Gait & Posture 74 (2019) 223–230

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Full length article

Inverse dynamic estimates of muscle recruitment and joint contact forces are more realistic when minimizing muscle activity rather than metabolic energy or contact forces

Azin Zargham[a,*], Maarten Afschrift[a], Joris De Schutter[b], Ilse Jonkers[a], Friedl De Groote[a]

[a] Department of Movement Sciences, KU Leuven, Leuven, Belgium
[b] Department of Mechanical Engineering, KU Leuven, Robotics Core Lab of Flanders Make, Belgium

ARTICLE INFO

Keywords:
Muscle redundancy problem
Muscle coordination
Gait
Musculoskeletal model
Optimization

ABSTRACT

Background: Assessment of contact forces is essential for a better understanding of mechanical factors affecting progression of osteoarthritis. Since contact forces cannot be measured non-invasively, computer simulations are often used to assess joint loading. Contact forces are to a large extent determined by muscle forces. These muscle forces are computed using optimization techniques that solve the muscle redundancy problem by assuming that muscles are coordinated in a way that optimizes performance (e.g., minimizes muscle activity or metabolic energy). However, it is unclear which of the many proposed performance criteria best describes muscle coordination.

Research question: Which performance criterion best describes muscle recruitment patterns and knee contact forces recorded using electromyography (EMG) and load cell instrumented prostheses?.

Methods: We solved the muscle redundancy problem based on six different groups of performance criteria: muscle activations, volume-scaled activations, forces, stresses, metabolic energy, and joint contact forces. Computed muscle excitations and knee contact forces during over-ground walking were validated against recorded EMG signals and measured contact forces for four subjects with instrumented knee prostheses in the "Grand Challenge Competition to Predict in Vivo Knee Loads" dataset.

Results: Performance criteria based on either stress or muscle activation (either unscaled or scaled by muscle volume), both to a power of 3 or 4, resulted in the best agreement between measured and simulated values. These performance criteria outperformed all other criteria in terms of agreement between simulated muscle excitations and EMG, whereas good agreement between measured and predicted contact forces was also observed for minimization of contact forces and metabolic energy.

Significance: Given the large differences in accuracy obtained with different performance criteria (e.g., root mean square errors of contact forces differed up to 0.45 body weight), the results of our study are important to improve the validity of *in silico* assessment of joint loading.

1. Introduction

Assessment of knee contact forces is essential for a better understanding of mechanical factors affecting osteoarthritis [1] and the longevity of total knee arthroplasty [2]. Since contact forces in intact knees cannot be measured non-invasively, computer simulations have been commonly used to assess joint loading [3]. A common approach is using musculoskeletal modeling combined with measured kinematics and external forces to compute muscle forces. Joint contact forces are then determined based on the resultant muscle forces [4]. However, estimation of muscle forces is complicated due to the overactuation of human joints. Optimization methods solve the muscle redundancy problem by assuming that individual muscle contributions to joint torques optimize performance [5].

Multiple performance criteria for solving the muscle redundancy problem have been suggested. Yet, it is unclear which criterion results in the most accurate estimate of muscle forces. The main performance criteria can be classified into minimizing (1) muscle activations [5], (2) muscle activations scaled by muscle volumes [6], (3) muscle forces [5,7], (4) muscle stresses [7–9], (5) muscle metabolic energy

* Corresponding author.
E-mail addresses: azin.zargham@kuleuven.be (A. Zargham), maarten.afschrift@kuleuven.be (M. Afschrift), joris.deschutter@kuleuven.be (J. De Schutter), ilse.jonkers@kuleuven.be (I. Jonkers), friedl.degroote@kuleuven.be (F. De Groote).

https://doi.org/10.1016/j.gaitpost.2019.08.019
Received 27 March 2019; Received in revised form 22 July 2019; Accepted 26 August 2019
0966-6362/

expenditure [10], and (6) joint contact forces [11]. The first four groups have been suggested to maximize muscle endurance [8]. For repetitive and prolonged activities like walking, endurance is presumed to play a key role in selecting muscle coordination [8]. Experimental studies found that muscle endurance is inversely related to muscle force to a power between 1.5 and 5 [12]. Minimizing muscle forces, however, does not account for differences in the muscles' potential for force production. Muscle stress is an alternative for muscle force that takes into account muscle strength by normalizing muscle force by physiological cross sectional area (PCSA) [8]. The instantaneous force generating potential of muscles is also function of their length and velocity, which are neglected in the stress performance criterion. Hence, muscle activation (i.e., the ratio of muscle force and instantaneous maximal force) accounts for the dependence of muscle force on length and velocity [5]. Scaling of muscle activation by muscle volume was introduced to more uniformly distribute stress over synergistic muscles [13]. Humans prefer to walk with a step length and speed that minimizes metabolic energy consumption. Accordingly, it has been hypothesized that minimization of metabolic energy underlies muscle selection [14]. A recent study suggested that minimization of joint contact forces results in more accurate contact force estimates by preventing excessive loading of the joints [11].

A comprehensive study comparing all these different criteria is lacking, although partial comparisons have been made. Monaco et al. compared performance criteria based on muscle stress with different powers and found that powers of 2.74–4 resulted in the best fit with electromyography (EMG) [9]. Pedotti et al. concluded that minimizing muscle activations with a power of 2 outperformed minimizing muscle forces, and muscle activations with a power of 1 [5]. Ackermann et al. compared muscle activations and volume-scaled muscle activations with different powers and found that minimizing volume scaled activations with a power of 10 produced realistic 2D gaits [6]. Collins et al. found that minimizing muscle forces, muscle stresses, muscle powers, and joint contact forces resulted in similar activity patterns during gait while minimizing ligament forces was least successful in reproducing EMG data [7]. However this study did not include minimization of metabolic energy expenditure, muscle activations with a power of 2 (the best criterion according to [5]), and stress with powers of 2.74–4 (outperforming power 1 according to [9]).

While previous studies evaluated optimality criteria based on the agreement between simulated muscle excitations and EMG, further insight can be gained by comparing measured and estimated contact forces. Joint contact forces are mainly determined by muscle forces, and hence, by muscle coordination [15]. Therefore, we used, for the first time to our knowledge, contact forces as an additional means over EMG signals to evaluate different performance criteria for multiple subjects. *In vivo* measured joint contact forces [16] that could be used for this purpose are available for subjects with instrumented knee prostheses. Comparing measured and simulated contact forces is especially useful since EMG is a qualitative measure restricted to a subset of superficial muscles.

