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Estimation of muscle forces in gait using a simulation of the electromyographic activity and numerical optimization

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Clinical gait analysis provides great contributions to the understanding of gait patterns. However, a complete distribution of muscle forces throughout the gait cycle is a current challenge for many researchers. Two techniques are often used to estimate muscle forces: inverse dynamics with static optimization and computer muscle control that uses forward dynamics to minimize tracking. The first method often involves limitations due to changing muscle dynamics and possible signal artefacts that depend on day-to-day variation in the position of electromyographic (EMG) electrodes. Nevertheless, in clinical gait analysis, the method of inverse dynamics is a fundamental and commonly used computational procedure to calculate the force and torque reactions at various body joints. Our aim was to develop a generic musculoskeletal model that could be able to be applied in the clinical setting. The musculoskeletal model of the lower limb presents a simulation for the EMG data to address the common limitations of these techniques. This model presents a new point of view from the inverse dynamics used on clinical gait analysis, including the EMG information, and shows a similar performance to another model available in the OpenSim software. The main problem of these methods to achieve a correct muscle coordination is the lack of complete EMG data for all muscles modelled. We present a technique that simulates the EMG activity and presents a good correlation with the muscle forces throughout the gait cycle. Also, this method showed great similarities whit the real EMG data recorded from the subjects doing the same movement.

Keywords: musculoskeletal model; muscle forces; clinical decision-making; gait analysis; electromyography

1. Introduction

Clinical gait analysis, through inverse dynamic models and electromyographic (EMG) data, provides great contributions to the understanding of gait disorders and also provides a means for a more comprehensive treatment plan (Wren et al. 2011; de Morais Filho et al. 2012). However, a complete distribution of dynamic muscle forces while walking is a challenge for many researchers (Erdemir et al. 2007; Amarantini et al. 2010; van der Krogt et al. 2012). Direct measures of muscle forces are difficult to obtain in clinical settings because it requires generally invasive techniques. Computational models that represent the human locomotor system are being proposed at present to sort out those limitations (Erdemir et al. 2007). So, it is possible to develop tools that help improving the clinical gait analysis and treatment of gait abnormalities, providing more effective strategies for therapeutic management (Arnold and Delp 2004).

A musculoskeletal model represents a numeric set of anatomical parameters to quantify their interaction. Hence, the muscles are described as a simple line between patches of origin and insertion, while the joints are represented as fixed centres of rotation (Kaufman et al. 1991a; Arnold et al. 2010). Estimation of muscle forces using musculoskeletal models usually requires solving an optimization problem regardless of the method used to solve the equations that describe the dynamics musculoskeletal system, inverse or forward dynamics (Erdemir et al. 2007). At this point, static optimization has proven to be more useful in problems related to gait analysis because it is more computationally efficient as it does not require multiple integrations, and provides similar solutions as dynamic optimization (Anderson and Pandy 2001).

Gait data combined with inverse dynamics and static optimization have been used for more than 30 years, commonly applied to estimate muscle forces in the lower limbs. Another approach that exploits gait data to estimate muscle forces is forward dynamics assisted by data tracking. However, this technique proved to be computationally expensive due to the multiple integrations needed to obtain optimal joint kinematics (Erdemir et al. 2007).

Thelen et al. (2003) have implemented an effective technique of forward dynamics to minimize tracking errors in joint kinematics during cycling into a feedback control system. Recently, computed muscle control (Thelen and Anderson 2006) was used to calculate the optimal muscle activation pattern that generates the necessary net joint moments to produce the observed

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kinematics and so evaluate the effect of weak muscles during walking with relatively little computer-processing time (van der Krogt et al. 2012).

However, low accuracy showed by inverse dynamics analysis, and high computational cost of forward dynamics have directed many researchers to search for some alternative strategies to estimate muscle forces on clinical applications (Erdemir et al. 2007).

Lloyd and Besier have presented an EMG-driven musculoskeletal model of the knee to predict its net moments using inverse dynamics, being their approach a good way to estimate *in vivo* muscle forces during movement tasks (Lloyd and Besier 2003). Amarantini and Martin (2004) have included EMG data in inverse dynamics with static optimization model to find the muscle forces and presented a dynamics analysis as a 2D model during half squats. Nevertheless, their approaches leave open the scope to generate 'real' 3D musculoskeletal models for a more comprehensive clinical assessment including additional EMG (Amarantini et al. 2010). At this point, these methods are limited due to the changing muscle dynamics and also due to possible signal artefacts, but their major limitation is the limited number of muscles that could be measured through surface EMG in the clinical setting and protocols. Moreover, the tissue underlying the EMG electrodes show a filter effect upon the muscle action potentials. Also day-to-day variation in the position of EMG electrodes, skin preparation, ambient temperature and electrical impedance could affect the data (Farina and Negro 2012).

The goal of this study was to propose a new generic musculoskeletal model of the lower limb that represents a new point of view from the inverse dynamics used on clinical gait analysis by including a simulation of the smoothed EMG data. We propose a complete representation of the EMG signal information of all modelled muscles through the linear combination of different Gaussian bells to model the smoothed EMG data. As our aim was to find the muscle forces on patients commonly treated in clinical settings, such as patients with cerebral palsy, we used a standard subject-specific anthropometric data to scale our model and used a nonlinear regression for adjusting the body segment parameters. Then, as a great number of patients treated in clinical gait laboratories are children with cerebral palsy, the performance of the proposed model was compared against the real EMG data and with other generic musculoskeletal model included in the OpenSim software that use forward dynamics approach to find the muscle forces in children.

2. Method

2.1. Participants and procedures

The study included a group of five healthy subjects that were examined by the team from Gait and Movement Laboratory at FLENI Institute for Neurological Research (Escobar, Argentina) and showed normal gait patterns, 7–11 years of age, 1.24–1.67 m in height and 22–53 kg in weight (Table 1).

Table 1. Description of participants, age, height, weight and spatiotemporal gait parameters, all presented as mean (min–max).

