

An EMG-driven musculoskeletal model to estimate muscle forces and knee joint moments in vivo

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Abstract

This paper examined if an electromyography (EMG) driven musculoskeletal model of the human knee could be used to predict knee moments, calculated using inverse dynamics, across a varied range of dynamic contractile conditions. Muscle–tendon lengths and moment arms of 13 muscles crossing the knee joint were determined from joint kinematics using a three-dimensional anatomical model of the lower limb. Muscle activation was determined using a second-order discrete non-linear model using rectified and low-pass filtered EMG as input. A modified Hill-type muscle model was used to calculate individual muscle forces using activation and muscle tendon lengths as inputs. The model was calibrated to six individuals by altering a set of physiologically based parameters using mathematical optimisation to match the net flexion/extension (FE) muscle moment with those measured by inverse dynamics. The model was calibrated for each subject using 5 different tasks, including passive and active FE in an isokinetic dynamometer, running, and cutting manoeuvres recorded using three-dimensional motion analysis. Once calibrated, the model was used to predict the FE moments, estimated via inverse dynamics, from over 200 isokinetic dynamometer, running and sidestepping tasks. The inverse dynamics joint moments were predicted with an average R^2 of 0.91 and mean residual error of ~ 12 Nm. A re-calibration of only the EMG-to-activation parameters revealed FE moments prediction across weeks of similar accuracy. Changing the muscle model to one that is more physiologically correct produced better predictions. The modelling method presented represents a good way to estimate in vivo muscle forces during movement tasks.

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1. Introduction

Measuring the forces applied to a joint and estimating how these forces are partitioned to surrounding muscles, ligaments, and articular surfaces is fundamental to understanding joint function, injury, and disease. Inverse dynamics can be used to estimate the external load applied to a joint, however, the contribution from muscles to support or generate this load is far more difficult to determine given the indeterminate nature of the joint. One solution to this problem is to estimate muscle forces based on an objective function within an optimisation routine, for example, minimising muscle stress. By default, the use of an objective function cannot account individual muscle activation patterns.

Another solution uses electromyography (EMG) in conjunction with an appropriate anatomical and muscle model to estimate the forces produced in each muscle (e.g. Lloyd and Buchanan, 1996; McGill, 1992). Since ‘EMG-driven’ models rely on measured muscle activity to estimate muscle force, these models implicitly account for a subject’s individual activation patterns without the need to satisfy any constraints imposed by an objective function. This is important if we wish to investigate tissue loading throughout a wide range of tasks and contractile conditions, as the activation of muscle depends on the control task and can be quite different for the same joint angle and joint torque (Tax et al., 1990; Buchanan and Lloyd, 1995). Indeed, in isometric tasks Lloyd and Buchanan (2001) showed quite different activation patterns between subjects to generate the same relative knee moments in flexion/extension and varus/valgus directions, resulting in quite different amounts of support provided by the muscles and ligaments.

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EMG-driven models have been developed to estimate muscle forces for the lower back (McGill and Norman, 1986; McGill, 1992; Granata and Marras, 1993; Thelen et al., 1994; Nussbaum and Chaffin, 1998), elbow (Soechting and Flanders, 1997; Buchanan et al., 1998), shoulder (Laursen et al., 1998), knee (White and Winter, 1993; Lloyd and Buchanan, 1996; Piazza and Delp, 1996), and ankle (Hof and van den Berg, 1981a, b). As direct measures of muscle force in vivo are difficult, EMG-driven models are typically validated to external joint moments measured using an inverse dynamics approach. The ability of EMG-driven models to predict joint moments during a wide range of activities has proven difficult in the past, and several methods have been devised to satisfy this moment constraint. One such method involves using an error term or ‘gain’ to ensure the predicted moments from a model match the externally measured moments for each task (e.g. McGill, 1992). An alternate method involves using a non-linear least squares optimisation procedure to alter specific parameters within the model to ensure that the moment constraints are closely met (Hatze, 1981; Lloyd and Buchanan, 1996). However, all previous EMG-driven models have been tested on either static/isometric tasks (e.g. Hatze, 1981; Thelen et al., 1994; Lloyd and Buchanan, 1996; Laursen et al., 1998) or a limited set of dynamic tasks (e.g. Nussbaum and Chaffin, 1998).

If EMG-driven modelling is to become a useful tool in estimating in vivo tissue loading, then we need to have confidence that models are indeed reflecting the actual activated muscles. This confidence can be attained if the model is capable of predicting joint moments over a varied range of dynamic contractile conditions, which is obviously a stringent requirement.

It can be argued that to predict joint moments across a wide range of tasks, the model must mathematically represent the underlying anatomy and physiology of the system. Thus, to allow predictions across a number of different subjects, it is important to calibrate the model to an individual by adjusting subject-specific model parameters (e.g. Hatze, 1981; Lloyd and Buchanan, 1996; Nussbaum and Chaffin, 1998). This adjustment is necessary as people are inherently different. For example, people have different strengths and variation in relative strength of the knee flexor and extensor muscles (e.g. Aagaard et al., 1997; Hayes and Falconer, 1992; Read and Bellamy, 1990). Additionally, quite different knee torque–angle relationships have been shown between runners and cyclists (Herzog et al., 1991) and that the peak of hamstring torque–angle relationships can be moved to longer muscle lengths from eccentric training of these muscles (Brockett et al., 2001). Thus, the models need to account for these differences, but as Nussbaum and Chaffin (1998) point out, earlier EMG-driven models that have used parameters or ‘gains’ with no physiological basis compro-

mise construct validity and perhaps limit the ability to predict across tasks and subjects. Model constructs and parameters should therefore have an anatomical and physiological basis that is constrained within a calibration process specific to an individual.