We evaluated an extensive set of performance criteria to identify the criterion that best predicts muscle recruitment and therefore results in the most accurate estimation of knee contact forces. We investigated six different groups of performance criteria, including muscle activations, muscle activations scaled by muscle volume, muscle forces, muscle stresses (each with powers of 1, 2, 3, 4, and 10), metabolic energy consumption and joint contact forces. We used a computationally efficient formulation for solving the muscle redundancy problem while accounting for muscle dynamics [17]. Accounting for muscle dynamics was essential for investigating performance criteria related to muscle states, such as metabolic energy consumption. Computed muscle excitations and contact forces were validated against EMG and measured contact forces in four subjects with an instrumented knee prosthesis [16].

2. Methods

2.1. Experimental data

Data was previously collected in four older adults with instrumented knee implants (mass = 72.9 ± 4.7 kg, height = 171 ± 6 cm, age = 86 ± 1 years) available through the third to sixth "Grand Challenge Competition to predict in vivo Knee Loads" [16] (see supplementary table S2 for subject specifications). For each subject, data for four gait trials (beginning at heel strike of the instrumented knee side) of over-ground walking at a self-selected speed (1 ± 0.24 m/s) was used. Data included marker trajectories, ground reaction forces, measured tibio-femoral contact forces, and EMG of 13 muscles.

2.2. Musculoskeletal model

Data was processed based on a generic musculoskeletal model (OpenSim Gait2392) [18] containing 6 rigid body segments (pelvis, femur, tibia, talus, calcaneus, and toes), 9 degrees of freedom (ball-–socket joints with 3DOF for hip and knee joints, and hinge joints with 1DOF for ankle, subtalar, and metatarsophalangeal joints), and 43 Hill-type muscle-tendon actuators per leg. The generic model was scaled based on marker positions collected during a static trial. Gastrocnemii and soleus tendon stiffness was reduced by 30 percent to better match experimental Achilles tendon stiffness in older adults [19].

2.3. Dynamic simulation of motion

Joint kinematics during walking were estimated from the 3D marker trajectories using a Kalman smoothing algorithm [20]. Inverse dynamics joint torques were then computed based on the estimated joint kinematics and measured ground reaction forces using OpenSim's Inverse Dynamics tool. Joint kinematics were input to calculate muscle-tendon lengths and moment arms using OpenSim's Muscle Analysis tool. Subsequently, the muscle redundancy problem was solved by minimizing a performance criterion while accounting for muscle dynamics using direct collocation [17]. Muscle dynamics consists of both activation dynamics, which relate muscle excitations to muscle activations [21], and Hill-type contraction dynamics, which relate muscle activations to muscle forces [22]. The muscle torques were imposed to match the inverse dynamics hip, knee flexion/extension, and ankle torques. The muscle redundancy problem could be solved for a single leg, since the muscle force distribution in one leg does not influence the force distribution in the other leg. We used six groups of performance criteria (Fig. 1B). The first four groups minimized the sum of muscle activations, volume-scaled muscle activations, muscle forces, and muscle stresses, each with powers of 1, 2, 3, 4, and 10. Muscle stress was defined as muscle force divided by PCSA, obtained by dividing the muscle's maximal isometric force by a specific tension of 61 N/cm^2 [23]. The fifth and sixth groups minimized metabolic energy expenditure, calculated using Umberger et al.'s model [24], and the sum of squared joint contact forces in the hip, knee, and ankle joints. Contact forces at each joint were calculated as the sum of the net intersegmental joint forces and muscle forces spanning the joint. The direction of muscle forces acting on each body were obtained using an OpenSim plugin [25]. Knee contact forces were calculated using OpenSim's Joint Reaction analysis based on calculated muscle forces. Fig. 1 summarizes this workflow.

2.4. Outcome measures

The first outcome to evaluate the different performance criteria was the correlation between predicted muscle excitations and EMG signals for 13 muscles for which EMG was measured (semimembranosus, biceps femoris, vastus lateralis, rectus femoris, medial and lateral gastrocnemius, tensor fasciae latae, tibialis anterior, peroneus longus,

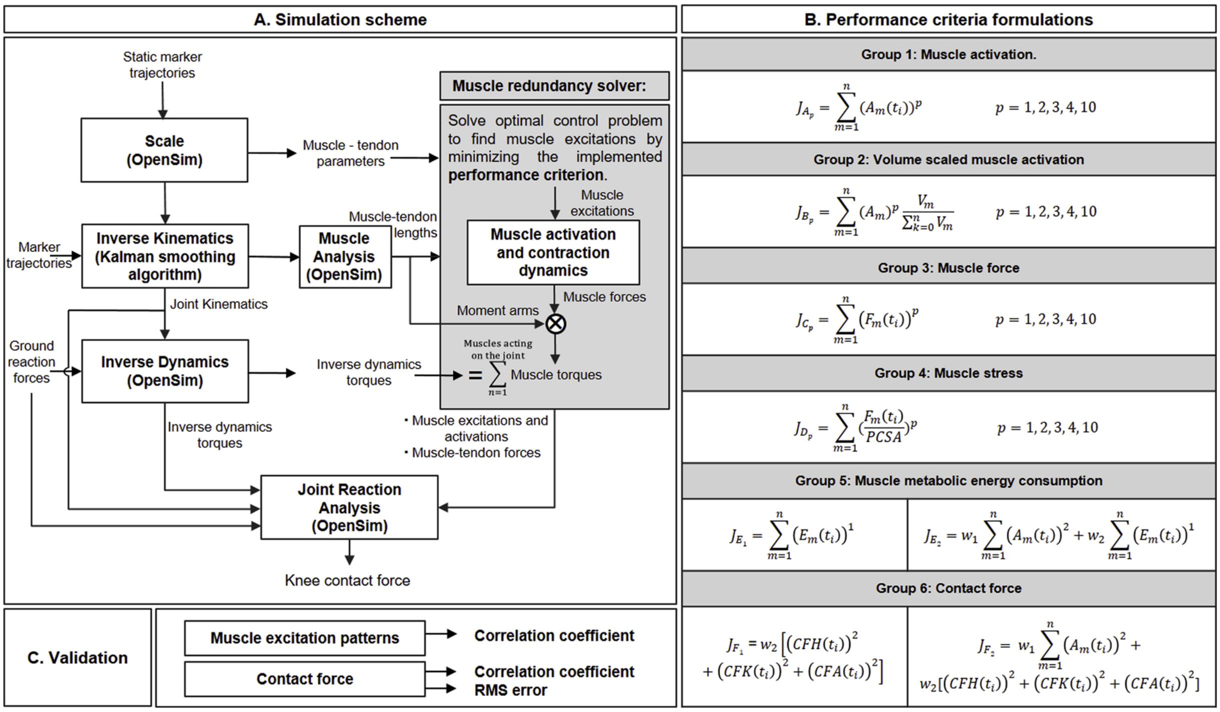

Fig. 1. Illustration of the inverse dynamics-based workflow for the estimation of muscle and contact forces (A) using 6 different groups of performance criteria (B).

