Biomechanical model of the lower limb based on relevant actions for the control of knee-rehabilitation parallel robots

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1 Introduction

Parallel robots are increasingly being used for rehabilitation of the lower limb due to their robustness, simplicity, versatility, load capacity and low cost. In the last decade, a few rehabilitation parallel robots (RPRs) have been developed, mainly for the ankle [1] and, more recently, for knee rehabilitation [2]. Unlike exoskeletons where mechanical actions are usually applied on the joint axis, RPRs exert mechanical actions over the distal end of the limb. For this reason, the control actions monitored from the robot may not correspond with those transmitted to the muscles and ligaments. This limits the effectiveness of the exercises as well as the possibility of developing dynamic safety systems. As a result, developing a biomechanical model for the estimation of the relevant forces in the knee, such as muscle, tendon, ligament, and tibial contact forces, while doing the exercise with the robot, is critical for practical implementation of RPRs.

Recently, a relatively high effort has been performed for developing muscle-skeletal models (MSM) in order to evaluate muscle-tendon forces and joint contact forces during motion of lower limb. The levels of complexity and accuracy of such models are quite diverse. For instance, references [3, 4] show that complex models in which many parameters are adjusted can provide good results. However, such models usually require expensive additional equipment, e.g. EMG measurements in vivo, MRI scans for model calibration parameters, etc., which makes them unsuitable for their use in clinical applications. On the other hand, the models can be quite sensitive to changes in the input parameters; sometimes these parameters are estimated through an optimization process, without ensuring their physical feasibility [5].

An alternative approach is to use simpler and more robust generic models, whose effectiveness can be increased by improvements or adjustments of some specific characteristics. A recent review [6] analyzes which are the most influential characteristics, such as the representation of the joint kinematics, which affects the lever arms of the muscles during movement, the number of lines of action of the muscles, the optimization process to solve the redundancy of the muscular problem, muscular activation models, among others.

Most applications of lower extremity MSM are associated with the study of human gait, while the effort devoted to the study of rehabilitation exercises and strengthening of the lower extremities remains weak [7]. In addition, common models in this field require a very high level of personalization and also use EMG signals as inputs to the model [8, 9]. This makes their implementation difficult in rehabilitation robots from a clinical point of view.

It is worth mentioning that MSM for rehabilitation robots are mainly oriented to the control of exoskeletons [10]. There is a wide variety of models in this field, from simple joint models for estimating joint moments [11-13], to models with more anatomical details that use EMG signals as inputs [14, 15]. In general, the models used in rehabilitation robots are usually simple with limited possibilities for personalization, although some works have also been published using much more detailed models developed in commercial software such as Anybody [16] and OpenSim [17, 18]. Moreover, the application of dynamic modeling along with RPRs is much more recent and less extended.

MSM for clinical applications in rehabilitation robots should work with low-cost systems, they should not imply the use of complex instrumentation and they should work with real time algorithms. Furthermore, they should provide precise estimations of internal forces at both muscle and joint levels. This implies a certain level of details as well as to be subject-adaptive. Satisfying these conflicting criteria, model simplicity and accuracy, can be performed by implementing a model that capture the most relevant aspects for the specific applications under consideration [6]. In this manner, model precision can be improved by implementing a parametric model that considers the most relevant anatomical and inertial characteristics and that can be subject-adaptive from anatomical landmarks. Moreover, a realistic definition of the joints, especially of the knee joint, is a critical issue which has a direct influence on the dynamic model accuracy [19].

Another important issue affecting the accuracy of the model is the number of muscles and muscle insertions being considered. It is evident that more details in muscle representation leads to more accurate MSM [20]. However, increasing the number of muscles requires more information about their anatomical characteristics, makes muscle actions a redundancy problem more difficult to solve, and it also increases the computational cost of the associated optimization problem. For this reason, in many works adjacent muscles are grouped or only a set of muscles are considered when solving the redundant problem [7].

In order to solve the problem of redundant muscular forces, many methods have been proposed. For instance, the reduction method [21], the method of addition [22] and the optimization method [23-26]. The latter provides more accurate estimates of muscular forces and is widely implemented. However, it has a relatively high computational cost. Therefore, it is not the most appropriate in systems requiring real-time calculations. Similarly, systems based on EMG signals [8, 9] are also discarded from their use in the clinical context because they require individual calibration in each session. For this reason, the problem of muscle strength redundancy must be adapted in order to make calculations in real time and with minimum equipment.