The aim of this paper was to determine if an EMG-driven model could predict joint moments across a wide range of tasks and contractile conditions, using the knee as an example. The model was based on anatomical and physiological characteristics of muscle and EMG, and calibrated to an individual using appropriate physiologically based parameters across a selection of varied tasks. An additional aim was to examine the ability of the model to predict knee joint moments across weeks using muscle model parameters obtained from an initial calibration. Finally, we tested if making the model less physiologically correct affected model predictions.

2. Methods

2.1. Model development

The model uses raw EMG and joint kinematics, recorded during a range of static and dynamic trials, as input to estimate individual muscle forces and, subsequently, joint moments. The model is generic in that it can be adapted to any joint, given appropriate anatomical and physiological data. For the purpose of this study, we have modelled the human knee joint. There are four main parts to this overall model: (1) Anatomical model, (2) EMG-to-activation model, (3) Hill-type muscle model, and (4) Model calibration.

2.2. Anatomical model

Using SIMM™ (Musculographics Inc.; Delp and Loan, 1995), a lower limb anatomical model was developed based on that created by Delp et al. (1990) and extended by Lloyd and Buchanan (1996). The anatomical model included 13 musculotendon actuators, represented as line segments that wrap around bones and other muscles. These were semimembranosus (SM), semitendinosus (ST), biceps femoris long head (BFL), biceps femoris short head (BFS), sartorius (SR), tensor fascia latae (TFL), gracilis (GR), vastus lateralis (VL), vastus intermedius (VI), vastus medialis (VM), rectus femoris (RF), medial gastrocnemius (MG), and lateral gastrocnemius (LG). The only 2 knee muscles not included were the plantaris and popliteus as they have very small physiological cross-sectional area (PCSA) and it was assumed that they provide a negligible contribution to the total knee flexion/extension (FE) moment.

Lower limb joint kinematic data were used as input for the anatomical model to determine individual muscle

tendon lengths and velocities for the modified Hill-type muscle model. Moment arms for each muscle in FE were also determined using the Anatomical Model. Input joint angles were FE for the hip, knee, and ankle, as well as adduction/abduction and internal/external rotation of the hip.

2.3. EMG-to-activation model

The purpose of the EMG-to-activation model was to represent the underlying muscle activation dynamics (Zajac, 1989). Firstly, the raw EMG were high-pass filtered using a zero-lag fourth-order recursive Butterworth filter (30 Hz) to remove movement artifact, then full wave rectified, and then filtered using a Butterworth low-pass filter with a 6 Hz low-pass cut-off frequency.

In the cat plantaris muscle, Herzog and colleagues showed two reasons for poor estimates of muscle forces from rectified and smoothed EMG, these being an: (i) inability to attain the time delay between EMG onset and force onset, and (ii) that the processed EMG signal has a shorter duration than the resulting force (Guimarães et al., 1995; Herzog et al., 1998). Similar conclusions were expressed by van Ruijven and Weijs (1990), who have shown that including the muscle's twitch response in the EMG-to-activation model can give better predictions of muscle force. The muscle twitch response is well represented by a critically damped linear second-order differential system (Milner-Brown et al., 1973), which can be expressed in a discrete form by using backward differences (Rabiner and Gold, 1975). To this end we have used a second-order discrete linear model Eq. (1) to model muscle excitation from the rectified and low-pass filtered EMG data, in the form of a recursive filter (Thelen et al., 1994; Lloyd et al., 1996). The filter we used is given by

$$u_j(t) = \alpha e_j(t - d) - \beta_1 u_j(t - 1) - \beta_2 u_j(t - 2), \quad (1)$$

where $e_j(t)$ is the high-pass filtered, full-wave rectified, and low-pass filtered EMG of muscle j at time t , $u_j(t)$ the post-processed EMG of muscle j at time t , α the gain coefficient for muscle j , β_1 , β_2 the recursive coefficients for muscle j , d the electromechanical delay.

To realise a positive stable solution of Eq. (1), a set of constraints were employed, i.e.

$$\beta_1 = C_1 + C_2,$$

$$\beta_2 = C_1 \cdot C_2,$$

where

$$|C_1| < 1 \quad \text{and} \quad |C_2| < 1.$$

In addition to these constraints, the unit gain of this filter was maintained by ensuring

$$\alpha - \beta_1 - \beta_2 = 1.0.$$

The values of C_1 and C_2 change the impulse response of the second-order filter. If C_1 and C_2 are both positive an under-damped response is created, however if C_1 and C_2 have negative values or of different sign with $|C_1| > |C_2|$ the filter has a damped response. The damped second-order response stretches the duration of the processed EMG and the electromechanical delay (d in Eq. (1)) improves the synchronisation between activation and force production, and thus accounts for the shortcomings expressed by Herzog and colleagues (Guimarães et al., 1995; Herzog et al., 1998).

In addition, the tissue underlying the EMG electrodes on the skin filter the muscle action potentials. The filtering characteristics of this tissue depend on day-to-day variation in the position of EMG electrodes, skin preparation, ambient temperature and electrical impedance. The tissue filtering characteristics are implicitly accounted for by the EMG-to-activation filter.