	Participants ($n = 10$ trials)
Age (years)	9.8 (7–14)
Height (m)	1.42 (1.24–1.67)
Weight (Kg)	36.60 (22–53)
Velocity (m/seg)	1.10 (0.97–1.28)
Stride length (m)	1.11 (1.07–1.18)
Cadence (steps/min)	117.2 (105–133)
Stance phase (%)	58.5 (57.5–59.5)

The Hospital Research Ethics Committee reviewed and approved this study. The protocol was explained to each subject and an informed consent was signed by their careers. Kinematic data were recorded by a motion capture system (Elite 2002 BTS Bioengineerin, Milan, Italy) with eight cameras (100 Hz) and two force plates (Kistler 9281E, Kistler Group, Winterthur, Switzerland). Twenty-two retro-reflective skin markers were placed over bony landmarks (as indicated by the Davis protocol; Davis et al. 1991). After measurement, all data were imported into MATLAB (MathWorks, Natick, MA, USA). Marker trajectories were filtered with a zero-lagged Butterworth filter with a cut-off frequency of 10 Hz and order 2. Electrical muscle activity data were recorded from the rectus femoris, semimembranosus, gastrocnemius and tibialis anterior muscle using surface dynamic EMG (Teleemg BTS Bioengineering, Milan, Italy) (Hermens et al. 1999). The eight channels of acquisition, half for each limb, were used with a sampling frequency of 2000 Hz.

The multi-segment model used in this study was based on a simple rescaling method, by adjusting the parameters using subject-specific anthropometric data. Height, weight, leg length, knee joint width and distance between anterior superior iliac spines for each participant were recorded by an experienced physiotherapist. A generic musculoskeletal model (3DGaitModel2392) with 23 degrees of freedom (DoF), 3 DoF for the hip, 1 DoF for the knee and 1 DoF for the ankle, available on the OpenSim software (Delp et al. 2007) was used for comparing the performance of our model.

2.2. Dynamics muscle force estimation algorithm

Our approach proposes a musculoskeletal model of the lower limb that simulates the EMG data (EMGsim) of all muscles modelled. The model used both inverse dynamics and static optimization to estimate the muscle forces

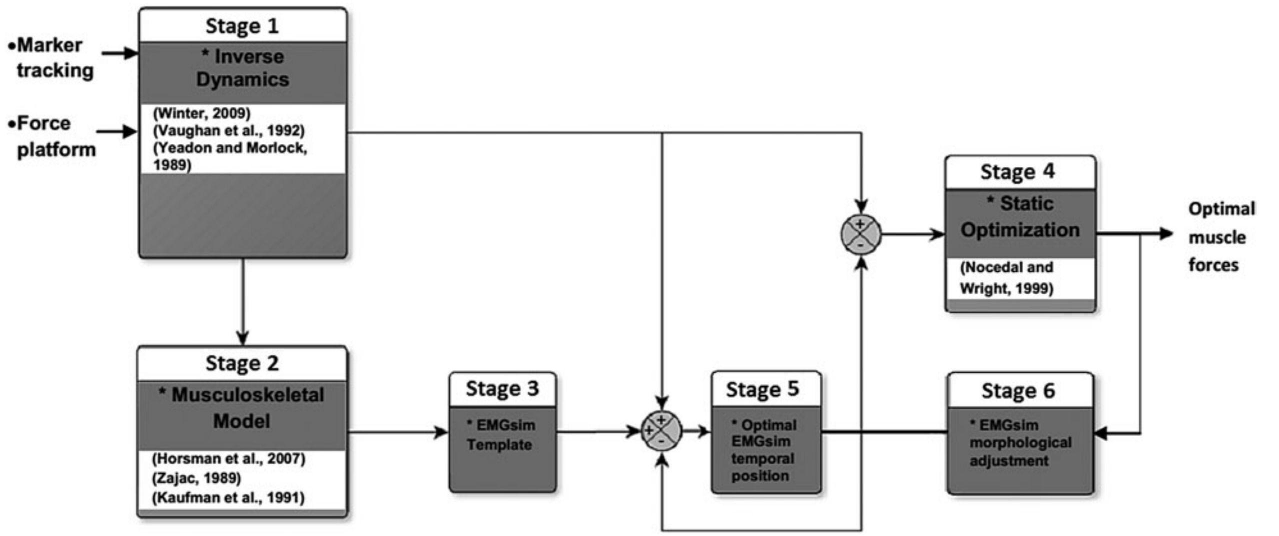

Figure 1. The dynamics muscle force estimation algorithm. Stage 1 is a set of tridimensional net joint torques was calculated from joint kinematics and ground reaction force data. Stage 2 is a tridimensional musculoskeletal model of the lower limbs was generated. This model represents the behaviour of the most representative muscles from the limbs. Stage 3 is the first EMG data were estimated, so a set of Gaussian functions was generated to find the optimal temporal positions of EMGsim (Stage 5). Stage 4 is the static optimization model. Stages 5 and 6 are an iterative process where the EMGsim estimated the real EMG, with the aim to achieve the major approximation of the net moment joints found in Stage 1.

throughout the gait cycle, and the algorithm comprised six stages (Figure 1).

2.2.1. *Inverse dynamics*

A traditional Newton–Euler inverse dynamics method was proposed to find the net joint torque at the ankle, knee and hip throughout the gait cycle (Vaughan et al. 1992, Winter 2009). The main contributors to uncertainties of inverse dynamics solutions are the models for the estimation of body segment parameters due to their influence and sensitivity over the net joint torque (Rao et al. 2006). So, a nonlinear approach to estimate the segmental moments of inertia from anthropometric measurements was used in order to obtain the best estimation even when the anthropometric measurements lie outside the sample range (Yeadon and Morlock 1989).

2.2.2. *Musculoskeletal model*

A musculoskeletal model of the lower limbs was proposed in this paper. The model consists of nine segments (1 pelvis, 2 femurs, 2 patellas, 2 tibia-perone and 2 feet), 36muscle elements representing 24 individual muscles and 14 DoF (3 DoF for each hip, 1 DoF for each knee and 3 DoF for each ankle).

As every other model, ours represents a simplification of the complete human locomotor system. So, the selection criteria used to choose the muscles were as follows:

- Muscles with greater physiological cross-section area (PCSA), in relation to the isometric muscle forces developed.
- Muscles with greater mass, in relation to the energy consumed by the muscle.

Under these criteria, the muscles modelled are represented in Table 2.

Cadaveric reference patches of origin and insertion (Horsman et al. 2007) and axis systems embedded and linked to the movement for each segment representing the lower limb were used. To calculate the time-varying muscle force vectors, the model assumed that the force transmitted by the muscle acts along a straight line

Table 2. Musculoskeletal morphological parameters.

