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**CONTROL OF MUSCULOSKELETAL ARM MODEL USING MUSCLE SYNERGY**

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**Preferred Presentation:** Oral Presentation
**If your abstract is not accepted as an oral do you wish to be considered for a poster?:** Yes
**Clinical Biomechanics Award:** No
**David Winter Young Investigator Awards:** Yes
**David Winter Award - presentation Preference:** Oral
**Emerging Scientific Award sponsored by Professor J De Luca:** Yes
**Promising Scientist Award sponsored by Motion Analysis:** Yes

**Introduction and Objectives:** Muscle synergy has been considered as a possible mechanism employed by the human nervous system to control movements [1]. This theory suggests that the nervous system may contain sets of muscle activity patterns, i.e. certain muscles are activated together via fixed patterns. Many researchers have studied the synergies by looking at the measured muscle activity signals, but few have used synergies to generate a desired action using the muscle synergy framework. In this project, we have used muscle synergies to control the motion of a musculoskeletal arm model.

**Methods:** A planar 2 degree of freedom musculoskeletal arm model is studied in this project. The arm muscles (Hill-type muscle model) are lumped into six muscle groups, including mono- and bi-articular flexors and extensors (see Fig. A). We have used muscle synergies to produce arbitrary hand acceleration, efficiently and in real-time. This two-stage process is described below.

**1. Identifying the synergies**

The measurable muscle activities during an action is the summation of multiple synergies. Non-negative matrix factorization (NNMF) is widely used to extract the underlying synergies from the measurable muscle activities [2], and has been used here to obtain the synergies.

First, we used a standard optimization routine to find the muscle activation levels that would result in a certain hand acceleration. This optimization problem was solved for a variety of joint angle configurations, and different directions of hand acceleration. Next, this large data set is used to obtain the muscle synergies. In each joint angle configuration, matrix $\mathbf{A}_{6\times24}$ containing the six muscle activities for 24 acceleration directions is formed. With NNMF, matrix $\mathbf{A}$ can be approximated as $\mathbf{A}_{6\times24} \approx \mathbf{S}_{6\times m}\, \mathbf{C}_{m\times24}$, where $m$ is the number of synergies, and $\mathbf{S}$ and $\mathbf{C}$ are the synergy and coefficient matrices, respectively.

For this project, it is assumed that the synergies are posture-dependent [3]; i.e. the synergy matrix $\mathbf{S}$ is a function of the two joint angles. Although the synergies are calculated at a limited number of joint angle configurations, it is possible to obtain the synergies at an intermediate posture by interpolating the synergy matrix data.

**2. Using the synergies to produce arbitrary hand accelerations**

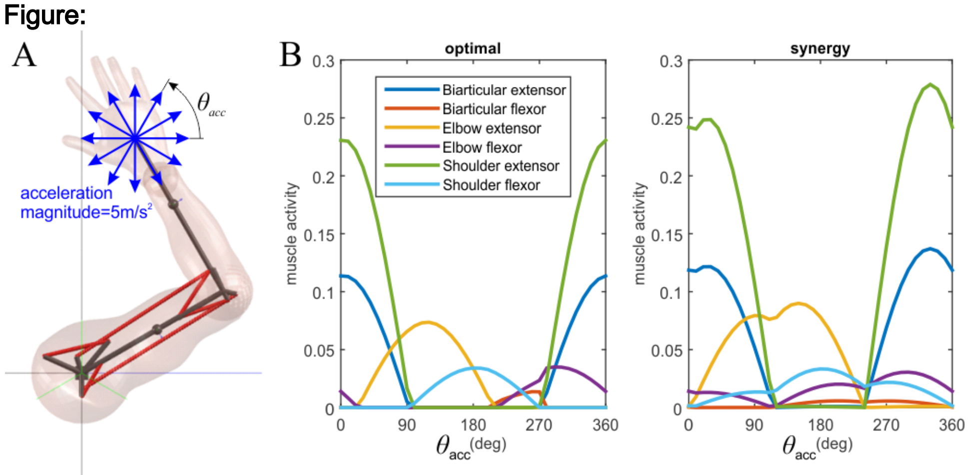
The activation of each synergy results in hand acceleration in a certain direction. The acceleration vectors resulting from all $m$ synergies can be considered as a basis set for the two-dimensional vector space. In other words, any arbitrary hand acceleration vector can be written as a linear combination of the synergy-produced acceleration vectors. Since the synergies can only be activated in one direction (muscles can only pull), the linear combination is meaningful only if the coefficients are positive, which leads to a positive decomposition problem.

Mathematically, in an $n$-dimensional space, $n$+1 basis vectors are necessary for positive decomposition of any arbitrary vector. With three synergies, our 2D decomposition problem will have a unique solution. The uniqueness of the answer is one fundamental aspect that is missing in many muscle synergy studies. In general, if the muscle synergies are obtained

so that the generalized forces generated by the synergies span the operational space, there will be a unique solution to the synergy-sharing problem, and consequently a unique solution for the muscle force-sharing problem.
Additionally, since the relation between the muscle activations and the resulting acceleration is linear in this approach, the same coefficients of the vector decomposition can be used to make linear combinations of the synergies, which will result in the desired hand acceleration.

**Results:** Fig. B shows the activity of the six muscles versus the direction of the hand acceleration. The synergy-based control is compared against the optimal solutions. As can be seen, the activity patterns are similar, but not identical. The small difference is unavoidable with the dimension reduction of muscle synergies. The time to calculate the solution, however, is substantially lower in the proposed synergy method (20 times faster than the optimization).

**Figure:**




**Caption:** A. The 2D arm model. B. Comparison of the muscle activities: muscle synergy versus optimization.

**Conclusion:** We showed that muscle synergies can be used to control a musculoskeletal arm in real-time. Using this muscle synergy approach, the indeterminate force-sharing problem reduces such that the solution is unique. Our results showed that the dimension reduction allows for the fast solution of the force-sharing problem in musculoskeletal systems, while resulting in close to optimal muscle activities. Our method can be enhanced by introducing closed-loop control logic that may include predictive and learning properties of the human motor control system.


**References:** [1] Bizzi et al., Brain Res Rev, 57 (1), p. 125-133, 2008.
[2] Moghadam et al., Comput Method Biomec, 16 (3), p. 291-301, 2013.
[3] de Rugy et al., Front Comput Neurosc, 7 (Mar), p. 1-13, 2013.


**Disclosure of Interest**: None Declared