soleus, gluteus maximus, adductor magnus, and sartorius). EMG signals were band-pass filtered (20–300 Hz), full wave rectified, and low-pass filtered (10 Hz). Pearson's correlation coefficient was used to evaluate the similarity between measured and predicted muscle coordination patterns independent of amplitude, which cannot be accurately obtained through EMG. The second outcome was the root mean square (RMS) error and the Pearson's correlation coefficient between predicted and measured knee contact forces. Correlation coefficients and RMS errors were calculated for each trial based on all time frames within the trial.

3. Results

Muscle excitations and knee contact forces were both estimated most accurately when using performance criteria based on either activation, volume-scaled activation, or stress with a power of 3–4 (Fig. 2A-B). These criteria resulted in the highest correlation coefficients for both contact forces and muscle excitations (Fig. 2A), and low RMS errors for contact forces (Fig. 2B). Activations, volume-scaled activations, forces, and stresses with a power of 1 were the least successful criteria in reproducing muscle recruitment patterns and/or knee contact forces (Fig. 2).

Activation, volume-scaled activation, force, and stress criteria with a power between 2–4 resulted in similar correlation coefficients between EMG signals and predicted muscle excitations. Correlations were markedly lower for activation, volume-scaled activation, force, and stress criteria with a power of 1, as well as for metabolic energy and contact force criteria. Correlations varied between different muscles (Table 1). None of the performance criteria accurately estimated rectus femoris, adductor magnus or sartorius activation (Table 1, Fig. 2).

The performance criteria influenced the amplitude of the estimated muscle excitations (Fig. 3 for subject 1 and Fig. S2-S5 in supplement for subjects 2–4). Scaling versus not scaling activations by muscle volume favored excitation of smaller muscles like tensor fascia latae, and lateral gastrocnemius and lowered the excitation level of larger muscles such as gluteus maximus, medial gastrocnemius, and soleus (Fig. 3A-B). Minimizing muscle forces resulted in high excitations of muscles with smaller maximal isometric forces (e.g., tensor fascia latae, sartorius, lateral gastrocnemius) and low excitations in muscles with higher maximal isometric forces (e.g., iliacus, psoas, soleus) (Fig. 3C). In contrast, scaling muscle forces by PCSA in the stress-based criteria resulted in higher excitations of muscles with smaller maximal isometric forces (Fig. 3D). In general, higher powers resulted in rather uniform excitations across muscles, whereas lower powers and minimizing contact forces and metabolic energy resulted in the recruitment of a limited number of muscles with high levels of excitation (Fig. 3). Minimizing metabolic energy resulted in high excitation of smaller muscles (e.g., tensor fascia latae, sartorius, lateral gastrocnemius; Fig. 3E). Minimizing contact forces led to low excitations of bi-articular muscles (e.g. medial gastrocnemius, semimembranosus, Fig. 3F). Unlike the other criteria, both metabolic energy and contact forces failed to predict the experimentally observed (EMG) co-contraction of antagonistic quadriceps-hamstrings muscles during loading response (Fig. 3E-F).

Best agreement between measured and predicted contact forces, i.e., high correlation coefficient (Fig. 4B) combined with low RMS error (Fig. 4A), was observed for activations, volume-scaled activations, and stresses with a power of 2–4, contact forces, and the criteria that combined minimization of metabolic energy and muscle activations with a power of 2 (Fig. 4). Activation-based criteria with a power of 10 resulted in high correlation coefficients for both muscle excitations and contact forces, yet high RMS errors in contact forces. Except for minimizing contact forces, all formulations tended to overestimate the second peak of the contact force (Fig. 5).

4. Discussion

We evaluated an extensive set of performance criteria that have been suggested to explain muscle coordination during walking by comparing both predicted excitations and contact forces against measured data. Accounting for muscle dynamics when solving the muscle redundancy problem allowed us to evaluate minimization of metabolic energy consumption using the model proposed by Umberger et al. [24]. This would not have been possible with a static optimization approach.

