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Musculoskeletal Synergies in the Grasping Hand

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***Abstract*— Investigations on how the central nervous system (CNS) effortlessly conducts complex hand movements have led to an extensive study of synergies or movement primitives. Of the different types of hand synergies, kinematic and muscle synergies have been widely studied in literature, but only a few studies have fused both. In this paper kinematic and muscle activities recorded from the activities of daily living were first fused and then dimensionally reduced through principal component analysis (PCA). By using these principal components or musculoskeletal synergies in a weighted linear combination, the recorded kinematics and muscle activities were reconstructed. The performance of these musculoskeletal synergies in reconstructing the movements was compared to the kinematic and muscle synergies reported previously in the literature by us and others. The results from these findings indicate that musculoskeletal synergies perform better than the synergies extracted without fusion. These newly demonstrated musculoskeletal synergies might improve neural control of robotics, prosthetics and exoskeletons.**

***Clinical Relevance*— In this paper, musculoskeletal synergies were extracted from the fusion of kinematic and muscle activities recorded from the activities of daily living. These newly demonstrated musculoskeletal synergies might enhance our understanding of neural control of robotics, prosthetics and exoskeletons.**

I. Introduction

Evolution and natural selection have promoted the development of a longer opposable thumb and shorter fingers in humans, enabling us to perform myriad grasping actions. But even the very basic activities that we perform in our daily lives with minimal dexterity have been a remarkably complex challenge to be replicated by robots. The challenge is in replicating how the central nervous system (CNS) can select appropriate groups of muscles to achieve a specific hand movement. The human hand has more than 20 degrees of freedom, which makes this challenge even more complex. Astoundingly the CNS has no difficulty in handling such complexity in controlling the human hand.

Several hypotheses like elimination hypothesis, optimization hypothesis and modularity hypothesis have been proposed by researchers to express how the CNS effortlessly achieves complex hand movements. Out of these, modularity hypothesis introduced by Bernstein in 1967 [1] proposes that a single variable named "synergy" controls a group of functional units and each of this group is formed by CNS. This hypothesis addressed the challenge of control and coordination of hand with vast degrees of freedom (DoF).

Inspired by the modularity hypothesis by Bernstein, many researchers came forward to solve the DoF problem through different concepts of synergies. Of them, some of the popular synergies includes postural synergies [2] kinematic synergies [3], dynamical synergies and muscle synergies [4]. It can be summarized that the complex interaction of neuromuscular processes leads to musculoskeletal movements and consequently an action is performed. At the musculoskeletal level, two complex tasks are achieved efficiently by this human biomechanical system. First, a group of muscles are selected by the CNS to perform the task at hand. Studies related to muscle patterns such as [5] found that muscle activity patterns can be reconstructed through a weighted linear combination of a limited number of muscle synergies. Second, a group of skeletal finger joints are actuated to enact the task. Findings from[2] [3] suggest that through a weighted linear combination of a limited number of kinematic synergies, joint angular velocities can be reconstructed.

Though kinematic and muscle synergies were studied separately, to our understanding, only a few studies have combined muscle and kinematic synergies. By fusing muscle and kinematic activities together as a single dataset and then performing dimensionality reduction, in this paper, we extract "musculoskeletal" synergies, that can enable collaboration between kinematic and muscle synergies. This formulation allows for kinematic and muscle synergies to inform each other about their covariant characteristics.

In this paper, the objective is to identify how musculoskeletal synergies compare to individual synergies in the reconstruction of movement kinematics and muscle activities. Findings from this paper might provide better insights to the use of synergies in the field of robotics, neurorehabilitation, prostheses, and exoskeletons.

II. Methods and analysis

A. Experiment

After careful evaluation and consideration, a publicly available dataset was used for data analysis in this paper. This publicly available dataset KIN-MUS UJI [6] consisting of twenty-two right-handed subjects of which 12 are males and 10 are females with a mean age of 35 ± 9 years. All the subjects

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had no prior upper limb movement disorders. Prior to the experiment, all participants were required to provide a written informed consent. All the experiments were conducted in alignment with the rules and regulations of the Ethics Committee of the Universitat Jaume I, Spain. In order to check the ability and quality of hand while performing activities of daily living Sollerman Hand Function Test (SHFT) was performed.

