to the control of flexion and extension postures only. In the work from

Santello et al. [6], the authors found that principal components analysis showed that the first two components could account for >80% of the variance, implying a substantial reduction from the 15 degrees of freedom that were recorded. Further synergies could explain specific features of objects. In this work, we instead show that the origin of neural pattern underlying motion when hand grasp and the dynamic phases of motion are included seem to be more complex and not based on two postural synergies only, especially when motion for preshaping and object release are involved. When the dynamic phases of motions are included more variability is introduced. A limited number of synergies might still be available for subject without being shared by others as the more complex movements introduce further sources of variability in how subjects perform the entire movement. In neurophysiological studies, the complex coordination of the hand was demonstrated outside of the synergistic framework. Indeed, numerous neurons distributed in different areas of the primary motor cortex are activated for performing hand movements, resulting in a complex motor control [37]. It is thus fully believable that 21 kinematic-muscular modules are needed to express the motion of the hand in a wide variety of hand grasps.

A second relevant factor that might have increased variability is the examination of multi-domain data (kinematics and EMG). It is possible the muscle patterns usually found in muscle synergy studies were associated with slightly different kinematic outputs, or vice versa. It is worth noting that, due to motor abundance [1], it is possible that the same output is generated by different muscles, thus increasing the number of kinematic-muscular synergies needed to reconstruct the original patterns; this phenomenon might have been highlighted by our methodology. Our results suggest that when investigating the causal kinematic-EMG relationships, some synergies typically merged with similar motor functions may split into more synergies with our approach. In our results, we purposefully grouped synergies by their physiological main function. There are some flexion synergies, extensor synergies, hybrid synergies, and grasping synergies that are distinguished often on the basis on the activated muscles. Probably, in previous single-domain (mostly kinematic) studies, they would be extracted together as a single ''flexion synergy'' or ''extensor synergy'' [9], [10]. It is possible that the motor outputs that are mostly similar at a kinematic level (extracted ''together'' in single-domain studies), might not be underlid by the same EMG neural activation. This process is known as the motor abundance feature of our control system [1], that states that similar or identical kinematic outputs can be achieved with non-identical EMG activations. Indeed, because of the redundancy of the musculoskeletal system there is a large space of EMG activation patterns that can generate the same joint torques, i.e. the same joint accelerations (also known as muscular null space [38]). Thus, different individuals may acquire a distinct set of muscle synergies with different muscular null space components when learning grasping and manipulation skills. With our algorithms, kinematic patterns are split into groups of synergies with similar functions, that can be distinguished with a higher level of detail due to different null space components of the EMG activations.

A third factor affecting variability might have been the large number of considered grasps (20), repetitions (6), and subjects (28), and signals (27). This number is higher than in most previous studies on muscle or kinematic synergies alone; the coordinated recruitment of a control space of such a dimension may be a source for differentiation among subjects. A fourth factor to consider is that this study was conducted on the very complex domain of hand coordination: some muscle structures might not have been exactly mapped and detected across subjects, for example due to physiological anatomical differences which are impossible to model. Despite the recorded forearm EMG relate to kinematic patterns, we have neglected hand intrinsic muscles, as in many applications they cannot be recorded as they are too small (and EMG electrodes would interfere with motion), or because applications to prosthetics do not allow to record hand activity. This choice of the recorded muscles may partially impact on the variability of the results achieved. At the same time, in a so comprehensive mapping of hand activations and movements, little differences found in DoF might lead to new synergies. We even argue that a full mapping, including also the missing hand and finger muscles, may generate an even wider and variable repertoire of multimodal synergies. On the contrary, we expect that probably, when considering gross motor control (for example in upper or lower-limb scenarios), the same approach might lead to less differentiation across subjects and to a low-dimensional, inter-individually consistent space of control.