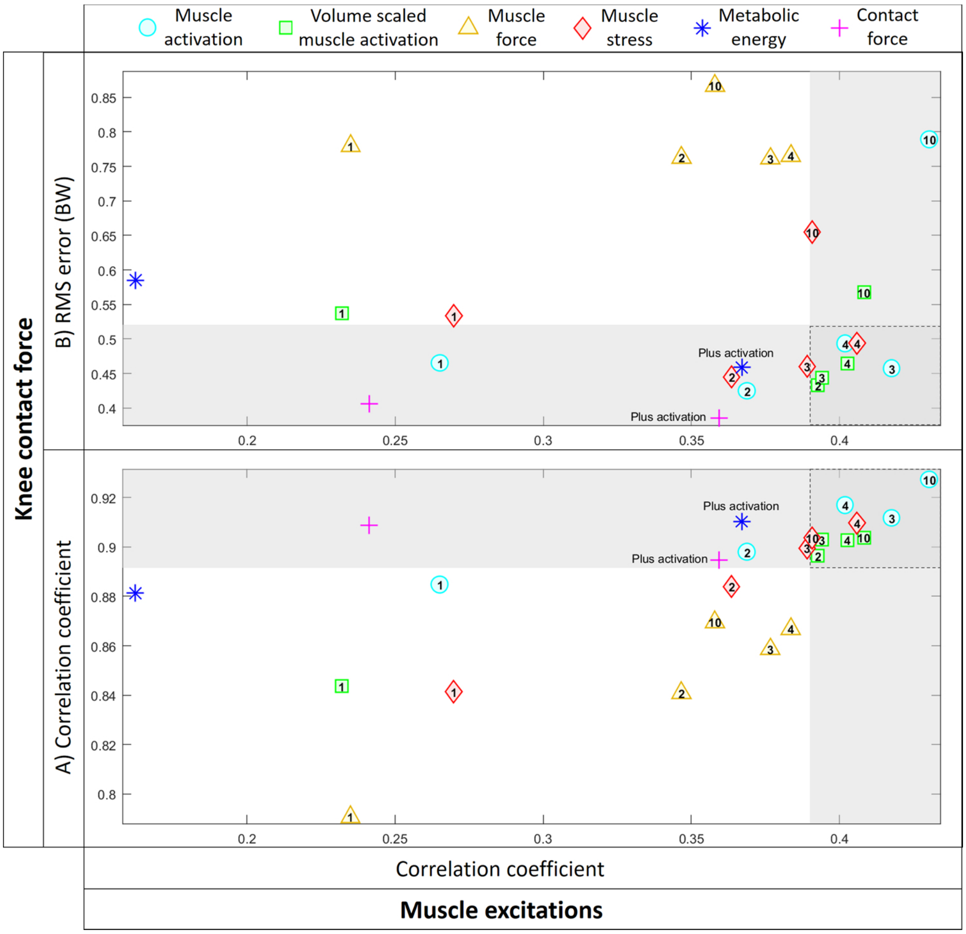

Fig. 2. Agreement between estimated and measured muscle excitations and knee contact forces. Coefficient of correlation between measured and predicted muscle excitations averaged over muscles and subjects, versus (A) coefficient of correlation and (B) RMS error between measured and predicted knee contact forces averaged over subjects for six groups of performance criteria: muscle activation, volume scaled muscle activation, muscle force, muscle stress, metabolic energy and joint contact force (sum of squared contact forces in the hip, knee, and ankle joints). Numbers inside the markers used to represent each group of performance criteria indicate the power to which the criterion was raised. For criteria based on metabolic energy and contact force, the marker's legend "plus activation" refers to adding muscle activation with a power of 2 to minimizing metabolic energy or contact forces.

Our results suggest that minimizing muscle activations or volume-scaled activations with exponents of 3 or 4 results in the most accurate prediction of muscle excitations and knee contact forces during walking. Combining EMG and measured contact forces to validate simulation outcomes was key to reach this conclusion. Neither EMG nor contact forces alone would have allowed us to distinguish the suitability of different criteria as clearly (see criteria that fall in one but not both gray bands in Fig. 2). In addition, we illustrated that the performance criteria had a large effect on the accuracy of the estimated contact force with RMS errors ranging from 0.39 to 0.86 BW. Hence, differences in contact forces between performance criteria are in the order of differences between healthy subjects and patients with osteoarthritis [26]

Table 1
Correlation coefficients between muscle excitations and EMG signals for each muscle, averaged over four trials and four subjects. For each muscle, top 30 percent correlation coefficients amongst different performance criteria are highlighted in green, and bottom 30 percent correlation coefficients amongst different performance criteria are highlighted in red. (For interpretation of the references to colour in this table legend, the reader is referred to the web version of this article).

Performance criteria		Correlation coefficients between muscle excitations and EMG signals, averaged over four subjects													
		semim	bif	vasl	recf	mgas	lgas	tfl	tiban	perl	sol	amag	gmax	sar	Average
Muscle activation	Power = 1	0.480	0.358	0.591	-0.262	0.588	-0.157	-0.050	0.591	0.710	-0.002	0.363	0.250	-0.015	0.265
	Power = 2	0.487	0.561	0.697	-0.245	0.644	0.812	0.041	0.600	0.741	0.012	0.393	0.317	-0.264	0.369
	Power = 3	0.428	0.620	0.729	-0.175	0.679	0.870	0.227	0.612	0.804	0.000	0.458	0.359	-0.182	0.418
	Power = 4	0.349	0.577	0.704	-0.124	0.660	0.817	0.249	0.616	0.754	0.014	0.377	0.340	-0.108	0.402
	Power = 10	0.322	0.662	0.779	-0.197	0.671	0.792	0.363	0.637	0.808	0.013	0.391	0.354	-0.001	0.430
Volume scaled muscle activation	Power = 1	0.380	0.200	0.145	-0.278	0.624	0.685	-0.179	0.454	0.749	0.156	0.079	0.052	-0.051	0.232
	Power = 2	0.542	0.583	0.741	-0.229	0.679	0.896	-0.191	0.601	0.799	0.106	0.478	0.321	-0.219	0.393
	Power = 3	0.482	0.623	0.727	-0.196	0.676	0.885	-0.008	0.606	0.805	0.025	0.438	0.350	-0.290	0.394
	Power = 4	0.454	0.637	0.719	-0.175	0.666	0.879	0.091	0.608	0.805	0.019	0.424	0.352	-0.244	0.403
	Power = 10	0.400	0.658	0.717	-0.188	0.673	0.858	0.202	0.630	0.793	-0.007	0.380	0.352	-0.160	0.408
Muscle force	Power = 1	0.217	0.214	0.102	-0.327	0.457	0.810	-0.051	0.557	0.663	0.029	0.393	0.207	-0.218	0.235
	Power = 2	0.336	0.438	0.653	-0.189	0.616	0.845	-0.057	0.580	0.791	0.140	0.333	0.325	-0.305	0.347
	Power = 3	0.323	0.527	0.637	0.034	0.611	0.844	0.032	0.575	0.799	0.154	0.309	0.369	-0.319	0.377
	Power = 4	0.276	0.539	0.626	0.124	0.609	0.841	0.120	0.561	0.797	0.144	0.301	0.378	-0.330	0.384
	Power = 10	0.174	0.553	0.604	0.062	0.585	0.780	0.071	0.564	0.783	0.158	0.376	0.332	-0.387	0.358
Muscle stress	Power = 1	0.474	0.215	0.699	-0.318	0.600	-0.111	-0.026	0.573	0.742	0.010	0.446	0.222	-0.018	0.270
	Power = 2	0.473	0.440	0.686	-0.238	0.647	0.804	0.035	0.608	0.799	-0.009	0.384	0.362	-0.265	0.364
	Power = 3	0.430	0.486	0.693	-0.170	0.632	0.828	0.202	0.615	0.815	-0.010	0.357	0.369	-0.188	0.389
	Power = 4	0.359	0.509	0.694	-0.084	0.620	0.835	0.265	0.619	0.823	0.006	0.367	0.371	-0.109	0.406
	Power = 10	0.233	0.493	0.669	-0.046	0.590	0.818	0.237	0.610	0.816	-0.040	0.417	0.374	-0.091	0.391
Metabolic energy	Plus activation	0.497	0.558	0.723	-0.256	0.617	0.779	-0.109	0.584	0.801	0.043	0.440	0.334	-0.239	0.367
	_	0.186	0.180	0.341	-0.166	0.020	0.100	-0.095	0.455	0.764	0.026	0.427	0.065	-0.192	0.162
Contact force	Plus activation	0.477	0.442	0.599	-0.267	0.691	0.783	-0.044	0.582	0.785	0.028	0.461	0.350	-0.215	0.359
	_	0.328	0.165	0.322	-0.179	0.650	0.534	-0.158	0.320	0.781	-0.073	0.451	0.104	-0.107	0.241