Finally, the acquisition of the input information of the model and the calculations must be compatible with the low-cost and the operation in real time. MSMs use input information associated with movements and external applied forces. In conjunction with the inertial and gravitational forces, they allow to solve the inverse dynamic problem and to obtain the actions at joint level. The incorporation of the anatomical features, along with the optimization process, provides an estimation of internal actions compatible with the result of the inverse analysis. In this process there are especially expensive phases in computational time which are difficult to compute in real time.

Furthermore, the complete kinematic analysis (positions, velocities and accelerations) implies the use of high cost video-photogrammetry systems as well as kinematic analysis and numerical derivation algorithms. In addition, the resolution of the inverse dynamic problem and muscle force optimization has also a high computational cost. However, when slow movements are performed, as is the case in rehabilitation robots, the effect of inertial forces could be relatively small, which allows the use of quasi-static analysis [8, 27, 28]. Moreover, if minimizing the sum of muscle stresses is selected as the optimization criterion [29], then the optimization problem can be extracted from the dynamic model and transformed in a position dependent problem that can be compute offline. By doing this, data acquisition process will be simplified drastically and the computational time will be lowered during measuring process.

The purpose of this study is to improve the computational efficiency of the generic dynamic model presented in [29] such that it can be used in control algorithms of a parallel robot designed for knee rehabilitation [2]. This model can be adapted to each person by using the position of the anatomical points after adequate three-dimensional scaling. Generally, the accuracy of generic models depend on many factors related to the mode of application. The most important factors are 1) the kinematic representation of lower extremity joints affecting largely muscle moment arms during motion, 2) the considered muscles and the method of their representation, and 3) the method adapted to solve the redundancy problem of muscle forces [6]. The latter factor corresponds to a very high computational cost especially when trying to solve this redundancy by a numerical optimization procedure. In this work, a direct and computationally efficient procedure is proposed to tackle this issue and to enable its use in real time control algorithms for rehabilitation robots.

This work is organized as follow: next section presents the material and methods related to the formulation of the problem. This section makes an overview about the theoretical background of biomechanical model, introduces the offline calibration stage, the calculation of the internal forces in the online stage, and the method adapted for model verification. The obtained results are presented in section 3. In section 4 results are discussed.

2 Material and methods

2.1. Biomechanical model

The proposed MSM models the lower limb by means of four segments: pelvis, femur, tibia and foot segments. The model was introduced initially in [29] for the estimation of relevant forces in the knee joint. For the sake of completeness, this section presents general information about the model giving more attention to modifications made to the model [29] to improve its efficiency and computational time. The improvements enable the model to work in real time for a rehabilitation tasks with a parallel robot. Additionally, a comparison between the muscle forces predicted by the model and the measured EMG signals is performed.

The inputs to the kinematic model are the coordinates of a set of anatomical landmarks, measured by a video-photogrammetry system (Fig. 1). The underlying kinematic model considers a three degrees-of-freedom (DoF) spherical joint to model the hip joint, one DoF four-bar mechanism for the knee joint and one DoF revolute joint at the ankle joint (AJC), leading to five independent generalized coordinates to describe the model. The location of the HJC is determined by using the functional method presented in [30] and implementing the protocol proposed in [31] On the other hand, the four-bar mechanism that best fits the relative motion between the femur and the tibia is determined using an optimal synthesis procedure based in the formulation introduced by [32] with some modifications. Lastly, the AJC location is in the midpoint between the medial and lateral malleolus.

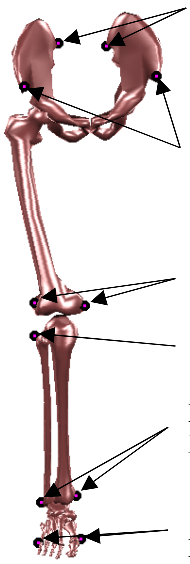

Figure (1). Anatomical points inputs to the kinematic model.

