XVII International Symposium on Computer Simulation in Biomechanics
July 28th – 30th 2019, Alberta, Canada

Methodological Choices in Synergy-Informed Optimization for Muscle Activation Estimation

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INTRODUCTION

Estimation of muscle forces during human movement could facilitate the development of improved interventions for disorders such as osteoarthritis, stroke, cerebral palsy, and Parkinson's disease [1]. Static optimization, applied one time frame at a time, is used to estimate muscle activations, which leads to minimized antagonistic coactivation. Muscle synergies from non-negative matrix factorization (NMF) have been used previously within static optimization (SO) to limit the achievable predicted muscle activations by reducing solution indeterminacy and increasing physiological co-activation [2]. Methodological decisions, such as EMG normalization and decomposition approach, highly influence the NMF results and should be studied.

This study describes a computational approach (synergy-informed optimization—SIO) for using muscle synergies to resolve indeterminacy in estimating leg muscle forces during walking and evaluates how the number of synergies, EMG normalization, and decomposition method affect muscle activation and joint moment estimates compared to experimental data.

METHODS

Walking data (Motion, ground reaction, and EMG of 10 trials at self-selected speed) from a previous study of a patient post-stroke with significant walking dysfunction were used [3]. A modified OpenSim ([4]) model with 31 degrees of freedom (DoFs; 5 per leg) and 35 leg muscles was used for an initial musculoskeletal analysis, including scaling and inverse kinematics and dynamics. Next, musculoskeletal parameters of the model were calibrated within an EMG-driven simulation [3].

EMG signals were normalized based on 4 different quantities: max value observed over all trials (MaxOver), max value per trial (MaxPer), unit variance (UnitVar), and unit 2-norm (MagPer). Two factorization analyses extracted muscle synergy commands and weights from normalized EMG signals: 1) Concatenated non-negative matrix factorization (CNMF) that decomposed EMGs from 9 arbitrarily chosen trials and 2) Traditional trial-specific NMF that decomposed EMGs of the remaining trial from the CNMF case. Note that CNMF assumed the synergy weights were fixed among all trials [5]. The resulting synergy weights of both NMF analyses were then passed to SIO to solve all time frames together for optimal muscle synergy commands C of the 10th trial by minimizing the error from tracking inverse dynamics moments (M) over one gait cycle. Synergy commands were parameterized with 21 control nodes and resampled to 101 points using B-splines. MATLAB *lsgnonlin* was used to solve the following:

$$\min_{C_k} \sum_{k=1}^{101} \left(\sum_{i=1}^{35} \sum_{j=1}^{5} (M_{jk} - \sum_{i=1}^{35} r_{ijk} F_{ik}(\mathrm{C_k}))^2 \right) \text{ with } \mathrm{C_k} \geq 0$$

where r and F are muscle moment arm and force, respectively. Note that the objective function above is only joint moment tracking, and no physiological effort minimization was assumed in this optimization.

RESULTS AND DISCUSSION

As the number of synergies increased, factorization variance accounted for (VAF) and average joint moment matching quality (R^2) was improved (Table 1). Cases with 2 and 3 synergies were deemed insufficient ($R^2<0$). MaxPer led to higher correlations between activations and EMGs, which might be due to the fact that NMF (and CNMF) works based on magnitude unlike PCA that is variance-based.

Muscle activations from the synergy-informed optimization approach showed a significantly higher correlation with EMG data compared to those from the traditional SO. As an example, for 6 synergies with MaxPer, mean correlation between estimated activations and EMGs were 0.88, 0.71, and 0.54 for SIO with NMF synergy weights, SIO with CNMF synergy weights, and SO, respectively (Fig. 1). NMF resulted in more accurate activations compared to CNMF, since SIO-NMF used trial-specific synergy weights.

Increasing the number of synergies did not increase the correlation between activation and EMG. This could be related to the increase of moment tracking that came at the cost of lower activation estimation quality.

In case 6 synergies were chosen, the number of unknowns was 126 (6 synergies x 21 control nodes) whereas the number of known equations were 505 (5 DoFs x 101 time frames), which made the problem overdetermined unlike the SO-based synergy optimization [2]. However with 7 and 8 synergies, SIO converged to different solutions once different initial guesses were used for the optimization. Although the number of unknowns (147 and 168, respectively) was still less than 505 and the optimization problem was theoretically over-determined, in practice, these two cases remained under-determined since neighboring time frames were not independent from one another.