Maximum voluntary contraction (MVC) EMG data were processed the same way as described above. For all trials, the processed EMG data from each muscle were divided by the single greatest value of the processed EMG data from all that muscle's corresponding MVC trials.

The normalised, processed EMG data were then adjusted to account for either a linear or non-linear EMG–force relationship. At the motor unit level increased muscle force is associated with an exponential increase in firing rate (e.g. Fuglevand et al., 1999). This is also reflected at the joint moment level, as various linear and non-linear relationships have been reported between individual muscle EMGs and joint moment (e.g. Woods and Bigland-Ritchie, 1983). The function used to account for the linear or non-linear EMG-to-force relationship was similar to that utilised by Potvin et al. (1996), i.e.

$$a_j(t) = \frac{e^{A u_j(t)} - 1}{e^A - 1}, \quad (2)$$

where $a_j(t)$ is the activation of muscle j , $u_j(t)$ the post-processed EMG of muscle j at time t , A the non-linear shape factor, constrained to $-3 < A_j < 0$, with 0 being a linear relationship.

The final activation time series were obtained for 10 of the 13 muscles previously mentioned (as per Lloyd and Buchanan, 1996). In addition, muscle activation from VI was estimated as an average of the VM and VL activation, whilst ST was assumed to have the same activation as SM and BFS was assumed to have the same activation as the BFL.

2.4. Hill-type muscle model

Individual muscle tendon length and activation data were then used as input to a modified Hill-type muscle model to calculate individual muscle forces. The muscle–

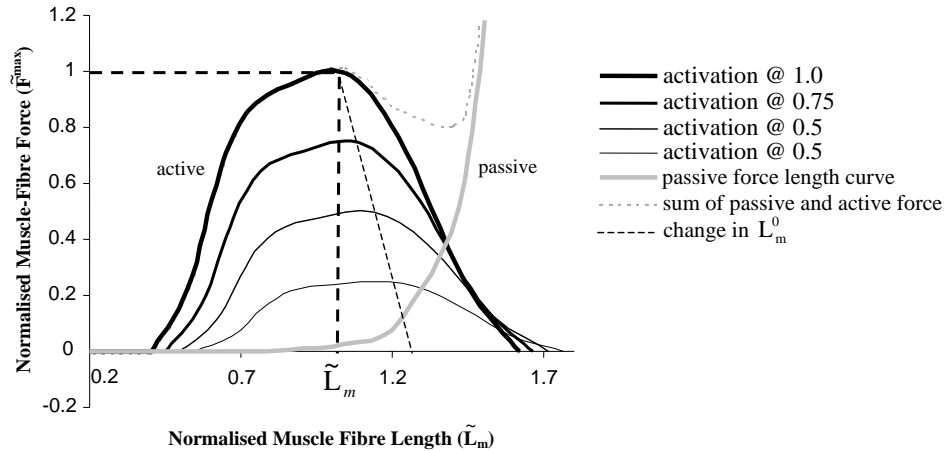


Fig. 1. Active and passive force length curves. Values are normalised by F^{\max} and L_m^0 with 1.0 being 100% activation. Optimal muscle fibre length (L_m^0) was scaled with activation (see text for details).

tendon unit was modelled as a contractile element in series with a tendon, a development of the model described by Zajac (1989). The force produced by each contractile element was estimated using as a Hill-type muscle model with a generic force–length ($f(l)$), force–velocity ($f(v)$) and parallel passive elastic force–length ($f_p(l)$) curves. These curves were normalised to maximum isometric muscle force (F^{\max}), optimal fibre length (L_m^0), and maximum muscle contraction velocity (v^{\max}). The tendon was modelled with a non-linear function, normalised to slack length (L_{ts}) and F^{\max} (Zajac, 1989). The general form of the equations for the force produced by the muscle–tendon unit ($F^{\text{mt}}(t)$) was given by

$$F^{\text{mt}}(t) = F^t \\ = F^{\max} [f(l)f(v)a(t) + f_p(l)] \cos(\phi(t)), \quad (3)$$

where F^t is the tendon force.

Pennation angle ($\phi(t)$) changed with instantaneous muscle fibre length by assuming the muscle belly had a constant thickness and volume (Scott and Winter, 1991; Epstein and Herzog, 1998). The following function was used to calculate pennation angle at time t :

$$\phi(t) = \sin^{-1} \left(\frac{L_m^0 \sin \phi_0}{L^m(t)} \right), \quad (4)$$

where $L^m(t)$ is the muscle fiber length at time t , and ϕ_0 the pennation angle at muscle optimal fiber length, L_m^0 .

The contractile element's force–length relationship ($f(l)$) was a curve created by a cubic spline interpolation of the points on the force–length curve defined by Gordon et al. (1966), normalised to maximum isometric force (Zajac, 1989). However, Huijing (1996) has shown that optimal fibre lengths increase as activation decreases (Fig. 1), which has also been reported by Guimaraes et al. (1994). This coupling between activation and optimal fibre length was incorporated into our

muscle model using the following relationship:

$$L_m^0(t) = L_m^0(\gamma(1 - a(t)) + 1), \quad (5)$$

where γ is the percentage change in optimal fibre length (see text for value used for this parameter), $a(t)$ the activation at time t , L_m^0 the optimal fibre length at maximum activation, $L_m^0(t)$ the optimal fibre length at time t and activation $a(t)$.