Once the kinematic joints are defined the dynamic model can be built considering the generalized coordinates describing these joints. More precisely, three generalized coordinates are needed for hip joint, one for the four-bar mechanism, and one for the revolute joint at the ankle. In function of these coordinate the dynamic model can be written as,

$$\vec{\tau}_I + \vec{\tau}_G + \vec{\tau}_{Mus} + \vec{\tau}_{Ext} = \vec{0} \qquad (1)$$

where, $\vec{\tau}_{Mus}$, $\vec{\tau}_I$, $\vec{\tau}_G$ and $\vec{\tau}_{Ext}$ are the generalized forces corresponding to muscles, inertia, gravity and external forces, respectively.

Note that all the generalized forces expressed in equation (1) are calculated by using the Jacobian transformation of the corresponding forces/moments [33]. For the inertial parameters they were estimated applying the equations provided in [34]. Note that the complete model introduced in [29] includes all the inertial effects and the corresponding inertial parameters. However, as will be shown in this paper, the inertial forces that affect the knee joint are very small. As a result, lower limb segments' masses and center of gravity positions are the only necessary inertial parameters.

With respect to the muscles, via points and via cylinders approaches were considered based on the measurements made in [35] with some modifications. The modelled muscles are, the following flexors: biceps femoris long head and short head (BicFemCL and BicFemCB), semimembranosus (SemMem) and semitendinosus (SemTend), gastrocnemius lateral and medial (GastLat and GastMed), gracilis (Gra) and sartorius (Sar).On the other hand, the following extensors: rectus femoris (RecFem), the two portions of the lateral vasti (VasLat), the three portions of the medial vasti (VasMedInf, VasMedMed and Vas-MedSup), the vasti inter-medial (VasInt) and tensor fascia latae (TenFacLat). Note that, as reported in [35], the rectus femoris muscle has two different insertion points on the femur (RecFem1 and RecFem2), while the vasti inter-medial and the lateral vasti present various. The last were regrouped into two principal points for each (VasInt1 and VasInt2) and (VasLatInf and VasLatSup), respectively, leading to a net of 10 extensor muscles. Moreover, the insertion points presented in [35] were measured for a given orientation of the leg and a given bone size. To make them available for any orientation of each bone, local reference systems were defined in which the insertion points were recalculated. Also a 3D scaling matrix, similar to the transformation introduced in [36], was implemented to adjust the recalculated local insertion points to any bone size.

2.2. Offline Calibration Stage

Before using the dynamic model to estimate the relevant forces in an online process, an offline calibration stage is accomplished to: a) estimate joint's parameters such as the position of the HJC and the dimensions of the four-bar mechanism, b) scaling lower limb model segments to actual sizes, and c) defining local anatomical coordinate systems (ACS) for each segment from the position of the anatomical landmarks, in which local coordinates of joint parameters, muscle's insertion points, center of mass locations and inertial parameters are calculated. Afterwards, in the online stage, global positions of each parameter can be reconstructed from these local coordinates and the position of the ACS.

In addition, to improve the efficiency and the computational time of the online force estimation stage, muscle's coefficients, or moment arms, were calculated in an offline process. For this purpose, a simulated model was built from the scaled lower limb segments and muscle's insertion points. Its workspace is defined as all the possible movements that the lower limb can perform in a given task as a function of the generalized coordinates. This workspace according to the maximum/minimum limits of the generalized coordinates with equal step-size for each one. Then muscle's coefficients were calculated at each point of the discretized workspace. As mentioned in [29], their values are obtained directly using the Jacobian calculation [33]. Jacobian calculation produces a more accurate estimation of muscle's coefficients as the four-bar mechanism reproduces better the relative motion between the femur and the tibia than a model based on a revolute joint. It worth mentioning that the Jacobian measures the moment arm of the considered muscle about an axis perpendicular to the plane of relative motion between the femur and the tibia and passing through instantaneous center of rotation. The axis perpendicular to the plane can be obtained directly from the four-bar mechanism [37].

