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Methodological Choices in Prediction of Unmeasured Muscle Excitations with the Measured Muscle Synergies

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INTRODUCTION

EMG-driven musculoskeletal modeling relies on measurements of muscle activity to estimate muscle forces, which is typically obtained with surface electromyography (sEMG). sEMG is non-invasive to record, but is unable to capture the activity of deeply located muscles that highly contribute to the generation of joint moments. As an alternative resource to measure muscle excitations, intramuscular EMG recording is potentially risky by applying the fine wire to the region where pathological tissue develops. One example, which is one of the long-term interests of this study, is the tumor growing up in the hip region of pelvic sarcoma patients and thus iliopsoas muscle groups cannot tolerate a fine wire.

To interact with the complex environment and accomplish the multidimensional dynamic motor tasks, the nervous systems simplify the motor control by identifying the coordinative modules [1]. Muscle synergies extracted from muscle excitations are commonly used representation of these coordinative modules. Previous work has shown that the muscle synergies extracted from a group of muscle excitations performed well in construction of the other muscle excitations [2]. Hence, it is convincing that the unmeasured deep muscle excitations may be able to be rebuilt by taking advantage of the extrapolative property of measured muscle synergies (henceforth called 'synergy extrapolation').

Numerous methodological choices are required throughout the synergy extrapolation process, which may have strong effect on prediction accuracy of the unmeasured muscle excitations. In this study, we assessed the impact of three major methodological decisions on the performance of synergy extrapolation: 1) two matrix factorization algorithms for identification of measured muscle synergies, 2) four EMG normalization approaches before synergy extraction and 3) number of synergies computed. We hypothesized that one or more methods would benefit the others in improving estimation accuracy of unmeasured muscle excitations.

METHODS

In this study, we used previously published dataset (joint kinematics, ground reaction force, 16-channel EMGs) that was collected from the non-paretic leg of a post-stroke patient during walking on an instrumented treadmill at his self-selected speed (0.5m/s) and relatively high speed (0.7m/s) (5 trials in each speed) [3]. Iliopsoas was taken out as 'unmeasured' muscle and the remaining 15 muscles were assumed to be 'measured'. All the experimental EMGs were processed by high-pass filtering (40 Hz), full-wave rectifying and low-pass filtering (3.5/tf, where tf is the period of the gait cycle being processed) before normalization with four different approaches [4]: 1) maximum value over all trials (MaxOver); 2) maximum value per trial (MaxPer); 3) unit variance per trial (UnitVar); 4) unit magnitude per trial (MagPer).

Principal component analysis (PCA) and non-negative matrix factorization (NMF) were applied on normalized measured muscle excitations to extract the measured muscle synergies and corresponding weights. The iliopsoas muscle excitations were then reconstructed with the measured synergies and the unmeasured weights and mean values for PCA. The last two quantities that could be identified during the optimization process as described below. The joint moments were estimated using a custom 35-muscle 5-DOF lower-extremity musculoskeletal model with both experimental measured muscle excitations and reconstructed unmeasured muscle excitations conveyed into it [3]. The optimal unmeasured weights and mean values for PCA were calibrated by minimizing the sum of the mean square differences between the predicted and experimental joint moments of all DOFs over all trials. The patient-specific muscle parameters in the model were optimized with all 16-channel EMG signals included in the beginning and then were held given during synergy extrapolation process. The similarity in the shape and amplitude between experimental and reconstructed iliopsoas muscle excitations was quantified by the root mean square error (RMSE) and Pearson correlation coefficient (r) with the number of synergies varying from 3 to 8.

RESULTS AND DISCUSSION

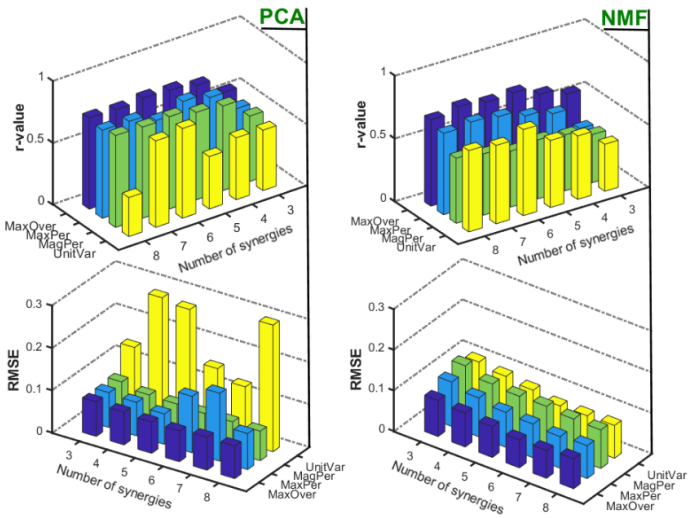

Fig 1: The averages of r and RMSE values between experimental and predicted 'iliopsoas' muscle excitations across all trials with different methodological choice.