Muscle	PCSA (cm^2)	Mass (g)	No. of elements
Adductor longus	21.23	237.83	3
Biceps femoris	19.50	179.50	1
Gluteus medius	49.35	219.75	3
Gluteus maximus	36.10	494.5	2
Iliopsoas	16.25	137.75	1
Rectus femoris	28.9	239.00	1
Semimembranosus	15.75	183.00	1
Vastus medialis	19.97	166.67	1
Vastus lateralis	34.85	308.00	1
Gastrocnemius	33.9	211.00	2
Soleus	90.1	238.5	1
Tibialis anterior	26.6	129	1

connecting the points of origin and insertion (Kaufman et al. 1991b).

A single straight-line model between the anatomical origin and insertion is not adequate for the rectus femoris, vastus medialis and vastus lateralis because the patella acts as an important lever in the knee joint. In this case, the action direction in the insertions was recalculated as the difference between a vector fixed for the tibia and another fixed for the femur (Yamaguchi and Zajac 1989). Mathematically, the direction of real action of these muscles was calculated as (Ravera et al. 2012)

$$\vec{r}_{\text{patella}} = \frac{\vec{r}_{\text{tibia}} + \vec{r}_{\text{femur}}}{\vec{r}_{\text{tibia}} + \vec{r}_{\text{femur}}}. \quad (1)$$

2.2.2.1. Modelled of muscle tissue. The muscle–tendon unit can be described by a lumped parameter (Zajac 1989). A contractile element was estimated using a Hill-type model with generic force–length $f_l(l_m)$ and force–velocity $f_v(v_m)$ functions and a parallel passive element represented by the force–length relationship $f_p(l_m)$ (Buchanan et al. 2004). In general, the equation that describes the muscle force produced by a unit muscle-tendon is

$$\begin{aligned} F_i^{\max} &= \text{PCSA}_i \sigma_{\max} \left[f_{l_i}(l_{m_i}) f_{v_i}(v_{m_i})\, a_i(t) \right. \\ &\quad \left. + f_{p_i}(l_{m_i}) \right] \cos(\varphi_i(t)), \end{aligned} \quad (2)$$

where PCSA is the physiological cross-section area, $\sigma_{\max}$ is the maximal stress in a muscle fibre (Horsman 2007), $a(t)$ is the time-varying function of the muscle activation and $\varphi(t)$ is the pennation angle (Lloyd and Besier 2003). As walking is a movement that develops near to optimal velocity of muscle shortening, it was assumed that $f_v(v_m) = 1$ (Horsman 2007). The following equation was used to represent the force–length function of the muscle:

$$\begin{aligned} f_l(l_m) &= 1 - \left| \left(1 - \frac{l_m}{l_m^0} \right) \right| \\ l_m^0 &= \text{median}\,(l_m). \end{aligned} \quad (3)$$

We used the following recurrence equation to model muscle excitation from the rectified and low-pass filtered EMG data (Lloyd and Besier 2003):

$$\begin{aligned} &u(t) = \alpha e(t - \tau_{\text{act}}) - \beta_1 u(t-1) - \beta_2 u(t-2) \\ &\alpha - \beta_1 - \beta_2 = 1 \\ &\beta_1 = \gamma_1 + \gamma_2 \\ &\beta_2 = \gamma_1 \gamma_2 \\ &|\gamma_1| < 1 \\ &|\gamma_2| < 1 \end{aligned} \quad . \quad (4)$$

Finally, we quantified the nonlinear relationship between neural excitation $u(t)$ and the time-varying function of the muscle activity $a(t)$ (Potvin et al. 1996) as

$$a(t) = \frac{e^{Au(t)} - 1}{e^A - 1} \quad -3 < A < 0, \quad (5)$$

where $\tau_{\text{act}} = 40$ ms, $\gamma_1 = \gamma_2 = -0.5$ and $A = -0.1$ (Buchanan et al. 2004).

2.2.3. *Simulating the smoothed EMG signal: EMGsim*

A Gaussian function (Equation (6)) was used to simulate the smoothed EMG signals. The reasons behind this choice were as follows: (1) these functions present good agreement with the theoretical morphology of smoothed EMG that is shown in the literature (Winter 2009); (2) only two parameters (μ and σ) and the use of linear combinations of these functions are needed to find an estimation of EMG patterns (Figure 2) (Farina and Negro 2012):

$$f(t) = \frac{1}{\sigma\sqrt{2\pi}} e^{((t-\mu)^2)/(2\sigma^2)}. \quad (6)$$

The parameter μ is the mean of theoretical time–area for each Gaussian function and σ is the sixth of the theoretical time–area length. Theoretical information (Winter 2009), such as the time when the muscles reach their maximum activations and the number of maximum activation shown on the EMG throughout the gait cycle, was used to generate a complete template of signals for all muscles modelled (Figure 3). Thus, some muscles such as biceps femoris, gluteus medialis, gluteus maximus, iliopsoas, semimembranosus, vastus lateralis, vastus medialis, soleus and gastrocnemius that presented only one peak of activation were modelled with only one Gaussian function, and the remainder muscles were modelled with two Gaussian functions because they present two areas of muscle activations. All simulated smoothed EMG signals were normalized to their maximum, with the objective of representing the theoretical muscles activation in a range from 0 to 1. The simulation of EMG data was further developed. The description of the process is completed in Sections 2.2.5 and 2.2.6 (Stages 5 and 6, respectively).

2.2.4. *Static optimization*

We define muscle force dynamics as the force developed by the individual muscles throughout the gait cycle. A nonlinear mathematical problem was used to calculate the individual muscle forces for each sample independently (Equation (7)).