The parallel passive elastic muscle force ($f_p(l)$) in the contractile element was obtained from an exponential relationship, which allowed for passive forces to be obtained regardless of fibre length, thus accounting for non-zero passive forces (Schutte, 1992). The force–velocity relationship ($f(v)$) was that employed by Schutte et al. (1993), which included a passive parallel damping element to prevent any singularities of the mass-less model when activation or isometric force were zero.

Muscle fibre lengths were calculated by forward integration of the fibre velocities obtained from the force–velocity and force–length relationships using a Runge-Kutta–Fehlberg algorithm. A method developed by Loan (1992) was used to estimate initial muscle fibre lengths and velocities by calculating the stiffness' of muscle fibre and tendon, and apportioning the total muscle tendon velocity to the muscle fibre and tendon based on their relative stiffness'. Once individual muscle forces were determined, these were multiplied by the muscle FE moment arms and summed to determine the total FE joint moment.

2.5. Calibration process

It was assumed that the summed FE muscle moments from the EMG driven model should equal the external FE moments estimated using an inverse dynamic model. To this end, a procedure was used to calibrate the model

and obtain a ‘global’ set of model parameters for each person to accurately estimate the net FE moments at the knee during five different calibration trials. The calibration trials included: (1) passive knee flexion-extension on a Biodex isokinetic dynamometer (Shirley, NY), (2) straight run, (3) sidestep to 30° from the direction of travel, (4) maximal isokinetic concentric knee flexion-extension at 120°/s on a Biodex dynamometer, and (5) crossover cut to 30° from the direction of travel.

Calibration tasks were chosen to encompass a wide range of contractile conditions. The passive FE Biodex trial was used to help constrain the estimates of tendon slack lengths for each muscle. The crossover task was included with the sidestepping task, as both have similar FE moments, but very different muscle activation patterns (Besier, 1999). The EMG-driven knee model should account for these different activation strategies and produce similar FE joint moments.

A non-linear least squares algorithm was used to alter model parameters to achieve the closest estimation of FE joint moments compared to that measured using an inverse dynamics approach. This technique was similar to that used by Lloyd and Buchanan (1996) to find a global set of parameters for each individual.

2.6. Adjustable and fix model parameters

There were 18 adjustable parameters in the calibration process. The adjustable parameters were grouped as 15 muscle model parameters and 3 muscle activation parameters (i.e. A , C_1 , C_2). The values and constraints of the muscle activation parameters are described above. The adjustable muscle model parameters are now discussed.

Tendon slack length is difficult to determine and has not been well established in the literature, so these were allowed to be adjusted in the calibration process. The initial values for each muscle were obtained from a combination of the data from Delp (1990) and Lloyd and Buchanan (1996), and constrained to be within $\pm 15\%$ of the initial value (see Table 3 for these values).

Flexor and extensor strength coefficients (δ and φ , respectively) were used to scale each muscle's F^{\max} to account for differences in muscle PCSA between people (Brand et al., 1986; Fukunaga et al., 1996), i.e. the different strength of the flexor and extensor muscles. These two global coefficients were used as opposed to individual muscle coefficients to maintain relative strength across flexors and extensors, respectively, and constrained to $\pm 50\%$ of F^{\max} . The F^{\max} for the muscles were determined from the average of the data presented in Yamaguchi et al. (1990). The $\pm 50\%$ range was set based on the size of standard deviations relative to the averages of the data for each muscle reported by different investigators as summarized by Yamaguchi et al. (1990).

In the pilot work on the model, a 40 ms electro-mechanical delay (d) gave good temporal synchronisation between estimated and measured knee joint moments, so it was fixed at that value. The pilot work also revealed that the percentage change in fibre length (γ) was consistently calibrated to approximately 15%, with little improvement in model predictions below 10% and above 20%. Therefore, it was decided to fix γ to a constant of 15% (0.15 in Eq. (5)). The other muscle parameters, L_m^0 and ϕ_0 , were fixed to values reported by Delp (1990).

2.7. Model validation procedures

The model was calibrated to six male subjects in total, chosen to be of similar build to the Anatomical Model (mean age: 20.5 ± 2.9 years; mean mass: 74.6 ± 8.6 kg). Following calibration, the activation and muscle model parameters were used to predict FE knee moments for approximately 30 other tasks for each subject, performed on a Biodex dynamometer or within the gait laboratory. The University of Western Australia Human Rights Committee approved all test procedures and all subjects gave informed written consent prior to commencing the experimental trials.

The dynamometer tasks predicted by the knee model included: maximum isometric contractions for flexors and extensors; eccentric hamstring and quadriceps contraction at 120°/s; low effort FE at 120°/s; combined FE with varus/valgus movements at 120°/s; and maximal effort FE at 60°/s. During these trials, knee FE torque, knee flexion angle, and EMG data were collected at 2000 Hz using Waveview data collection software (Eagle Technology, Cape Town). An inverse dynamic model was developed to determine the net muscular FE moment using the torque from the Biodex machine and knee flexion angle measured from an electrical goniometer attached to the knee. Bipolar surface EMG electrodes were used to collect muscle activity from 10 knee joint muscles (as stated above) using a ten-channel EMG system (Motion Lab Systems, Baton Rouge, LA). Hip and ankle angles were measured using a hand held goniometer and were assumed to be constant for each trial as the subject was strapped into position, allowing movement only at the knee joint.

The net FE muscle moment and knee flexion angle obtained from the Biodex trials were filtered using a zero-lag low-pass Butterworth filter with a cut off frequency of 6 Hz, then downsampled to 100 Hz for input into the model.