Across all EMG normalization approaches, for PCA-based synergy extrapolation, MaxOver and MagPer could generate significantly more accurate and stable prediction than the other two methods (Fig.1, left column). For NMF-based synergy extrapolation, MaxOver, MaxPer and UnitVar could produce comparable levels of performance in tracking experimental iliopsoas muscle excitations ($r>0.6$, $RMSE<0.1$), while MagPer was not able to reproduce the iliopsoas muscle excitations properly (Fig.1, right column).

Between two matrix decomposition methods, with MaxOver, both PCA and NMF demonstrated similar ability of resembling the iliopsoas muscle excitations during swing phase (60-100% of a gait cycle), but the PCA was more capable to rebuild the iliopsoas excitations during stance phase (0-60% of a gait cycle) (Fig. 2). However, with MagPer, the performance in synergy extrapolation differs substantially between PCA and NMF. Generally, PCA-based synergy extrapolation with MagPer produced the best prediction of iliopsoas muscle excitations among all methods at various number of synergies.

With either MaxOver or MagPer normalization, note that both r and RMSE values approached a plateau with increasing numbers of synergies and for both the PCA and NMF, the iliopsoas muscle excitations were rebuilt fairly accurately well by six synergies or above.

PCA operation can be thought of as revealing the internal structure of the data in a way that best explains the variance in it. That might be the reason why the measured synergies extracted from normalized EMGs of unit variance (UnitVar) using PCA failed in synergy extrapolation. This also explains the subtle fluctuations of the muscle excitations during stance phase could be better represented by PCA-based synergies than NMF-based ones. Similarly, NMF decomposition is based on assessment of quality of the magnitude approximation. MagPer normalization was not suitable for NMF-based synergy extrapolation, because normalization to the norms shrunk the peaks in the original measured muscle excitations, which provided the inaccurately shrunken synergies.

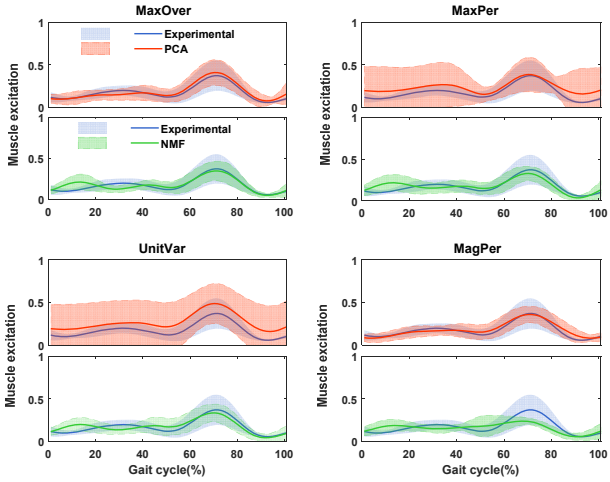

Fig 2: Representative average and standard deviation of experimental and predicted iliopsoas muscle excitations across all trials with four EMG normalization and two matrix factorization methods at 6 synergies.

CONCLUSIONS

Methodological choices had exhibited a profound influence on the performance of synergy extrapolation. MaxOver and MagPer were the best performing methods across all four EMG normalization approaches. However, MagPer normalization could be more beneficial than MaxOver, because the intrinsic challenge in attaining true maximum muscle excitations could be circumvented by performing normalization within individual trials. Also, PCA could provide us more benefits in finding quick, unique, and reliable muscle synergies for extrapolation and in estimating the unmeasured muscle excitations through the entire gait cycle than NMF could. The prediction of unmeasured muscle excitations is a crucial piece in improvement of subject-specific EMG-driven musculoskeletal modeling and thus offering better assessment of different surgical and rehabilitative strategies.

REFERENCES

1. Tresch MC, et al. *J Neurophysiol* **95**, 2199-2212, 2006.
2. Bianco NA, *J Biomech Eng* **140**: 011011, 2018.
3. Meyer AJ, *PloS One* **12**: e01796, 2017.
4. Banks CL, *Front Comput Neurosc* 11: 78, 2017.

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