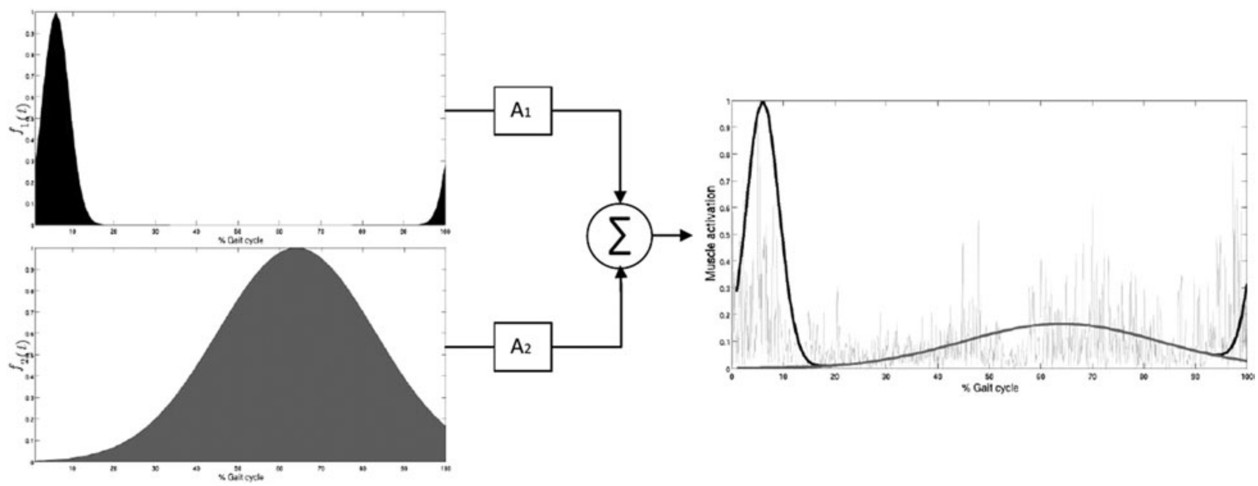

Figure 2. Example of the linear combination of Gaussian functions to generate the EMGsim for the tibialis anterior into the complete template of all muscles modelled. A_1 and A_2 are the weight constants that form the linear combination, so $\mathrm{EMG_{sim}} = A_1 f_1(t) + A_2 f_2(t)$.

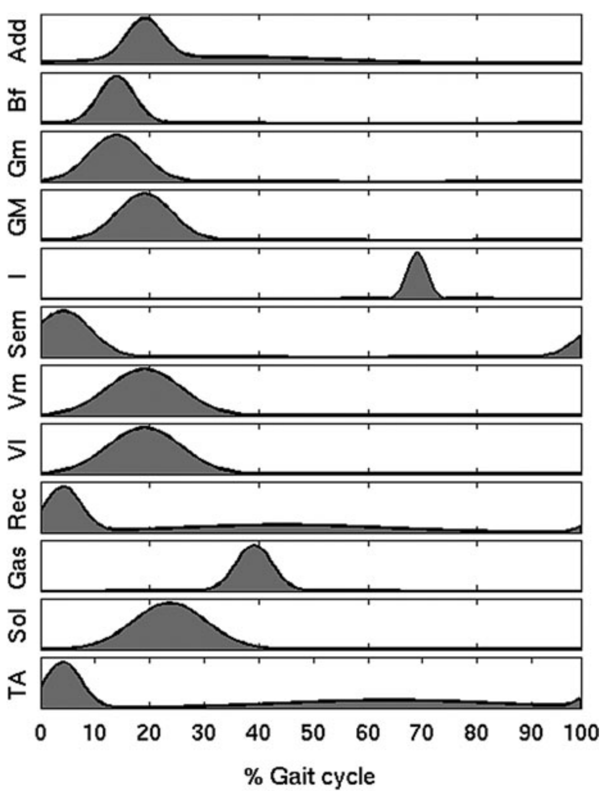

Figure 3. Template of EMGsim for adductor longus (Add), biceps femoris (Bf), gluteus medius (Gm), gluteus maximus (GM), iliopsoas (I), rectus femoris (Rec), semimembranosus (Sem), vastus medialis (Vm), vastus lateralis (Vl), gastrocnemius (Gas), soleus (Sol) and tibialis anterior (TA). All muscles modelled were normalized with their maximum, representing the theoretical muscles activation in the range of 0–1.

$$\begin{aligned}
&\operatorname*{Min}_{f} G\left(f_i^{(m)}\right)\\
&\text{subject to:}\\
&\textstyle\sum_{i=1}^{12} f_i^{(m)}\left(\vec{r}_i \times \vec{\tau}_i\right)_k = \vec{M}_k; \quad k = 1, 2, 3.\\
&0 \le f_i^{(m)} \le F_i^{\max}; \quad i = 1, 2, \ldots, 12.
\end{aligned} \tag{7}$$

where $G\left(f_i^{(m)}\right)$ represents the cost function, $\vec{M}_k$ the net joint moments (obtained in Stage 1), $f_i^{(m)}$ the norm of the ith muscle, $(\vec{r} \times \vec{\tau})$ the time-varying muscle moments (Kaufman et al. 1991b) and $F_i^{\max}$ the maximal force that the muscles may develop (Equation (2)). Optimizations were performed using the sequential quadratic programming (SQP) algorithm and the Broyden–Fletcher–Goldfarb–Shanno method to approximate the Hessian matrix (Nocedal and Wright 1999).

2.2.4.1. Cost function. The muscle forces distribution problem is then solved for each instant in time, minimizing an objective function subject to constraints. A variety of optimization criteria have been used in the literature to solve this problem. Some of the criteria have been selected arbitrarily, whereas others have been based on various physiological reasons (Prilutsky and Zatsiorsky 2002). Among the latter are versions of minimum muscle fatigue, minimum muscle stress and minimum metabolic energy expenditure.

The cost function used in model (Equation (8)) represents the two major consumption of energy on the muscle, the detachment of the cross bridges and the reuptake of calcium (Praagman et al. 2006):

$$G\left(f_i^{(m)}\right) = f_i^{(m)} l_{m_i} + m_i c_1 \times \left\{ \frac{f_i^{(m)}}{\mathrm{PCSA}_i \sigma_{\max} f_{l_i}(l_{m_i})} + c_2 \left(\frac{f_i^{(m)}}{\mathrm{PCSA}_i \sigma_{\max} f_{l_i}(l_{m_i})} \right)^2 \right\}, \tag{8}$$

where $c_1 = 100(\mathrm{m/s})^2$, $c_2 = 4$, $\sigma_{\max} = 27\,\mathrm{N/cm}^2$ (Horsman 2007), m is the muscle mass and $f_l(l_m)$ is the force–length relationship of the muscle.

2.2.5. *Temporal variations of EMGsim*

Human gait implies complex movements that require a correct synchronism of all muscles of the lower limbs (Winter 2009). In complex tasks, with several active muscles, the neural input to different muscles is not independent. For example, a common drive in the oscillation of discharge rates of motor units has been observed across synergistic muscles, indicating a common input to these muscles. These results suggest that motor control by the central nervous system may be organized by a relatively small number of signals that act on motor modules, activated by descending neurons and combined to produce a wide range of movements (Farina and Negro 2012).