Another important issue related to muscle force estimation is the redundant system of actuators. To solve this issue, constraint optimization procedure was implemented in [29], in which co-contraction between muscles was observed when minimizing the sum of muscle stress as an objective function, equation (3). Fortunately, this type of problem can be solved analytically using Lagrange multipliers and in the offline stage, see [38]. Leading to a high computationally efficient algorithm. To illustrate this concept, consider σ_i is the stress in the ith muscle, i.e.

$$\sigma_i = \frac{F_i}{A_i} \qquad (2)$$

Where, F_i corresponds to the ith muscle force and A_i its cross-sectional area. Then the objective function proposed previously will have the form,

$$\min\left[\sigma_1^{\,2} + \sigma_2^{\,2} + \cdots + \sigma_n^{\,2}\right] \qquad (3)$$

Note that muscle forces must confirm equation (1). i.e.

$$C_1F_1 + C_2F_2 + \cdots + C_nF_n = \tau_{Mus} \qquad (4)$$

where, C_i corresponds to ith muscle coefficient. Note that only one generalized coordinate is considered here that corresponds to the knee joint. This equation can be rewritten as,

$$B_1\sigma_1 + B_2\sigma_2 + \cdots + B_n\sigma_n = \tau_{Mus} \qquad (5)$$

where, $B_i = C_iA_i$

Then, in terms of σ_i the objective function is equation (3) subject to constraints provided in equation (5). One can prove that, using Lagrange multipliers, this minimization problem has the following analytical solution,

$$\sigma_i = \frac{\lambda B_i}{2} = \frac{B_i\tau_{Mus}}{\sum_{j=1}^{n} B_j^2} \qquad (6)$$

Where λ is the Lagrange multiplier and has the form,

$$\lambda = \frac{2\tau_{Mus}}{B_1^2 + B_2^2 + \cdots + B_n^2} = \frac{2\tau_{Mus}}{\sum_{i=1}^{n} B_i^2} \quad (7)$$

Hence, the magnitude of i^{th} muscle force simply is,

$$F_i = \frac{A_i B_i \tau_{Mus}}{\sum_{j=1}^{n} B_j^2} \quad (8)$$

Now take,

$$\varepsilon_i = \frac{A_i B_i}{\sum_{j=1}^{n} B_j^2}, \quad (9)$$

Then,

$$F_i = \varepsilon_i \cdot \tau_{Mus}, \quad (10)$$

Which is a direct relation to obtain the magnitude of muscle force from the generalized muscle force. Note that ε_i is kinematics dependent variable that can be calculated in the offline stage, which has a great effect on the computational time of the online one.

2.3. Estimation of muscle force in real time – the online stage

Once the offline calibration stage is performed, one can proceed with the online force estimation in muscles, meniscus contact and knee ligaments.

For the considered rehabilitation task, the motion of the anatomical landmarks is recorded by videophotogrammetry. The reaction force/moment between the foot and the parallel robot is measured by a force sensor. Based on these inputs, ACS are defined and model motion is reconstructed. Linear and angular velocities and accelerations are estimated using local cubic fit. Then the generalized inertial, gravitational and external forces are calculated as mentioned previously. Using equation (1) the generalized muscle forces are obtained. According to the current value of the generalized coordinates the values of ε_i is retrieved from the stored offline values using local linear interpolation. Consequently, the magnitudes of muscle forces can be calculated using equation (10). Finally, important knee forces such as normal force on the meniscus and ligament forces are calculated from the tibia free body diagram.

In this context, and in order to check whether the offline calculation stage affects the estimated force, the forces are compared with the ones obtained by the complete model presented in [29].

Although the offline calculation of the muscle coefficients implies a significant reduction in the computational cost online, there are still relatively expensive calculations associated with the estimation of the generalized inertial forces. It implies the calculation of the linear and angular velocities and accelerations, that is held by applying a local curve fit to the measured positions of the anatomical point to filter the data and to obtain the first and second time derivatives. In addition to the calculation of the Jacobian to obtain the generalized forces. It worth mentioning that local fit algorithms and subsequent derivatives implies a high computational cost. Also the derivatives are not reliable since accelerations correspond to the current state of the net forces and not from time history of the measured data. Moreover, knee rehabilitation tasks are of low speed and produces relatively low inertial forces in comparison with external and gravitational forces. As a result, they can be considered negligible from the dynamic model leading to a quasistatic problem. In fact, same conclusion was drawn in [29, 39]. To support this hypothesis another comparison is made in the next section between the modified dynamic model after removing the inertial forces and the original one.