Hand movements were captured by the CyberGlove (CyberGloveSystems, San Jose, CA) at a sampling rate of 100 Hz. Ten of the sensors that correspond to the metacarpophalangeal (MCP) and interphalangeal (IP) joints of the thumb and the MCP and proximal interphalangeal (PIP) joints of the other four fingers were used. Muscle activities were recorded by an 8-channel surface electromyography (sEMG, Biometrics, Ltd.) device at a sampling rate of 1000 Hz. The electrodes were placed in seven most representative areas of the forearm to capture major muscle activities. These were — (i) Flexor carpi ulnaris (FCU) (ii) Flexor carpi radialis (FCR) and palmaris longus (PL) (iii) Flexor digitorum superficialis (FDS), Flexor digitorum profundus (FDP) and Flexor pollicis longus (FPL) (iv) Abductor pollicis longus (APL) and externsor pollicis longus (EPL), and brevis (EPB) (v) Extensor digitorum communis (EDC) (vi) Extensor Carpi Ulnaris (ECU) (vii) Brachioradialis (BR), Pronator teres (PT), Extensor carpi radialis brevis (ECRB) and longus (ECRL).

B. *Preprocessing*

The raw sensor data recorded from the CyberGlove were converted to joint angles. The conversion procedures performed were based on non-linear calibration protocols discussed in [7]. These joint angles were then normalized by the maximum joint angle for each subject. Finally, the data were filtered with a second-order low-pass Butterworth filter and Savitzky-Golay filter. The sEMG data collected was normalized by the maximum sEMG values recorded for that particular area for each subject. The sEMG were ultimately filtered with a fourth-order bandpass filter between 25-500 Hz, rectified, filtered by a fourth-order low-pass filter at 8 Hz, and gaussian smoothing. Both joint angles and sEMG datasets were then synchronized by the acquisition software as mentioned in [6] to match the start and stop instants of each movement. The dataset consisting of 26 activities of daily living (ADL) and instrumented activities of daily living (IADL) tasks as mentioned in [6] was split into two sets containing equivalent tasks — a training set with 16 tasks that were used for extraction of synergies and a testing set with 10 tasks that were used for testing the reconstruction with the extracted synergies.

C. *Derivation of Synergies*

In this paper, synergies were derived from hand kinematics and muscle activities. These synergies were used to reconstruct the testing data comprising of new hand kinematics and muscle activities, thus realizing the generalizability of kinematic and muscle synergies. Of the several models available, we used both time invariant and time-variant synergy models [3]. But we found that time variant synergy model provides the best results, hence for this paper we make use of time variant synergy mode. In a time-variant synergy model, a time-varying movement pattern can be generated by combining the time-varying synergies with scaling coefficients. Hence, different movement patterns can be obtained by changing the time shifts and scaling coefficients. The following equation describes a time-variant synergy-based movement generation model expressed as a weighted linear combination of principal components or synergies.

$$M(t) = \sum_{i=1}^{N} A_i \, S_i(t - t_i)$$

where, $M(t)$ represents the generated movement at time t, A_i represents the coefficient or weight, S_i represents the ith synergy and N is the number of synergies. For determining the optimal number of synergies, based on our prior works, we used approximately 90% of the variance accounted for curve (see Fig. 1).

Kinematic and Muscle Synergies

To obtain kinematic synergies, first, a posture matrix was prepared as discussed in [3] with 16 columns corresponding to the 16 ADL tasks grouped under training dataset. Each column was formed by cascading normalized angular velocities of 10 hand joints as listed under Section II(A). Then, principal component analysis (PCA) was performed on this matrix to obtain PCs that account for maximum variance. We observed that the first 7 PCs were able to account for a variance greater than 90%. These PCs were termed as kinematic synergies.