Despite this fact and in order to achieve a best computational performance of this musculoskeletal model, we assumed independency between the different muscle patterns activations. Hence, to find the temporal position of each Gaussian function, we assumed that each EMGsim was independent. Our approach to find the optimal temporal position of each Gaussian function that represents the EMGsim was based on obtaining the solution of the static optimization problem (Stage 4) for different temporal positions of EMGsim. For each iteration, we found a new estimation of the net joint moments using estimations of dynamic muscle forces $\left(f_i^{(m)}\right)$ and time-varying muscles moment $(\vec{r} \times \vec{\tau})$ as follows:

$$\tilde{M} = \sum_{i=1}^{12} f_i^{(m)} \left(\vec{r_i} \times \vec{\tau_i} \right). \tag{9}$$

At the start time, the Gaussian functions of all EMGsim were temporarily positioned in the areas that presented their more important activations according to the literature (Winter 2009). Later, the EMGsim had some DoF to shift its temporal positions, changing the μ parameter. In our model, this parameter can take five time steps at 10%, around its initial position, equally spaced (Figure 4A). Then, the optimal temporal position achieved when the minimum error joints (Equation (10)) between the net moments (M_k, obtained by the inverse dynamics in Stage 1) and the net moments recalculated (Equation (9)) was found:

$$e_t = \sum_{j=1}^{R} \sqrt{\frac{1}{N} \sum_{i=1}^{N} \left(M_{k_{ij}} - \tilde{M}_{ij} \right)^2}, \tag{10}$$

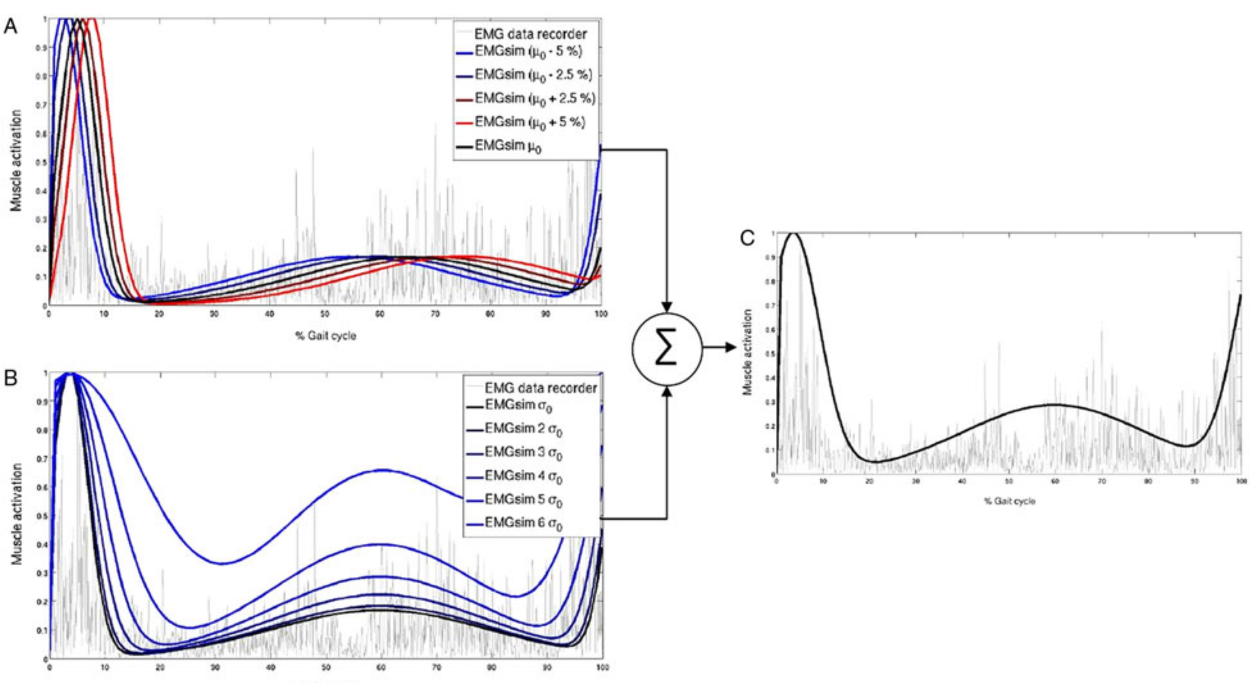

Figure 4. Example of the simulated smoothed EMG signal of the tibialis anterior. (A) Temporal variations of EMGsim (Stage 5). (B) Six of 24 steps of morphological variations of EMGsim (Stage 6). (C) The optimal EMGsim at the end of the algorithm.

where R is the DoF and N the number of data time. It was assumed that while one muscle changes its temporal position, the other muscles are motionless remaining in their theoretical positions. Once this process was repeated for all muscles modelled, we found the optimal temporal position for all EMGsim. We used a computer cluster (48 PCs Intel Pentium 4–3 GHz and 2 GB of memory RAM) to compare the hypothesis of the temporal independency of the EMGsim proposed.

2.2.6. *Morphological variations of EMGsim*

Once the EMGsim was temporarily positioned, it was necessary to fit the Gaussian function to find the optimal morphological condition. When σ is the sixth of the theoretical activation time–area length (condition of Stage 5 and initial condition of Stage 6) in the static optimization problem, Stage 4, the estimation of the net joint moments through Equation (9) produced a suboptimal solution.

The problem arises from the rigidity of the upper boundary conditions shown in Equation (7), for which the optimal solutions derived from the SQP algorithm were $f_i^{(m)} = F_i^{\max}$ and $\tilde{M} < M_k$. The rigidity of the upper boundary conditions was due to the fact that EMGsim played an important role in the modulation of the possible maximum amplitudes of each muscle forces through $a(t)$, see Equation (2). Hence, we adjusted the Gaussian function at the optimal morphological condition of the smoothed EMG using the σ parameter. So, σ was increased on each step by 12.5% of its start condition to relax the upper boundary condition (Figure 4B). This iterative process was continued until the recalculated net joint moments using the dynamics muscle forces (Equation (9)), estimated at Stage 4, were similar to the net joint torques found at Stage 1. We used two methods to determine the end of morphological adjustment, visual and numerical error feedback:

$$e_{\text{join}} = \sum_{i=1}^{R} \left\| \left(M_{k_i} - \tilde{M}_i \right) \right\|_{\infty}, \tag{11}$$

where R is the DoF, M_k are the net joint moments obtained in Stage 1 and $\tilde{M}$ are the recalculated net joint moments.