Subjects also performed a series of running trials in the gait laboratory including a straight run, sidestep to 60° and 30° from the direction of travel, and a crossover cut to 30° from the direction of travel (Besier et al., 2001). These tasks were performed at ~ 3 m/s. Lower limb joint kinematic data were collected with a 6-camera

50 Hz VICON Motion Analysis system (Oxford Metrics Ltd, Oxford, UK) utilising a VICON Clinical Manager (VCM) marker set (Kadaba et al., 1990). Force data were collected simultaneously at 2000 Hz using an AMTI force plate, and input into an inverse dynamic model to calculate knee FE moments across stance phase for each manoeuvre (Kadaba et al., 1990).

Hip, knee, and ankle kinematic data from the dynamometer and gait trials were used as input into the dynamic knee model along with the corresponding raw EMG data. Predicted FE muscle moments were then compared with the external FE moments measured from inverse dynamics. A coefficient of determination (R^2) was used to indicate the closeness of fit in conjunction with the slope and intercept to indicate the linear relationship between estimated and measured FE moment, and the mean residual error to indicate the magnitude of the error. Nussbaum and Chaffin (1998) and Laursen et al. (1998) used similar measures to validate their EMG driven models.

Four subjects were tested three weeks following the initial test session to examine the reliability of the estimated muscle model parameters. It was assumed that muscle model parameters (L_{ts} , ϕ and δ) would not change between testing sessions, hence, only the 3 muscle activation parameters were altered in the calibration for the second session. This was deemed appropriate to account for different electrode placements and skin preparation between testing sessions. A single factor ANOVA was performed between the two

testing sessions to determine any significant difference in model predictions across sessions.

The effect of the model physiological correctness on the model predictions was also examined. To this end we decided to remove the linear change in optimal fibre length with activation (γ), which was originally set at $\gamma = 15\%$ (see Eq. (4)). This phenomenon has been stated to be important for modelling skeletal muscle as it is a physiologically correct expression of the muscle fibre's force-length relationship (Huijing, 1996). We re-calibrated the model for three randomly selected subjects but with the change in optimal fibre length removed, i.e. $\gamma = 0\%$. The difference in the predicted joint moment R^2 was tested using Wilcoxon Signed Rank test.

3. Results

Following calibration, the model predicted FE knee moments with a mean (S.D.) R^2 of 0.91 ± 0.04 across 204 running, sidestepping, and dynamometer trials (Table 1). Mean residual error for these predictions was ~ 12 Nm (Table 1) and when normalised to body weight was less than 0.2 Nm/kg. Tables 2 and 3 summarise the global parameters for each subject following calibration. The dynamic knee model was capable of predicting FE moments across a wide range of tasks from running, to crossover cutting and eccentric dynamometer tasks.

Fig. 2 illustrates the ability of the model to well predict FE moments at the knee for a single subject

Table 1
Summary of model predictions of external torque for running, cutting, and dynamometer tasks

Subject	R^2	S.D.	Slope	S.D.	Intercept	S.D.	MRE (Nm)	S.D.	MRE (Nm/kg)
1	0.921	0.030	0.975	0.151	2.74	3.19	10.69	3.85	0.144
2	0.921	0.034	0.897	0.128	6.27	5.16	15.88	3.09	0.182
3	0.865	0.052	0.792	0.123	1.74	5.08	12.48	3.1	0.192
4	0.938	0.029	0.903	0.042	2.49	2.83	10.97	1.53	0.137
5	0.921	0.046	0.894	0.121	4.6	5.4	12.99	3.86	0.172
6	0.884	0.072	0.905	0.177	0.48	5.28	9.08	2.73	0.138
Mean	0.908	0.044	0.894	0.124	3.05	4.49	12.02	3.03	0.16

Mean and standard deviations are given for the 204 trials performed.

MRE (Nm)=mean residual error.

MRE (Nm/kg)=mean residual error normalised to subjects body weight.

Table 2
Flexion/extension coefficients (δ and ϕ , respectively) and activation parameters for each subject following calibration

Subject	δ	ϕ	C_1	C_2	A
1	1.025	1.125	-0.033	-0.019	-0.200
2	1.216	1.461	-0.091	-0.093	-1.975
3	0.867	1.234	0.265	-0.182	-0.955
4	1.025	1.125	-0.097	-0.313	-1.287
5	0.893	1.325	0.006	-0.014	-0.938
6	1.110	1.203	0.015	-0.033	-0.708

Table 3

Tendon slack lengths (L_{tsj}) for each muscle following calibration, the initial values prior to calibration (obtained using data from Lloyd and Buchanan (1996)), and data from Delp (1990)