Similar procedure was repeated on muscle activities to obtain muscle synergies. Here, a muscle activity matrix was prepared with 16 columns corresponding to 16 ADL tasks grouped under training dataset. Each column was formed by cascading normalized root mean squared (RMS) muscle activities from 7 muscle areas listed under Section II(A). It was noted that the first 3 PCs were able to account for a variance greater than 90%. These PCs were termed as muscle synergies.

Musculoskeletal Synergies

To obtain musculoskeletal synergies, the normalized muscle activities were fused or concatenated with normalized joint angular velocities. Before this fusion, we performed an important step of changing the polarity of extensor muscles (4 through 7) to negative to match with the negative polarity of extension of joint angular velocities. Resultant matrix formed

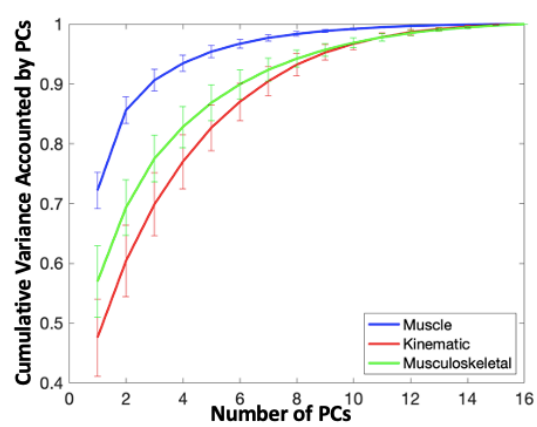

Fig. 1. Mean of muscle (in blue), kinematic (in red) and musculoskeletal (in green) variance of each PC for all subjects with error bars indicating standard deviation are illustrated here.

has 16 columns corresponding to 16 tasks. Each column was obtained by concatenating the normalized activities of muscles and joint angular velocities. This matrix was further normalized with zero mean and unit variance. PCA was performed on this matrix resulting in PCs, now termed as musculoskeletal synergies. It was noted that the first 6 musculoskeletal synergies accounted for 90% of total variance. The musculoskeletal synergies were then split into musculoskeletal kinematic synergies and musculoskeletal muscle synergies. As an example, Fig. 2 represents the first 6 musculoskeletal synergies of subject 1. To enable the comparison between the usage of kinematic, muscle and musculoskeletal synergies in reconstruction, it was required that we either use the same number of components or use same variance that is over a given threshold variance (≥ 90% here). Considering the same number of components implies comparison using the same number of synergies which is ideal for this study's use case. Thus, throughout this paper we will be using 6 PCs for each type of synergies.

D. *Reconstruction of Kinematics and Muscle Activities*

The joint angular velocities and the muscle activities in 10 testing tasks were reconstructed by the four types of synergies. Kinematic synergies and musculoskeletal kinematic synergies reconstructed the recorded movement kinematics. Muscle synergies and musculoskeletal muscle synergies reconstructed the recorded muscle activities. Reconstruction was performed by using the l_1-norm minimization detailed in [8]. The reconstruction error between the recorded movements (M_i) and the reconstructed patterns (X) was determined as follows.

$$err = \frac{\sum_i (M_i - X)^2}{\sum_i M_i^2}$$

III. Results

From movement kinematics and muscle activities recorded from 16 ADL and IADL tasks, six muscle synergies and six kinematic synergies were extracted using PCA. On an average, for all the subjects, the first synergy accounted roughly around 55% of the total variance. As mentioned in [8], in this paper as well it was noted that, while the first synergy significantly contributed to more than 50% of the total variance. This indicates that a relatively small set of the total number of synergies could adequately represent the movement. As shown in Fig. 1, 6 PCs accounted to about 87% of total variance for kinematic synergies. 6 PCs accounted for 96% of total variance for muscle synergies. 6 PCs accounted for 90 % of total variance for musculoskeletal synergies. 10 DoF joint kinematics had highest variance, then was the fused kinematic and muscle activities and lastly was 7 DoF muscle activities with least variance. Musculoskeletal synergies obtained from fusion were then split to musculoskeletal kinematic and musculoskeletal muscle synergies as shown for subject 1 in Fig. 2.