D. PHYSIOLOGICAL FUNCTION OF SYNERGIES

We identified several types of kinematic-muscular synergies, each apparently performing some specific physiological function. Three flexion synergies were used to flex several DoF of the hand. In these synergies, co-activation of a set of flexor muscles is associated with flexion of the DoF (both EMG and kinematic loads are positive). In particular, the flexion of the joints of the second to fifth fingers are controlled with separated synergies: one synergy flexes the MCP joint of the four fingers, and the other flexes the PIP joint of the same fingers. Then, an additional synergy represents the flexion of all the joints. Seven extensor synergies were used to extend the hand. In these synergies, co-activation of a set of extensor muscles is associated with extension of the DoF (kinematics loads are negative). Two synergies controlled the extension of the MCP joints of the four fingers, coupled with extensor muscles. Two synergies showed the extension of all the joints, with the activation of extensor muscles and minor flexor muscles activations, while another one showed the activation of the flexor muscles related to a small extension of the joints. Other two synergies represented the extension of the joints of the thumb. Seven hybrid synergies represented complex coordination patterns including a mixture of flexions and extensions depending on the joint (kinematic loads are part positive, part negative). In some of these synergies, the extension of PIP joints was coupled with the flexion of MCP joints and, in other synergies, the flexion of PIP joints was coupled with the extension of MCP joints. Three synergies showed a major activation of thumb joints, associated with minor activities of the other kinematic joints. Finally, static grasping synergies are a special case where the hand is not moving and only muscle patterns are active. These kinematic-muscular synergies appear as mostly muscle synergies. Four muscular patterns were found: extensor and ulnar deviator muscles; extensor muscles; extensor and ulnar deviator muscles and extensor digitorum; flexor muscles and flexor digitorum.

From our results, we can notice that fingers (from the second to the fifth) are controlled together, but their joints, so MCP and PIP, can be controlled by separated synergies. The thumb, instead, is generally controlled by separated synergies. Although the kinematic part of the kinematic-muscular synergies that we found can describe well the control of hand and fingers during grasp, it is difficult to define a clear physiological relationship between the kinematic and the muscular activations. In fact, extension of joints was sometimes coupled with flexor muscles, and vice versa. This issue could be related to the complex structures that underlie the hand and fingers control.

E. APPLICATION OF THE STUDY TO A VARIETY OF SCENARIOS

Kinematic-muscular synergies provide a new attempt towards a synthetic description of the organization of the neuromotor system, that can lead to new perspectives in the analysis of motor control in clinical practice. The concept of modular organization has been already used in rehabilitation for muscle and kinematic synergies, since changes in their structure and number allow to discriminate pathological conditions [39]. Therefore, kinematic-muscular synergies may allow to assess the coordination of movements in a more comprehensive way, linking directly muscular and kinematic patterns. Moreover, many devices are used for hand rehabilitation [40], and synergy-based paradigms may allow to improve the restoration of motor functionality [41]. The association between muscular and kinematic patterns can provide more insights on grasp patterns to improve hand rehabilitation devices [42].

Kinematic-muscular synergies for hand movements can also lead to applications in prosthetics. Dexterous, naturally controlled surface EMG prostheses better allow amputees to perform personal needs such as eating or using tools. Prosthetics companies and scientific research are advancing toward this goal but dexterous naturally controlled prosthetic hands are not yet available, neither on the market nor in scientific research mainly due to control problems [43] related to robustness. Clinical parameters of the amputees were demonstrated to affect control capabilities [15]. In order to foster the improvement of control systems for sEMG hand prostheses, a publicly available dataset for robotic hand prosthesis control (the Ninapro database1) was released in 2014 [24], and extended with several additional datasets afterwards [44], [45]. Currently, the database includes over 130 subjects (including 11 trans-radial amputees), repeating as naturally as possible up to 53 hand movements with several acquisition setups ranging in price from a few hundred to several thousand dollars. The aim of Ninapro is to foster the improvement of the field by allowing the development and test of advanced machine learning methods. However, the path to natural control of dexterous prosthetic hands can also be paved by the simplification of the problem, for instance via the identification of a set of motor modules sufficient to control a comprehensive set of hand grasps.