3. Results

One assumption made was the temporal independency of the EMGsim (Stage 5). Table 3 shows the mean and SD of the minimum errors (Equation (10)) for both independency of EMGsim and dependency of EMGsim studied using a computer cluster due to its high computational cost. The comparison between the approaches shows no statistically significant differences, so we considered the EMGsim as part of our model (Stages 3 and 5) to be temporarily independent.

The net joint moments of normal subjects obtained from our link model segment and generic musculoskeletal model of OpenSim (Delp et al. 2007) are both within the values shown in the literature (Winter 2009). Figure 5 represents the net joint moments of all DoF for both musculoskeletal models.

The main differences between both inverse dynamics models are present during the swing phase because the model used from OpenSim was scaled from adult models, whereas our model used a nonlinear regression (Yeadon and Morlock 1989) to scale it.

The static optimization problem finds the optimal muscle forces throughout the gait cycle that best represents the net joint moments. Figure 6 shows the differences between the inverse kinematic and static optimization results calculated using Equation (11) for each DoF modelled for both musculoskeletal models.

Figure 7 shows the mean and SD of the dynamic muscle forces throughout the gait cycle for all muscles modelled with both models (OpenSim and our model). Both generic musculoskeletal models present similarities in the muscle forces behaviour. They show the peaks of muscle forces around the same areas of the gait cycle and an equivalent scale of muscle forces.

We showed that the more important differences between both models were given on the stance phase for the biceps femoris, semimembranosus and rectus femoris. The differences may be attributed to the increase in some muscle forces, resulting in an increase in the other muscles by their antagonistic behaviour. Tibialis anterior and gastrocnemius also show differences in the stance phase, but we assume that they are probably because our model has three DoF in the ankle joint and these muscles not only play an important role in the flexion–extension of the ankle joint but also in the abduction–adduction and

Table 3. A Student's t-test ($p < 5\%$) on the temporal behaviour of EMGsim.

	Non-temporal independency of EMGsim	Temporal independency of EMGsim	p-value
Error hip (N m)	4.8979 ± 2.5662	6.8470 ± 3.1088	0.1930
Error knee (N m)	0.0792 ± 0.0506	0.0792 ± 0.0506	0.9999
Error ankle (N m)	5.8010 ± 5.5316	7.0478 ± 7.0318	0.6994

Note: Errors of Stage 5 under the assumption of the temporal and non-temporal independency of EMGsim are presented as mean ± SD.

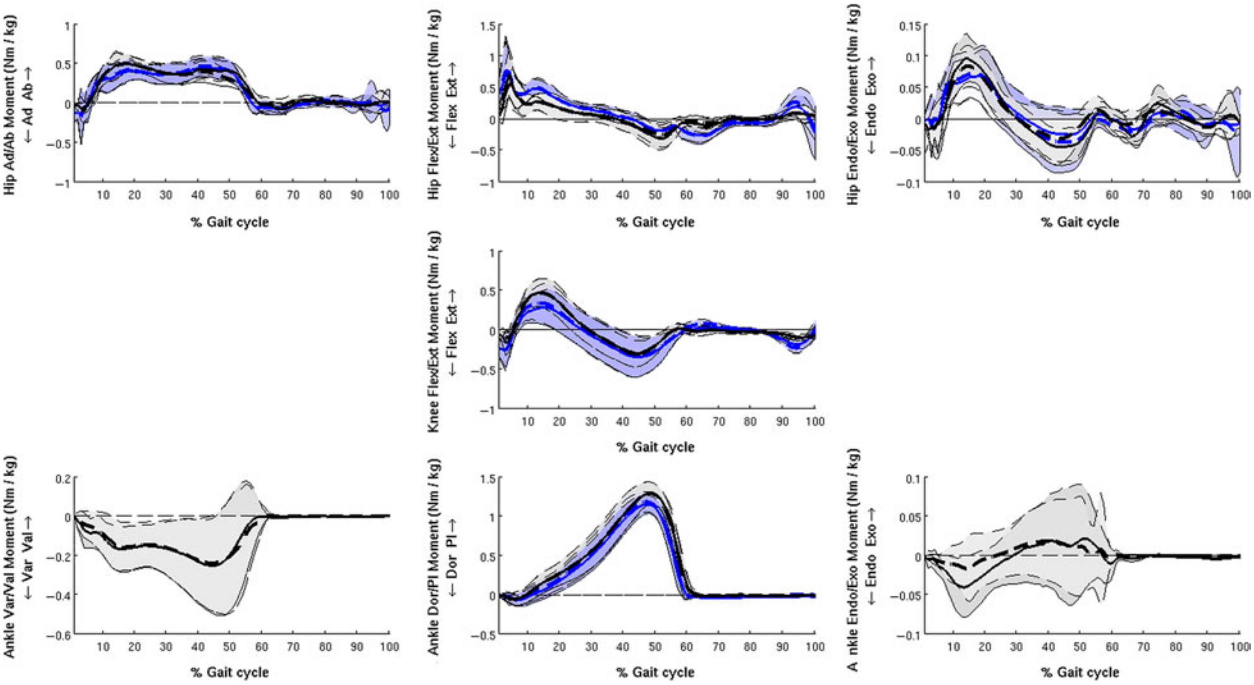

Figure 5. Mean and SD of moments of hip, knee and ankle joints of our model (black) and OpenSim (blue). Solid lines represent the inverse dynamics and dashed lines show the static optimization results of both models.

the internal–external rotation. Also, in our model, the soleus muscle provides movement in the flexion–extension of the joint ankle alone, in accordance with 3DGaitModel2392.

We compared the final configuration and position of the EMGsim with the real EMG recorded in clinical setting for each subjects, as shown in Figure 8. This model shows good agreement between the data of EMG activity in different muscle groups and the EMGsim.