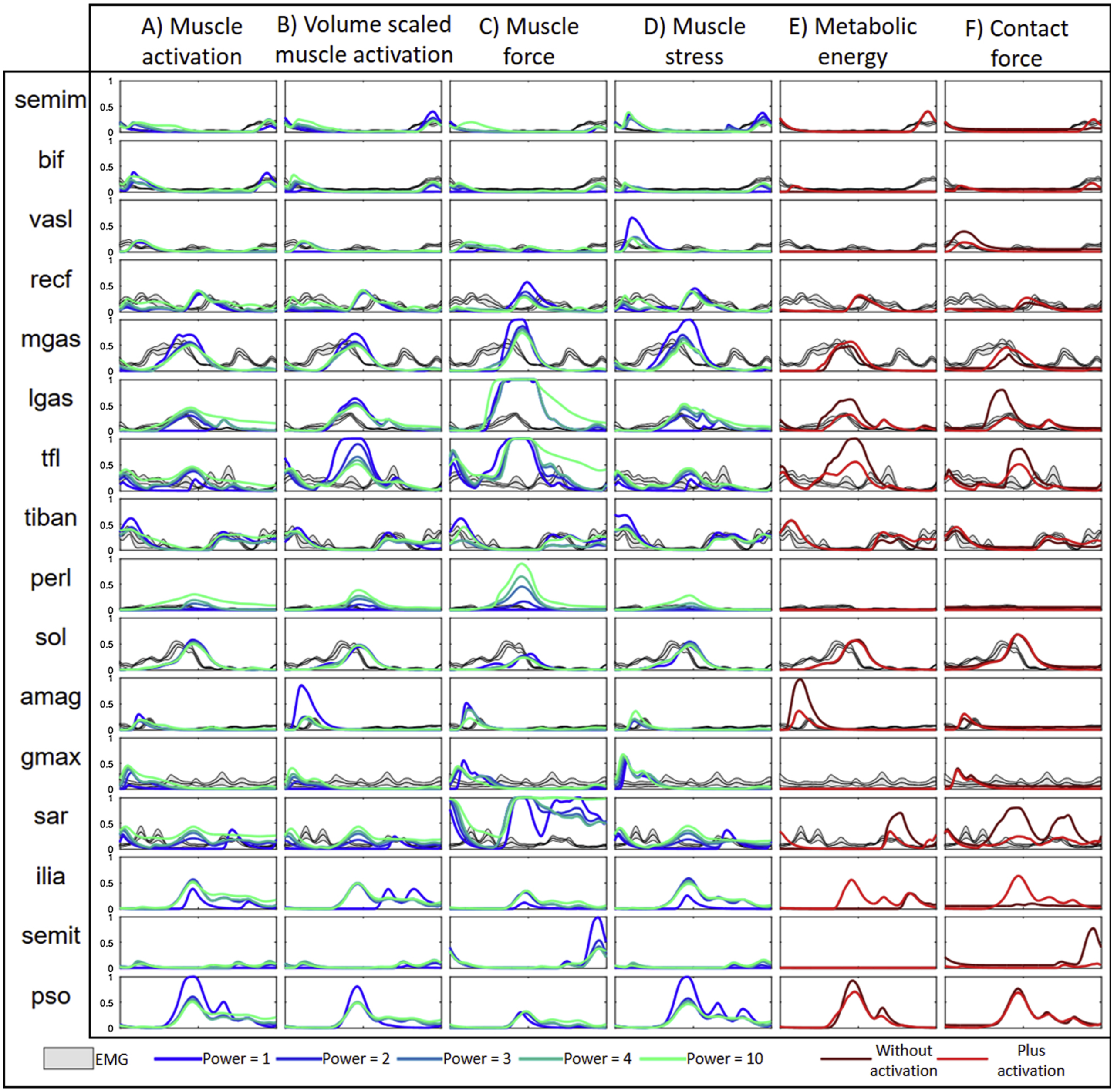

Fig. 3. Muscle excitations patterns shown for subject 1. Excitations patterns estimated based on different performance criteria (muscle activation, volume scaled muscle activation, muscle force, muscle stress, metabolic energy and joint contact force) were averaged over four trials. Available EMG signals (gray areas) were averaged over four trials and were scaled to the average maximum excitation predicted in the activation-based criteria for 13 muscles (semimembranosus (semim), biceps femoris (bif), vastus lateralis (vasl), rectus femoris (recf), medial (mgas) and lateral gastrocnemius (lgas), tensor fasciae latae (tfl), tibialis anterior (tiban), peroneus longus (perl), soleus (sol), gluteus maximus (gmax), adductor magnus (amag), and Sartorius (sar)). Estimated excitations are also plotted for Iliacus (ilia), semitendinosus (semit), and psoas (pso) muscles.

and are thus clinically relevant.

The more accurate estimation of contact forces and EMG signals based on activation, volume-scaled activation and stress criteria compared to force-based criteria indicates the importance of accounting for the (instantaneous) potential of the muscles to generate force. Overall, criteria based on volume-scaled activation on the one hand, and stress and activation on the other hand reproduced measured data equally well. However, they resulted in different estimates of excitations and contact forces as volume-scaled activation criteria favored excitation of smaller muscles [6] (Fig. 3B). Comparison between EMG and computed muscle excitations suggests that criteria that distribute excitations across all muscles fairly uniformly (i.e., formulations with a power of 3–10) better capture muscle recruitment than linear criteria (Table 1). This is in agreement with previous results for gait [6,9]. Contact forces are estimated equally well when using activation-based criteria with a power of 2 versus a power of 3 or 4. However, the higher accuracy of estimated muscle excitations obtained with higher powers suggests that a power of 2 underestimates the cost of high muscle activations. Although using a power of 10 results in high correlations for both contact forces and excitations, the high RMS errors of the estimated contact force suggests that this criterion overestimates the total muscle force.