Reconstruction of the 10 ADL and IADL test tasks were performed using the muscle synergies, kinematic synergies and musculoskeletal muscle synergies and musculoskeletal kinematic synergies. Fig. 3 presents an example of reconstruction of recorded activity using these four types of synergies for subject 1 for task 8 of picking up the phone and placing it on the ear and hanging up. As mentioned in Section II(D), the reconstructed movement kinematic and muscle activities were compared with recorded activities using the least squares error between them. Figure 4 represents a comparison of the reconstruction of 10 testing tasks reconstructed using kinematic synergies and musculoskeletal kinematic synergies, and muscle synergies and musculoskeletal muscle synergies, across all subjects. Comparing the reconstruction errors across all tasks and all types of synergies, musculoskeletal synergies performed better than the synergies extracted without fusion.

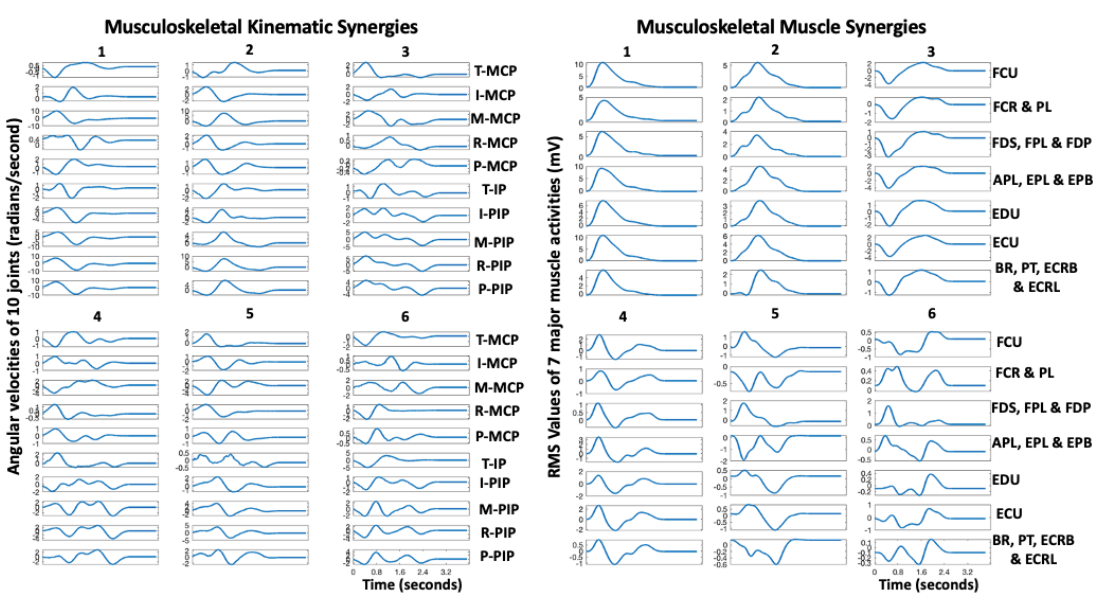

Fig. 2. First six musculoskeletal kinematic (left) and musculoskeletal muscle (right) synergies extracted from the training data of subject 1 are illustrated here. The joint angular velocities of 10 joints (MCPs of four fingers and thumb, IP of thumb and PIP of other 4 fingers) and RMS of the muscle activities from seven major muscle groups were shown here.