Muscle	Tendon slack lengths for each subject (m)						Mean	S.D.	Initial value	Delp
	1	2	3	4	5	6				
SM	0.408	0.407	0.410	0.337	0.412	0.405	0.396	0.029	0.370	0.359
ST	0.262	0.288	0.301	0.280	0.265	0.278	0.279	0.015	0.265	0.262
BFL	0.360	0.403	0.405	0.372	0.379	0.373	0.382	0.018	0.360	0.341
BFS	0.247	0.243	0.246	0.241	0.285	0.248	0.252	0.017	0.250	0.100
SR	0.038	0.040	0.041	0.050	0.043	0.045	0.043	0.004	0.038	0.040
RF	0.332	0.338	0.335	0.330	0.324	0.334	0.332	0.005	0.311	0.346
TFL	0.390	0.393	0.394	0.378	0.395	0.375	0.387	0.009	0.391	0.425
GR	0.190	0.192	0.191	0.196	0.193	0.193	0.192	0.002	0.191	0.140
VM	0.108	0.117	0.118	0.116	0.107	0.111	0.113	0.005	0.112	0.126
VI	0.137	0.139	0.133	0.139	0.133	0.131	0.135	0.003	0.135	0.136
VL	0.148	0.153	0.157	0.158	0.148	0.149	0.152	0.005	0.156	0.157
MG	0.394	0.379	0.379	0.385	0.388	0.384	0.385	0.006	0.395	0.408
LG	0.370	0.353	0.358	0.389	0.387	0.386	0.374	0.016	0.365	0.385

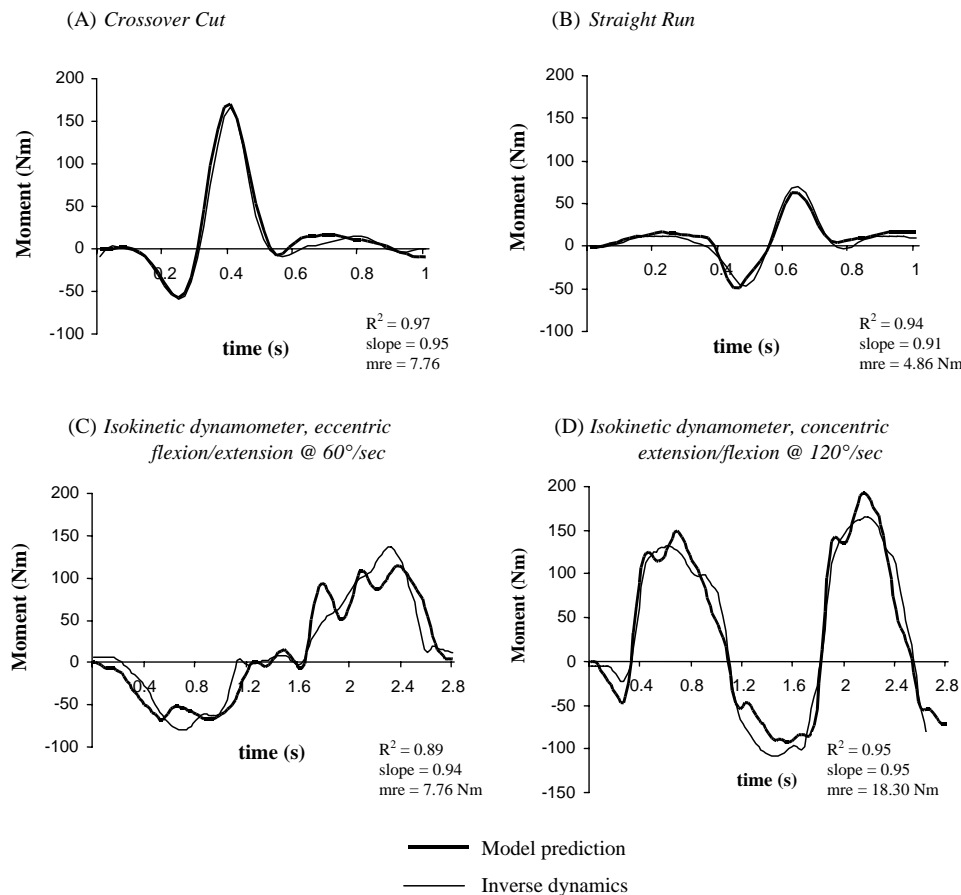


Fig. 2. Comparison of model predictions of knee flexion/extension muscle moments and knee joint moments measured externally for subject 1. Extension moments are positive on all graphs.

across a range of tasks, including a crossover cut (2A), straight run (2B), eccentric FE at $60^\circ/\text{s}$ (2C), and concentric FE at $120^\circ/\text{s}$ on a dynamometer (2D). Note the ability of the model to predict both large and small

extension moments during the crossover cut and run (2A and 2B, respectively). There was greater variation in the shape and magnitude of the FE moments during the dynamometer trials (Figs. 2C and D), although the

Table 4
Model predictions across different testing sessions

Subject	Session 1 R^2	Session 2 R^2	p
1	0.921	0.926	0.76
2	0.921	0.920	1.00
5	0.921	0.916	0.87
6	0.884	0.859	0.18

model was still able to predict the FE moments (mean $R^2 = 0.76 \pm 0.2$). Temporal synchronisation of the moment data was maintained across all trials using the 40 ms delay in the EMG-to-Activation model (Eq. (1)).

The model also predicted FE joint moments in the four subjects who returned for a repeat testing session one week later, using the muscle model parameters from the previous weeks' calibration, but with re-calibration of EMG-to-activation parameters. A one-way ANOVA revealed that there were no significant differences in the model predictions between different testing sessions (Table 4).

Making the model less physiologically correct compromised the ability of the model to predict the inverse dynamic joint moments. The predicted joint moment R^2 significantly reduced from 0.91 to 0.85 ($p < 0.001$), when model was re-calibrated with $\gamma = 0\%$.