Although minimization of metabolic energy is thought to drive gait selection based on the observation that humans prefer walking speeds and step frequencies that minimize metabolic energy consumption [27], this criterion resulted in poor estimates of muscle excitations and contact forces. Minimizing metabolic energy heavily penalizes

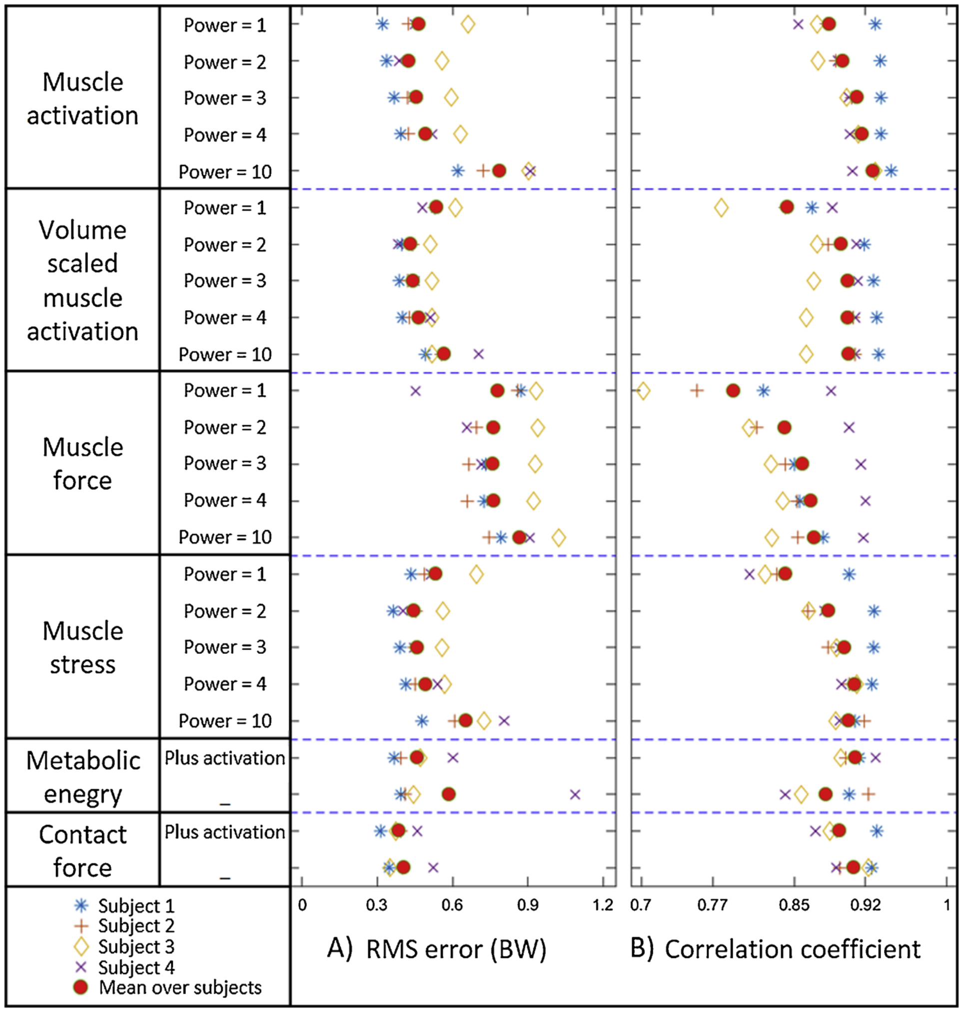

Fig. 4. Fit between measured and simulated knee contact forces for individual subjects. RMS error (A) and coefficient of correlation (B) between measured and predicted knee contact forces are depicted for four subjects and different performance criteria in six groups: muscle activation, volume scaled muscle activation, muscle force, muscle stress, metabolic energy and joint contact force (sum of squared contact forces in the hip, knee, and ankle joints).

excitation of big muscles such as vastus lateralis and semimembranosus and therefore, does not capture the observed co-contraction of quadriceps and hamstrings in early stance (Fig. 3E). This in turn leads to a small first peak of the estimated knee contact forces (Fig. 5E). The higher accuracy of predicted muscle excitations when minimizing a weighted sum of metabolic energy and activations with a power of 2 suggests that a multi-objective performance criterion might better capture muscle recruitment during walking than minimizing metabolic energy alone (Fig. 2).

Minimizing joint contact forces in the ankle, knee and hip resulted in estimates of knee contact forces that were as good as estimates obtained with activation-based criteria but at the cost of poor correlations between EMG and estimated excitations (Fig. 2). Minimizing a weighted sum of activations with a power of 2 and contact forces, however, improved the accuracy of predicted muscle excitations while retaining accurate estimates of the knee contact forces (Fig. 2). This suggests that minimization of contact forces does not explain muscle recruitment by itself but might be a contributing factor. Our dataset of relatively healthy walking movements might not allow enlightening the role of contact force minimization in muscle recruitment, as a previous study found that contact forces played an important role in muscle recruitment in a pathological (ruptured vastus lateralis) animal model [28].

The present study had some limitations. First, the subjects in this study were older adults with artificial knees and might not be fully representative for healthy young adults with native knee joints. Second, we used a scaled generic musculoskeletal model. The accuracy of estimated contact forces relies on both the musculoskeletal model and the approach used to solve the muscle redundancy problem. It is likely that errors in modeling musculoskeletal geometry (e.g. muscle moment arms) and muscle-tendon properties contributed to differences in accuracy between subjects (e.g., generic model might have been closer to subject 1 than to subject 3). For example, adjusting maximum isometric forces using subject-specific values has been shown to improve the accuracy of estimated knee joint contact forces [29]. Third, muscle recruitment patterns were computed based on a very simple model of motor control, i.e., the minimization of a simple performance criterion. We did not explore the combination of more than two criteria, although it seems likely that multiple criteria are simultaneously optimized during walking. Additionally, the absence of spinal reflexes in our model might explain why we were unable to reproduce the EMG for some muscles. For rectus femoris, crosstalk in the EMG signal caused by the neighboring muscles (vasti muscles) might have contributed to the poor correlation with estimated muscle excitation [30].