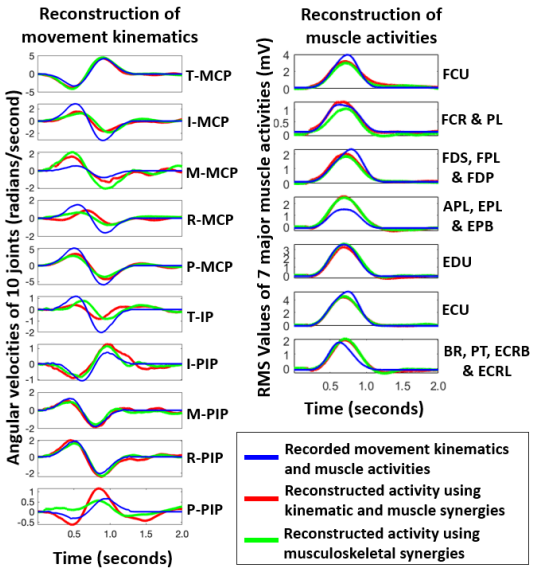

Fig. 3. Reconstruction of test task 8 (picking up the phone, placing it on his/her ear and hanging up the phone) of both movement kinematics (left) and muscle activities (right) of subject 1 is shown here.

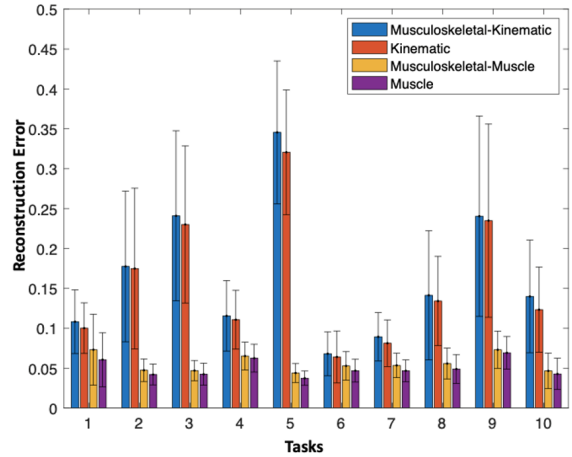

Fig. 4. Reconstruction error obtained while reconstructing the 10 ADL test tasks using synergies obtained with and without fusion for all subjects are shown here. Overall musculoskeletal synergies performed better than synergies extracted without fusion. Bars indicate mean and errors bars indicate standard deviation across all subjects.

IV. Discussion

This paper presents a new method of fusion of movement kinematics and muscle activities and then derives musculoskeletal synergies. To our best knowledge, this is one of the first attempts to simultaneously extract kinematic and muscle synergies. Such fusion enables full interaction across multiple recording modalities such as kinematics and sEMG. We hypothesized that such mutually informed interaction will lead to improved representations in lowdimensional spaces. Before we performed the fusion, we added a critical step of changing the polarity of extensor muscles as explained in Section II(C). Thus, when the fusion occurs, the extension in kinematics is strengthened by the extension reflected in muscle activities. Without this change in polarity all RMS muscle activities remain positive for both flexor and extensor muscles and in contrast, all kinematic activities remain positive for flexion and negative for extension. Fusion, without taking this polarity into account can be detrimental.

Several studies have demonstrated strong correlations between neural, muscle and kinematic synergies. In [4] it was shown that muscle synergies align with kinematic synergies. In [9] muscles synergies were used as a predictive framework for the EMG patterns of new hand postures. In [10] it was found that spinal motor neuronal activities exhibit a synergistic organization that could be reflected in the neural drive received by muscle synergies. Inspired by these studies, in this paper, we allowed for the fusion of two modalities: movement kinematics and muscle activities. This fusion encourages the collaboration of both activities thus promoting learning between each other. Overall, the results reflect that the musculoskeletal synergies obtained from such fusion perform better in reconstruction of movements as shown in Fig. 4 when compared to the synergies extracted without fusion.

V. Conclusion

In this paper, we proposed a new method to extract musculoskeletal synergies using fusion and PCA. In the near future, we will substantiate these results over larger datasets, and we will further improve these fusion synergies by incorporating other dimensionality reduction methods such as independent component analysis, independent vector analysis and nonnegative matrix factorization. Embedding these fusion synergies into robotics [11] and exoskeletons can possibly enhance their performance.

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