4. Discussion

Many studies have shown the promise of EMG-driven musculoskeletal models to estimate muscle forces and predict human joint moments over a limited set of test data. The current model, following subject-specific calibration, predicted the inverse dynamic FE knee joint moments determined from a wide range of tasks and different contractile conditions, thus supporting the hypothesis of this study. The same muscle model parameters were also used to give close predictions of knee joint moments across different testing sessions, which give confidence that the model and the subject-specific parameters are representing the anatomy and physiology of the system. The ability to predict gait tasks as-well-as tasks performed using an isokinetic dynamometer indicated that the model was not just predicting moments for tasks that had similar patterns of EMG and movement. The predictions were sensitive to the physiological correctness of the model, where a less physiologically correct model produced poorer predictions. Finally, compared to previous EMG driven models, the current model was better at predicting joint moments calculated using inverse dynamics (Table 5).

Comparison of direct measures of muscle forces with the EMG driven model estimates would be an ideal method to validate the model. Unfortunately, ethical

Table 5
Comparison of previous EMG driven models and the current dynamic knee model

	Joint modelled	No. of subjects	Total no. of trials	Isometric or dynamic model?	Range of tasks performed	Predictions (R^2)
White and Winter (1993)	Hip, knee, and ankle	2	2	Dynamic	Calibrated to dynamometer, tested during gait	~0.79 for knee
Granata and Marras (1995)	Lower back	10	703	Dynamic	Isokinetic and free lifting	0.81
Nussbaum and Chaffin (1998)	Lower back	10	398	Dynamic	Manual lifting and lowering	0.76 sagittal plane
Laursen et al. (1998)	Shoulder	6	NA	Isometric	Isometric pushing and pulling	0.74
Lloyd and Buchanan (1996)	Knee	7	108	Isometric	Isometric flexion/extension and varus/valgus contractions	CV = 17%
Current Study	Knee	6	204	Dynamic	Wide range of dynamometer, running, and cutting tasks	0.91

and methodological considerations prevent in vivo measures of muscle forces at the human knee. Inverse dynamics calculations were used to calibrate the model to an individual and as a means for an indirect validation. This raises a question regarding the accuracy of estimating joint moments using an inverse dynamics approach. The FE moments, used to calibrate and validate the model, are least susceptible to assumptions associated with inverse dynamics calculations (e.g. segmental inertial parameters—Pearsall and Costigan, 1999, and movement of markers—Holden et al., 1997). The assumed FE axis of the knee may also influence the inverse dynamics FE moments (Holden and Stanhope, 1998), however, the transepicondylar line as used in the gait and isokinetic dynamometer trials in this study has been shown to be a very good approximation of this axis (Hollister et al., 1993; Churchill et al., 1998). Nevertheless it is difficult to speculate on the size of the error in inverse dynamics FE moments estimated from the gait trials because of the lack of a gold standard. In the inverse dynamics calculations from the dynamometer trials, the moment estimates were corrected for angular acceleration of the limb and the dynamometer arm, inline with the findings of Herzog (1988b). Thus accurate measures of the FE torque (about $\pm 5\%$) generated by the knee were expected from the dynamometer trials (Herzog, 1988b).

It may be argued that this model represents nothing more than a curve-fitting exercise that has no physiological basis, given the number of parameters within the model. However, there were only 18 free model parameters that were adjusted in the calibration process to fit 5 trials of data, with over 100 data points in each trial (i.e. 18 parameters adjusted to fit over 500 data points). In the data from the repeat experiments two weeks later only 3 parameters were varied, for the same number of calibration trials and data points. Moreover, the calibrated models predicted on average about 30 trials of 100 points each for each subject. Thus the model was very underdetermined. Additionally, the curve-fitting argument could be raised if the adjustment of model parameters were unconstrained. However, there are many forms or levels of constraints inherent in the construction of this model that ensures the model represents the physiology and anatomy of the system. Firstly, the mathematical constructs for the anatomy and physiology constrain how elements in the model behave. For example, the mathematical description of the muscle and tendon model constrain how the muscles generate force. Secondly, the calibration procedure requires that the actual passive and active torque generating capacity of the muscles are maintained for each person. Thirdly, where muscle parameters required adjustment, most changes were kept within bounds as suggested in the literature. This was not the case for tendon slack length as this has not been well established

in literature, but initial values were set on based previous modelling work (Delp, 1990; Lloyd and Buchanan, 1996) with adjustment permitted within a small $\pm 15\%$ range. Therefore, the constraints inherent in this model greatly reduce the parameter solution space that will allow good predictions of the net FE joint moments.

It could be argued that the physiological correctness of a model will have little effect on the accuracy of the moment predictions as the calibration procedure makes the model a simple curve fitting exercise. To this end, we examined if the predictive ability of the model became worse by removing the linear change in optimal fibre length with activation, i.e. setting $\gamma = 0\%$ in Eq. (4). The predicted joint moment R^2 significantly reduced from 0.91 to 0.85 ($p < 0.001$). This result not only shows the importance of modelling such physiologically phenomenon, but that the final calibrated model accuracy was sensitive to the physiological correctness of the model, i.e. the more physiological correct model gave better predictions. It is anticipated that other physiological phenomena will have to be included in future models to better predict muscle behaviour at a macro level. For example, incorporating non-linear changes in v^{\max} with the active state of muscle can easily be adapted to the current model (Hatze, 1977). Similarly, history dependence of muscle force (force depression/enhancement) can also be added to the current model by linking activation and previous mechanical work performed within the contractile component (Herzog, 1998a; Meijer et al., 1998), and may improve predictions in the dynamometer trials.