In conclusion, we found that muscle coordination and contact forces could be more accurately estimated from kinematic and kinetic data collected during walking by minimizing muscle activations, volume-scaled activations or stresses rather than muscle forces, metabolic energy or joint contact forces to solve the muscle redundancy problem. Our results suggest that using activations to a power of three or four

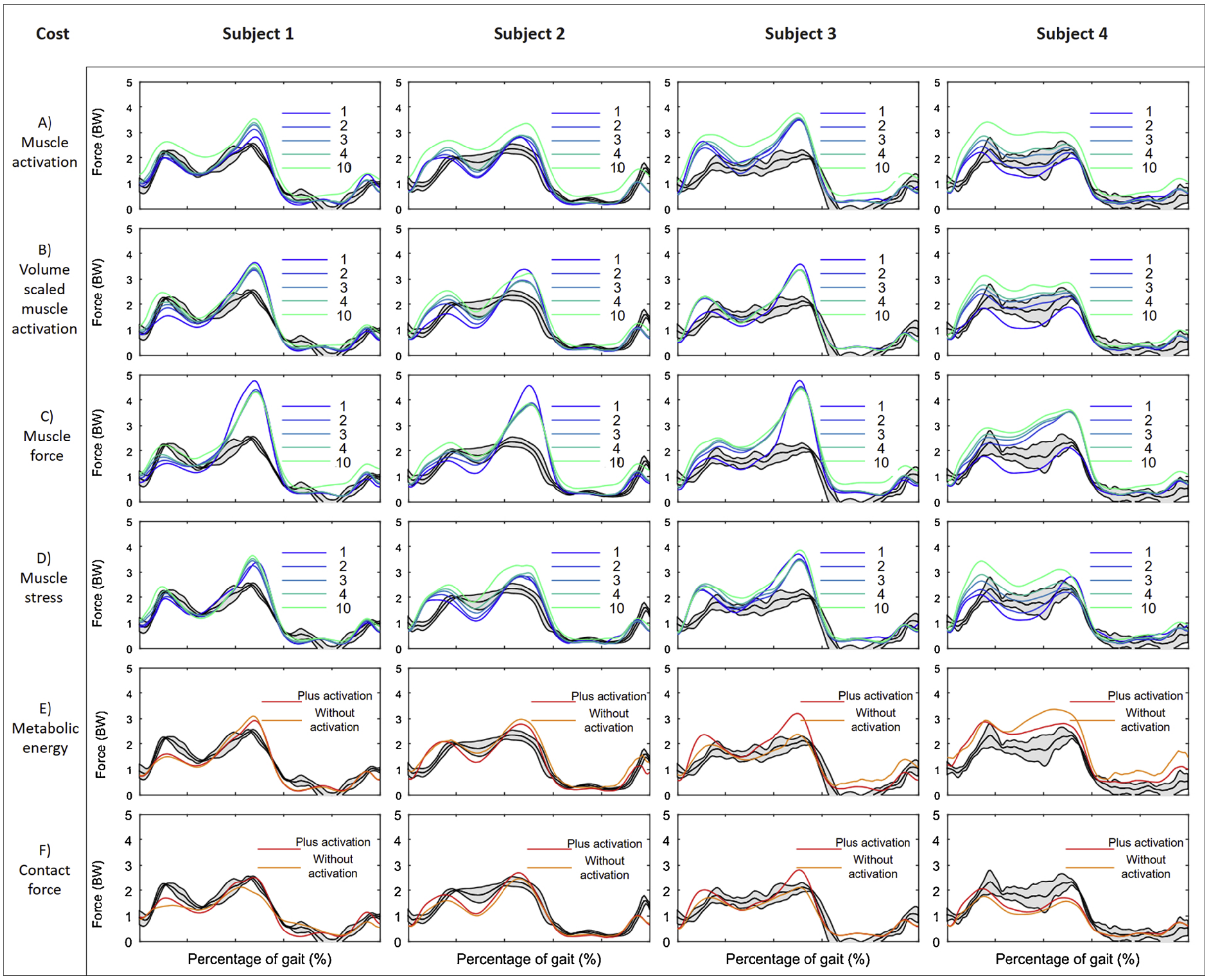

Fig. 5. Comparison between measured (gray areas) and estimated contact forces for individual subjects. Knee contact forces were estimated based on the performance criteria within six different groups: muscle activation, volume scaled muscle activation, muscle force, muscle stress, metabolic energy and joint contact force (sum of squared contact forces in the hip, knee, and ankle joints). Data was normalized to 100% for one gait cycle (starting at heel contact) and averaged over four trials per subject. The average measured contact forces over the four trials as well as the average contact forces plus and minus one standard deviation are plotted in black.

yields more accurate results than the more commonly used criterion, activations with a power of two.

Declaration of Competing Interest

None.

Acknowledgements

This work was supported by the Research Foundation - Flanders (FWO), Brussels, Belgium [Research Project G079216N].

Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.gaitpost.2019.08.019.