The application of muscle and postural hand synergies to myoelectric hand prostheses development and low-level control was recently suggested in the literature and tested in specific settings, while high level control strategies are still not extensively explored. The application of postural hand synergies to hand prostheses development is particularly evident in the development of the PISA/IIT Softhand, a robotic hand actuated by a single motor [46]. The application of postural hand synergies to low level control approaches can be defined as controlling a dexterous robotic hand with few (usually 4) independent input signals that modulate some of the first synergies (usually the first one or two) in the robotic hand, leading the robotic hand to reproduce several hand grasps [47], [48], [49].

F. LIMITATIONS AND FUTURE WORK

Our analysis included 27 ''mixed channels'' (kinematics + EMG) that provide a complex and multifactorial assessment including a comprehensive mapping of DoF. While the assessment is ''advantageous'' on one side since it provides a high dimensional mapping, a multi-modal dataset may at the same time carry artifacts due to the pre-processing steps needed to provide coherent data to feed to the extraction algorithm. It is not trivial to compare signals from multiple domains and there are of course several factors that might have affected the analysis. First, the choice of using acceleration for describing kinematics; it is possible that using angular position, ranges of motion or velocities, results might be interpreted differently. Second, the various steps for signal analysis and normalization might impact the results (however, this consideration is valid for any study on synergies and is not related to our experimental set-up, protocol or analysis pipeline). Moreover, with respect to previous studies in the field, the number of DoF is increased and may lead to higher variability. There is also a lack of comparative studies. Even more, the delays between kinematic variables and EMG signals are considered with a simple fixed delay model [29].

Moreover, although the analyzed grasps are representative of a realistic scenario, in which movements are not constrained, the proposed mapping is still limited by the adoption of a laboratory setup not yet integrated in a real-life scenario. Boundary conditions related to interaction with objects or force application were not considered in this study. The different weights of the objects were not considered in this study; future work will investigate the effects of the weight of the objects on muscle synergies.

A very important question to consider is that MMF algorithm implicitly assumes that kinematics and muscle activity share a linear relationship, while the dynamic of muscle contraction and effector muscles might be non-linear [50]. This might imply that the model for capturing relationships between muscle and kinematic coordination requires a non-linear modelling needed for a more precise interpretation of the results, which is not considered in this study. Furthermore, while the synergy approach has shown to be compatible with experimental findings, in this study its transportability to the effector space has to be demonstrated [51]. In this study, as well as in the majority of muscle synergy works, it is not demonstrated that the set of extracted synergy is able to define the same motor output as the original kinematics and EMG did, but only that it reconstructs effectively the signals used as input for our novel algorithm.

While the range of applications may vary and unravel toward several fields, it is likely that depending on the applications the findings of this study can be furtherly refined. For example, the application of this database to neurological patient performance might benefit from fine-tuned recordings for the matching of the reference database to the peculiar features of motor impairment (e.g. reduced range of motion, jerky movements, lack of repeatability), which were not investigated in this study.

V. CONCLUSION

In this paper, kinematic-muscular synergies were extracted for the first time from EMG and kinematic data recorded during the performance of several hand grasps. The procedure allows to describe hand movements with a reduced set of multimodal components. The variability of the extracted synergies was investigated to evaluate the repertoire available to healthy people and characterize the kinematic-muscular synergies.

We found that a limited number of spatial synergies, modulated by a time-varying activation signal, underlies the execution of a large variety of upper-limb exploration movements. However, synergies were not always consistent across subjects, revealing a large inter-individual variability in hand control strategies. In general, considering a wide repertoire of movements, as well as reducing their constraints, leads to the identification of a more flexible modular architecture with respect to the ones identified in previous studies.

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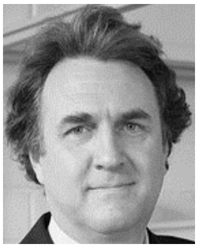

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