There is still the possibility that the estimated muscle forces are different to the actual muscle forces. This may especially be true for muscles with small cross-sectional area as these muscles' contribution to the knee flexion/extension moments are small relative to the larger muscles (Lloyd and Buchanan, 2001), and the final solution may not be very sensitive to change in the smaller muscles' parameters, i.e. tendon slack length. This may not be a problem in the cases where EMG driven models are used to estimate the load sharing between ligaments and muscles, and joint contact forces, as these are mostly determined by the activation and co-contraction of the larger muscles (Lloyd and Buchanan, 2001). The predicted action of the larger muscles should be closer to the actual muscle forces as the final joint moments depend substantially on the action of these muscles in the model. It is our experience that the model needs all the large muscles acting in physiological reasonable states for the model to predict both passive joint torque and the joint moments in the maximally activated trials. However, to ensure better estimation of muscle forces future implementations of the model should include a greater number of specifically chosen calibration trials and physiological/anatomical measures

that will act to further constrain the solution space of the model. For example, the larger prediction errors of the dynamometer trials may have been due to only having one active dynamometer trial within the calibration process. Therefore, increasing the number of dynamometer trials within the calibration process may constrain the parameter space to be more physiologically representative and achieve better overall predictions. Systematically changing the hip and ankle joint angles in some calibration dynamometer trials will better constrain the solution of the two joint muscles (Herzog and ter Keurs, 1988), thereby producing better solutions for the single joint muscles.

A number of improvements can also be made to scale the anatomical model of the lower limb to subjects' anthropometry. The anatomical model used in this study was a generic model of the lower limb based on male cadaver data (Delp et al., 1990) and it was assumed that the subjects were of similar anthropometric proportions. For future modelling studies, a set of scaling factors could be used (based on subject anthropometric data) to alter the size and shape of bone and muscle structures, as performed by Arnold et al. (2000). This would allow for more representative estimations of muscle tendon length and muscle moment arms for individuals. It may also be possible to represent muscles as multiple line segments to account for functionally different segments of individual muscles. To differentiate between mechanically functional different areas of the muscles may also require information regarding the activation of separate muscle segments and the use of EMG electrode clusters. However, recently it has been shown in the VL that very similar EMG-joint moment relationships exist from quite different electrodes positions (Onishi et al., 2000).

Subject-specific optimal fibre lengths for each muscle could also be included in the calibration process of the dynamic knee model to account for changes in optimal fibre length that may exist between different populations. Lloyd and Buchanan (1996) altered optimal fibre lengths using a non-linear least squares parameter calibration process in their isometric model. For the purpose of this model, the optimal fibre lengths were set to mean values determined by Lloyd and Buchanan (1996), thereby reducing the number of variables in the calibration process. Further calibration data may be required if optimal fibre lengths are to be altered in the calibration process so the model solution is suitably constrained.

The 40 ms time delay used in the current model seems to be an overestimate of the physiological electromechanical delay, believed to be ~ 10 ms (Corcos et al., 1992). Future modelling attempts should reduce this delay to 10 ms and account for temporal synchronisation of the joint moments by modelling the delay of muscle force production within the musculotendon unit.

Following this, it is anticipated that the parameters in the recursive EMG-to-activation model would be adjusted differently to account for the temporal synchronisation. This may also permit better predictions of the FE moment data collected from the isokinetic dynamometer.

The inclusion of muscle-specific activation parameters will allow for individual linear or non-linear force–EMG relationships (shape factor, A) for each muscle, which is more appropriate physiologically (Woods and Bigland-Ritchie, 1983), and may also result in better predictions of muscle force and joint moments. For future studies, the full parameter model ($n = 56$) may be used with genetic algorithms or simulated annealing to allow for muscle specific EMG-to-Activation parameters to be included in the model. Of course this will require a larger set of calibration trials so the model solution is suitably constrained.

It has been a point of discussion in the biomechanics community regarding the apparent disagreement between isokinetic dynamometer and inverse dynamic estimates of joint torque (see BIOMCH-L discussion on Isokinetics and Inverse Dynamics by Devita, P., 1999). However, in this study, the dynamic knee model predicted FE moments for both the gait and isokinetic dynamometer trials, albeit with a small reduction in accuracy in the dynamometer trials. The ability to predict both gait and dynamometer trials was because the model included physiological means of increasing force generating capacity of the muscles (i.e. eccentric muscle action and storage of elastic energy in tendon via stretch shorten cycle). Additionally, even though we searched for the highest EMG during a number of MVC trials at different knee angles, muscle activation in the model could go above 1 in any of the experimental trials. Therefore inhibition of muscles during the isometric MVC tasks could have occurred as has been suggested by Suter and Herzog (1997) and was accounted for. Further studies using such models could help to identify the source of this apparent disagreement between estimates of joint torque.

This paper has presented a generic EMG driven musculoskeletal model using existing tools available to the biomechanics community. This work has shown that a non-linear least squares approach can be used with an appropriate set of calibration data to obtain model parameters that can be used in the musculoskeletal model to predict inverse dynamic joint moments. The model was cross validated across such a wide range of tasks, whereas previous models have only been tested on a limited set of tasks and better predicts these inverse dynamic joint moments than previous models. A novel approach was used to account for tissue filtering characteristics and muscle activation dynamics. Importantly our work also showed that the more physiologically representative model gave better predictions.

Further work will attempt to include other known muscle contractile behaviour such as force depression/enhancement, and individualised anatomical models.

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