References

[1] M.R. Maly, Abnormal and cumulative loading in knee osteoarthritis, Curr. Opin. Rheumatol. 20 (2008) 547–552, https://doi.org/10.1097/BOR.0b013e328307f58c.
[2] W.F. Zimmerman, M.A. Miller, R.J. Cleary, T.H. Izant, K.A. Mann, Damage in total knee replacements from mechanical overload, J. Biomech. 49 (2016) 2068–2075, https://doi.org/10.1016/j.jbiomech.2016.05.014.
[3] F. Moissenet, L. Modenese, R. Dumas, Alterations of musculoskeletal models for a more accurate estimation of lower limb joint contact forces during normal gait: a systematic review, J. Biomech. 63 (2017) 8–20, https://doi.org/10.1016/j.jbiomech.2017.08.025.
[4] K.M. Steele, M.S. DeMers, M.H. Schwartz, S.L. Delp, Compressive tibiofemoral force during crouch gait, Gait Posture (2012), https://doi.org/10.1016/j.gaitpost.2011.11.023.
[5] A. Pedotti, V.V. Krishnan, L. Stark, Optimization of muscle-force sequencing in human locomotion, Math. Biosci. 38 (1978) 57–76, https://doi.org/10.1016/0025-5564(78)90018-4.
[6] M. Ackermann, A.J. van den Bogert, Optimality principles for model-based prediction of human gait, J. Biomech. 43 (2010) 1055–1060, https://doi.org/10.1016/j.jbiomech.2009.12.012.
[7] J.J. Collins, The redundant nature of locomotor optimization laws, J. Biomech. 28 (1995) 251–267, https://doi.org/10.1016/0021-9290(94)00072-C.
[8] R.D. Crowninshield, R.A. Brand, A physiologically based criterion of muscle force prediction in locomotion, J. Biomech. 14 (1981) 793–801, https://doi.org/10.1016/0021-9290(81)90035-X.
[9] V. Monaco, M. Coscia, S. Micera, Cost function tuning improves muscle force estimation computed by static optimization during walking, Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. EMBS (2011) 8263–8266, https://doi.org/10.1109/IEMBS.2011.6092037.
[10] R.H. Miller, B.R. Umberger, J. Hamill, G.E. Caldwell, Evaluation of the minimum energy hypothesis and other potential optimality criteria for human running, Proc. R. Soc. B Biol. Sci. 279 (2012) 1498–1505, https://doi.org/10.1098/rspb.2011.2015.
[11] M.S. DeMers, S. Pal, S.L. Delp, Changes in tibiofemoral forces due to variations in muscle activity during walking, J. Orthop. Res. 32 (2014) 769–776, https://doi.org/10.1002/jor.22601.
[12] R.T. Hermiston, F. Bonde-Petersen, The influence of varying oxygen tensions in inspired gas on 133Xenon muscle clearance and fatigue levels during sustained and dynamic conctractions, Eur. J. Appl. Physiol. Occup. Physiol. 34 (1975) 291–302,

https://doi.org/10.1007/BF00999942.

[13] R. Happee, F.C.T. Van der Helm, The control of shoulder muscles during goal directed movements, an inverse dynamic analysis, J. Biomech. 28 (1995) 1179–1191, https://doi.org/10.1016/0021-9290(94)00181-3.

[14] G.J. Bastien, P.A. Willems, B. Schepens, N.C. Heglund, Effect of load and speed on the energetic cost of human walking, Eur. J. Appl. Physiol. 94 (2005) 76–83, https://doi.org/10.1007/s00421-004-1286-z.

[15] W. Herzog, D. Longino, A. Clark, The role of muscles in joint adaptation and degeneration, Langenbecks Arch. Surg. (2003) 305–315, https://doi.org/10.1007/s00423-003-0402-6.

[16] S.A. Banks, D.G. Lloyd, T.F. Besier, M.G. Pandy, D.D. D'Lima, S.L. Delp, B.J. Fregly, Grand challenge competition to predict in vivo knee loads, J. Orthop. Res. 30 (2011) 503–513, https://doi.org/10.1002/jor.22023.

[17] F. De Groote, A.L. Kinney, A.V. Rao, B.J. Fregly, Evaluation of direct collocation optimal control problem formulations for solving the muscle redundancy problem, Ann. Biomed. Eng. 44 (2016) 2922–2936, https://doi.org/10.1007/s10439-016-1591-9.

[18] F.E. Zajac, E.L. Topp, M.G. Hoy, J.M. Rosen, J.P. Loan, S.L. Delp, An interactive graphics-based model of the lower extremity to study orthopaedic surgical procedures, IEEE Trans. Biomed. Eng. 37 (2002) 757–767, https://doi.org/10.1109/10.102791.

[19] T. Delabastita, S. Bogaerts, B. Vanwanseele, Age-Related Changes in Achilles Tendon Stiffness and Impact on Functional Activities: A Systematic Review and Meta-Analysis, J. Aging Phys. Act. 27 (2018) 116–127, https://doi.org/10.1123/japa.2017-0359.

[20] F. De Groote, T. De Laet, I. Jonkers, J. De Schutter, Kalman smoothing improves the estimation of joint kinematics and kinetics in marker-based human gait analysis, J. Biomech. 41 (2008) 3390–3398, https://doi.org/10.1016/j.jbiomech.2008.09.035.

[21] C.C. Raasch, F.E. Zajac, B. Ma, W.S. Levine, Muscle coordination of maximum-speed pedaling, J. Biomech. (1997), https://doi.org/10.1016/S0021-9290(96)00188-1.

[22] F.E. Zajac, Muscle and tendon: properties, models, scaling, and application to biomechanics and motor control, Crit. Rev. Biomed. Eng. (1989), https://doi.org/10.1016/j.pcad.2015.11.006.

[23] E.M. Arnold, S.R. Ward, R.L. Lieber, S.L. Delp, A model of the lower limb for analysis of human movement, Ann. Biomed. Eng. 38 (2010) 269–279, https://doi.org/10.1007/s10439-009-9852-5.

[24] B.R. Umberger, Stance and swing phase costs in human walking, J. R. Soc. Interface 7 (2010) 1329–1340, https://doi.org/10.1098/rsif.2010.0084.

[25] R.J. Van Arkel, L. Modenese, A.T.M. Phillips, J.R.T. Jeffers, Hip abduction can prevent posterior edge loading of hip replacements, J. Orthop. Res. 31 (2013) 1172–1179, https://doi.org/10.1002/jor.22364.

[26] S. Meireles, F. De Groote, N.D. Reeves, S. Verschueren, C. Maganaris, F. Luyten, I. Jonkers, Knee contact forces are not altered in early knee osteoarthritis, Gait Posture (2016), https://doi.org/10.1016/j.gaitpost.2016.01.016.

[27] J.E.A. Bertram, A. Ruina, Multiple walking speed-frequency relations are predicted by constrained optimization, J. Theor. Biol. 209 (2001) 445–453, https://doi.org/10.1006/jtbi.2001.2279.

[28] C. Alessandro, B.A. Rellinger, F.O. Barroso, M.C. Tresch, Adaptation after vastus lateralis denervation in rats demonstrates neural regulation of joint stresses and strains, Elife 7 (2018), https://doi.org/10.7554/elife.38215.

[29] D.G. Lloyd, T.F. Besier, An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo, J. Biomech. 36 (2003) 765–776, https://doi.org/10.1016/S0021-9290(03)00010-1.

[30] A. Nene, C. Byrne, H. Hermens, Is rectus femoris really a part of quadriceps? Gait Posture 20 (2003) 1–13, https://doi.org/10.1016/s0966-6362(03)00074-2.