The musculoskeletal model used in this study had been calibrated using an EMG-driven framework. This made the EMGs consistent with the joint moments and therefore might have increased the chance of SIO to find more accurate activations. Future work on using a generic musculoskeletal model with this approach seems warranted.

Although activation minimization has been commonly used in musculoskeletal simulations of healthy subjects (despite poor agreement with the activation estimates and EMG), there is no evidence that subjects with movement or neurological disorders apply this assumption as their neural control strategy. SIO may be the approach to estimate muscle activations and forces in different populations with no assumption on the physiological optimality, unlike static optimization.

CONCLUSIONS

Synergy-informed optimization requires *a priori* muscle synergy information, which in the case of CNMF can be from a limited number of trials. Despite that, SIO did not make any assumption about effort minimization and with a suitable EMG normalization method such as MaxPer showed to be promising in the estimation of muscle activation.

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ACKNOWLEDGEMENTS

Cancer Prevention Research Institute of Texas (CPRIT) funding RR170026

Table 1. Effect of 4 different normalization methods, 2 different factorization ways, and number of synergies on the quality of joint moment tracking (mean R^2 across all degrees of freedom) and correlation of muscle activation estimates and EMG (mean Pearson correlation across all muscles)

Normalization	# Synergies	4		5		6	
	Factorization	CNMF	NMF	CNMF	NMF	CNMF	NMF
MaxOver	VAF	98.8	99.2	99.4	99.6	99.7	99.7
	r	0.69	0.82	0.53	0.63	0.54	0.73
	R^2	0.93	0.98	0.96	0.99	0.99	0.99
MaxPer	VAF	94.9	98.4	96.4	98.8	97.9	99.4
	r	0.59	0.83	0.56	0.83	0.71	0.88
	R^2	0.93	0.98	0.98	0.99	0.99	0.99
UnitVar	VAF	95.6	98.5	97.6	98.8	98.2	99.3
	r	0.65	0.83	0.67	0.85	0.67	0.79
	R^2	0.96	0.98	0.98	0.99	0.99	0.99
MagPer	VAF	95.2	98.6	96.6	98.9	97.7	99.5
	r	0.65	0.82	0.65	0.84	0.59	0.88
	R^2	0.96	0.98	0.97	0.99	0.99	0.99

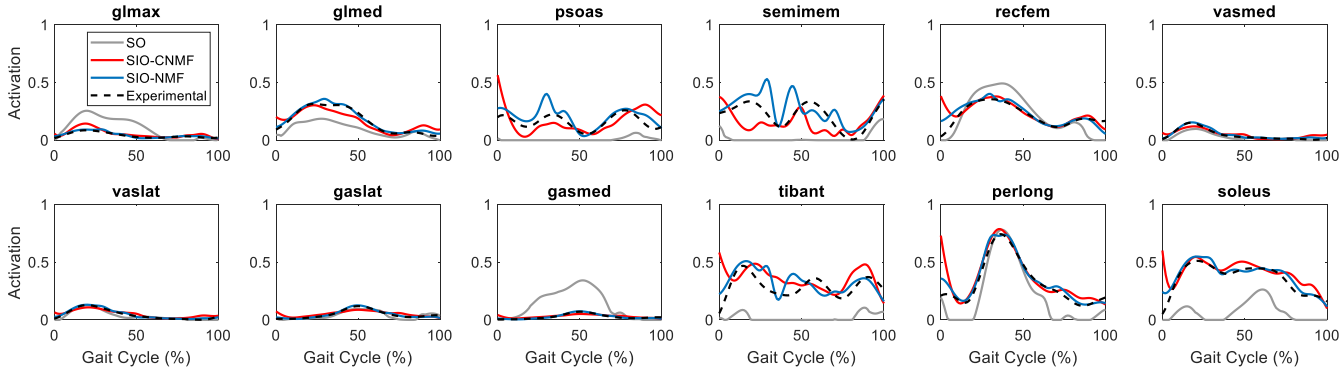

Figure 1: Muscle activation estimates of synergy informed optimization (SIO-CNMF: SIO using CNMF synergy weights; SIO-NMF: SIO using trial-specific NMF synergy weights) using 6 synergies and MaxPer normalization versus static optimization (SO) and experimental muscle activity for gluteus maximus (glmax), gluteus medius (glmed), psoas, semitendinosus, rectus femoris, vastus medialis (vasmed) and lateralis (vaslat), gastrocnemius lateralis (gaslat) and medialis (gasmed), tibialis anterior (tibant), peroneus longus (perlong), and soleus.