4. Discussion

Inverse dynamics with static optimization and computer muscle control using a forward dynamic to minimize

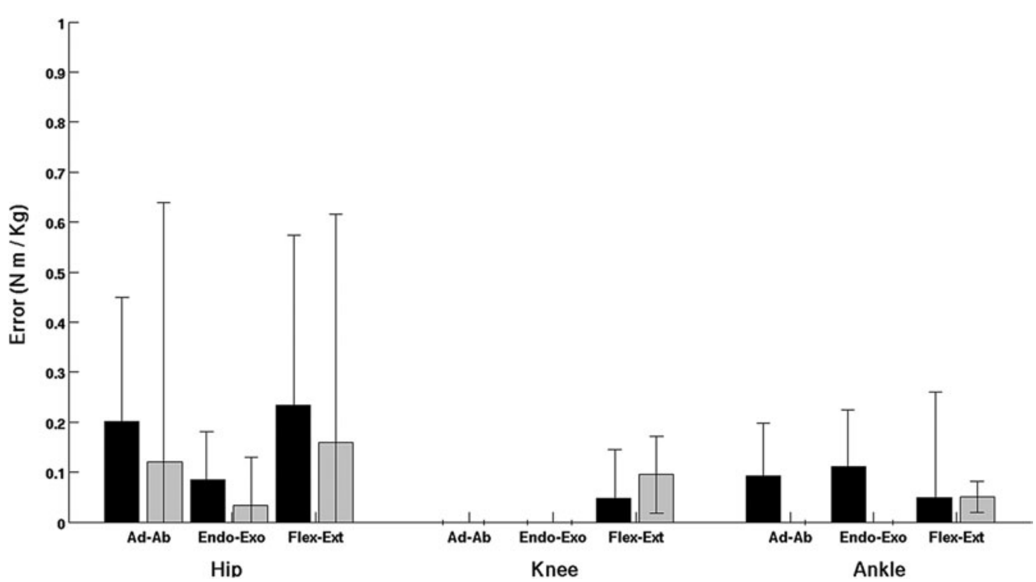

Figure 6. Infinity norm of the difference between the net joint moments found from the inverse dynamics and static optimization. Bars represent the confidence interval at 95% from each DoF of OpenSim (grey) and our model (black).

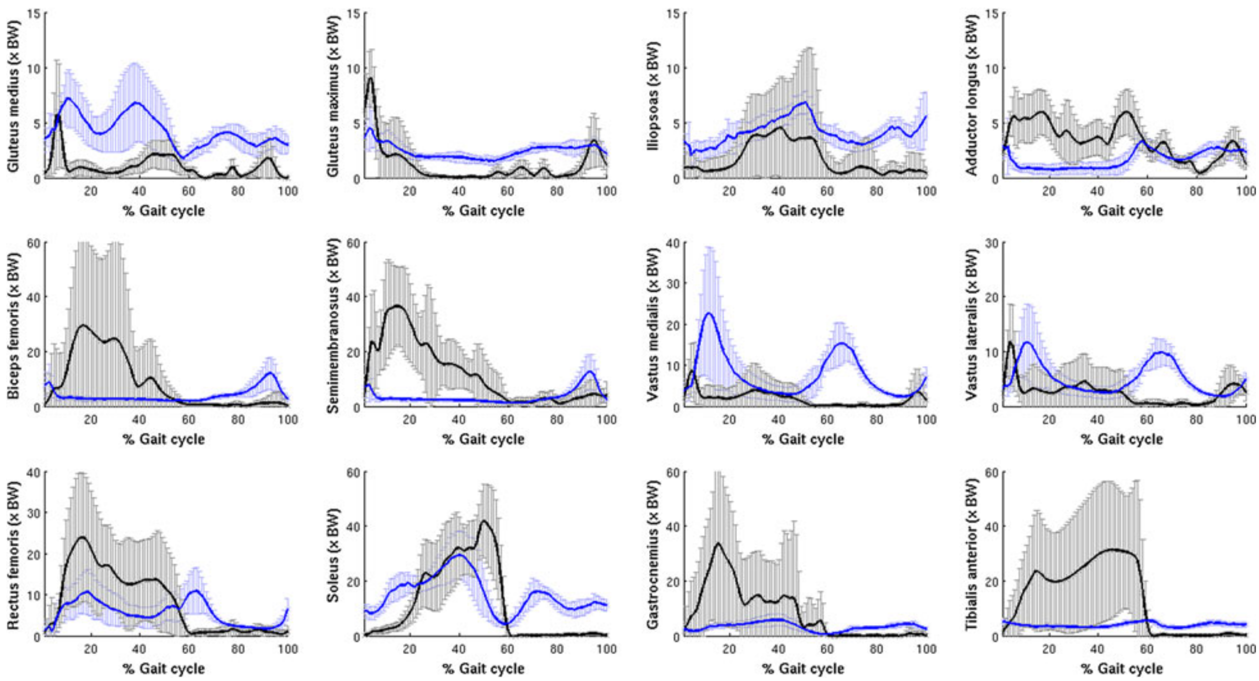

Figure 7. Mean and SD of muscle forces throughout the gait cycle normalized by bodyweight (BW) for healthy subjects, using OpenSim (blue) and our model (black).

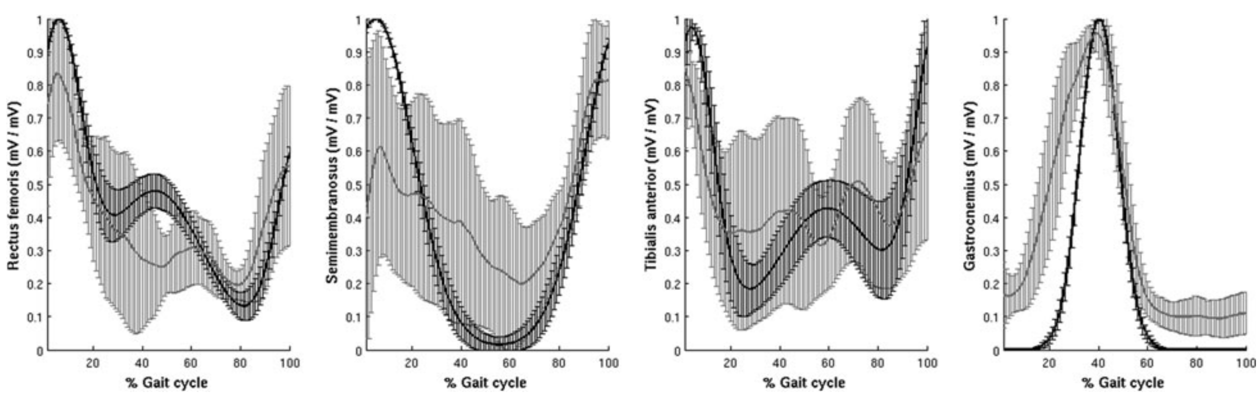

Figure 8. Mean and SD of the smoothed real EMG data (grey) and EMGsim data (black).

tracking (Thelen et al. 2003) are two techniques used to estimate muscle forces. However, inadequate kinematic models to represent the motion of interest and inaccuracies of experimental data have been identified as weaknesses of the methodology (Erdemir et al. 2007). Inverse dynamics with static optimization has limitations due to changing muscle dynamics and possible signal artefacts that depend on day-to-day variation in the position of EMG electrodes, skin preparation, ambient temperature, electrical impedance, the number of muscles EMG signal possible to measure in the clinical setting and protocols. Nevertheless, in clinical gait analysis, the method of inverse dynamics is a fundamental and commonly used computational procedure to calculate the force and torque reactions at various body joints (Whittle 1996, Winter 2009).

Our aim was to develop a generic musculoskeletal model that could be able to be applied in clinical settings. Our musculoskeletal model of the lower limb presents a simulated smoothed EMG data to address the limitations of these techniques. We propose a complete representation of the EMG signal of all modelled muscles, simulating the smoothed EMG data through the linear combination of different Gaussian bells. The use of inverse dynamic and static optimization with EMGsim enables to estimate the muscle forces produced during walking; however, there are also limitations to this method. To calculate the muscle forces, an objective function should be minimized. Especially for sub-maximal activities, it is often assumed that movements are performed by minimizing energy consumption (Prilutsky and Zatsiorsky 2002); yet, only a few energetic cost functions are assumed to be related to physiological costs such as energy consumption or fatigue and their relationships have not been clearly proven. In our musculoskeletal model, we used an objective function that showed to be a better measure for muscle energy consumption, which leads to more realistic predictions of muscle activation and have a validation with an indication of muscle energy consumption *in vivo* (Praagman et al. 2006).

Moreover, static optimization used to decompose the net joint moments into the individual muscle forces has a long history, but has problems when it is applied to study the muscle coordination because the optimization criteria inherent in this approach present low confidence (Zajac et al. 2002). However, a scaled generic musculoskeletal model may assist clinicians in the diagnosis and treatment of individuals with gait abnormalities, due to their accuracy and low cost (Correa et al. 2011). So, we use a set of equations to scale the body segment parameters of the musculoskeletal model based on a nonlinear regression and this approach provides a reasonable estimation of the moments of inertia of the segments outside the sample range (Yeadon and Morlock 1989). This approach is more useful in a clinical setting due to the heterogeneous population of patients. In addition, we modelled the knee mechanics through a single joint in accordance to other authors (Delp et al. 2007) and used a planar model of joint because this essentially replicates the same mechanical process as the more complex model (Yamaguchi and Zajac 1989).

Estimation of muscle forces using static optimizations, regardless of inverse or forward dynamics, to solve the equations of movement of the musculoskeletal system depends on the behaviour of the net joint moments. Both generic musculoskeletal models (3DGaitModel2392 and our model) have similar performances, showing little differences in joint moments mainly during the swing phase. Rao et al. (2006) and Riemer et al. (2008) observed that deviations in the estimations of net joint forces and torques are especially due to the effect of varying simultaneously the mass, moments of inertia and the centre of mass location values, according to the underlying relationship of interdependency linking each component. So, the main contributors to these uncertainties were identified to be the inaccuracies in estimated body segment parameters.

On the other hand, the hip joint flexion/extension moment during the swing phase is highly sensitive to the model used in the estimation of body segment parameter (Rao et al. 2006). Hereby, we believe that these differences exist because these musculoskeletal models do not use the same estimation of body segment parameters. Further investigations remain necessary to clarify the impact that the estimation of body segment parameters has on the estimation of muscle forces; and so to improve the models, while simultaneously improving the rigor and objectivity of clinical interpretations. Also, both musculoskeletal models used a different cost function in static optimization.

The main problem of these methods to achieve correct muscle coordination is the lack of a complete inclusion of EMG data for all muscles modelled. We present a new technique that simulates the EMG activity and presents a good correlation with the muscle forces during walking. We present a clear way to simulate the EMG data of all muscles modelled and assume that this way presents a temporal independence, improving the timing for the numerical solution. To demonstrate the independency of EMGsim, a statistical analysis was performed and showed no statistically significant differences with the dependent approach. However, further studies with a larger number of subjects are needed to generalize the results. Despite the relatively small sample size used in this study, we consider it sufficient to outline the trend. Also, this method showed great similarities with the real EMG data recorded from the subjects doing the same movement.

Changes in model parameters of one muscle can change the predicted forces for the same muscle and other muscles by several times and can also change the number of non-zero forces in the optimal solution and the set of muscles with active states (Raikova and Prilutsky 2001). Only a few differences between the two models are shown. It was on the forces of the muscles that cross the ankle joint. We believe that the differences are because our model has more DoF than the OpenSim one. In addition, the estimation of muscle forces is more sensitive to changes in moment arms than to changes in PCSA, and changes in model parameters have stronger effects on the magnitude of predicted forces than on their patterns (Raikova and Prilutsky 2001). Given that the goal of our model is to be used in the clinical settings and for the major number of gait abnormalities, we think that abnormal patterns found on frontal and coronal planes have the same relevance that in the sagittal plane.

In conclusion, this paper presents a generic musculoskeletal model of the lower limb that uses only subject-specific anthropometric data, commonly recorded in the clinical setting. Our model uses inverse dynamic and static optimization to find the muscle forces throughout the gait cycle. We proposed a new method that includes the EMG information and showed how to simulate the smoothed EMG data through the sum of different Gaussian bells. Taking into account the history of musculoskeletal modelling in biomechanics, we think that the use of musculoskeletal models in the clinical setting is changing its paradigms, becoming a challenge for the clinical teams that may start to include them in the process for decision-making in the treatment of patients with abnormal gait.

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Conflict of interest statement

We do not have any financial or personal relationships with other people or organizations that could inappropriately influence our manuscript.

Notes

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