In conclusion, the inverse dynamic system expressed by equation (1), after removing the inertial componets, leads to the following simple equation,

$$\vec{\tau}_{Mus} = -\left(\vec{\tau}_G + \vec{\tau}_{Ext}\right), \qquad (11)$$

where the gravitational generalized force will be,

$$\tau_G = J_{G_{Tib}}^T \cdot \begin{bmatrix} 0 & 0 & W_{Tib} \end{bmatrix}^T + J_{G_{Foot}}^T \cdot \begin{bmatrix} 0 & 0 & W_{Foot} \end{bmatrix}^T, \quad (12)$$

and,

$$\tau_{Ext} = J_{P_{Ext}}^T \cdot \vec{F}_{Ext} + J_{\omega_{Foot}}^T \cdot \vec{M}_{Ext}, \qquad (13)$$

Where, $J_{G_{Tib}}^T$, $J_{G_{Foot}}^T$, $J_{P_{Ext}}^T$, and $J_{\omega_{Foot}}^T$ are the Jacobians relating the gravitational forces of the tibia W_{Tib} and the foot W_{Foot}, and the external force $\vec{F}_{Ext}$ and moment $\vec{M}_{Ext}$, respectively, with the generalized coordinate at the knee. After the calculation of the generalized muscle force τ_{Mus} muscle forces can be obtained directly by applying equation (10). All the previous equations are simple, direct and computationally efficient ones, which enable real-time muscles' force calculation which is one of the objective of this paper.

2.4. Validation: Coherence level between the estimated forces and the EMG signals

Given that it is not possible the direct measurement of muscle forces, model validation is limited to a comparison between the proposed model and EMG signals. Experimental validation was accomplished using slow motion squat exercises. It was selected because this motion imposes high force levels at knee joint that induce moments and muscle forces higher than those resulted in normal gait motion. For this reason, this kind of motion was selected in previous studies for the validation of lower extremity dynamic model [40, 41]. Note that this exercise is faster than rehabilitation exercises with robots. However, as will be shown in results section, the inertial forces presents relatively negligible effect, supporting the hypothesis for neglecting them from the dynamic model.

In this experiment, a standard biomechanical analysis device was used for capturing motion and measuring external forces, which was validated in previous studies. It consists of two Dinascan IBV force platforms for ground reaction forces [42] and a Kinescan video-photogrammetry system for the analysis of the motion of corporal segments [43].

In this preliminary study experiment was accomplished by only one subject. The considered squat exercise consisted on repetitive cyclic motion, up and down with three load levels, each of two trials: i) with no load (L0), ii) with a 6 kg backpack (L1), and iii) with a 12 kg backpack (L2). The subject signed an informed consent and all the tests were approval by the Ethics Committee of the Polytechnic University of Valencia.

For each case the EMG signals were recorded for the following muscles: gastrocnemius, biceps femoris, vastus medialis and vastus lateralis muscles, using a Noraxon equipment. The signal was rectified and the RMS signal was used as an estimator of the level of muscle activity.

With respect to model based force estimation, two versions of the dynamic model were considered:

a) A full dynamic model (FDM), with the resolution of the inverse dynamic problem including the inertial forces and an muscle force optimization process based on minimum stresses criterion [29]. Calculations were made after completing the experiment, starting from the measurements taken simultaneously by the video-photogrammetry system and the force platforms.
b) A simplified version based on muscle coefficients and without inertial forces, static geometric model (SGM). In this case, the muscle coefficients were previously calculated from the data of the model's calibration tests . This model has the same inputs as the full one, however, only the generalized coordinates are calculated, then, as mentioned before,

the values of ε_i is retrieved from the stored offline values by interpolation, and the magnitudes of muscle forces are calculated using equation (10).

Starting from the obtained results, three verifications were made. In first place, the starting hypotheses was verified (little influence of the inertial forces, which leads to the possibility of rewriting the dynamic problem of slow motion into geometric terms (quasi-static)). To do this, the forces estimated by both models were compared. This comparison was made for each muscle using the intraclass correlation coefficient (ICC) between the estimates of the FDM and SGM models and the standard error of the measurements (SEM), as described in [44]. These calculations have been performed in a functional way obtaining a value for each trial [45].

Once verified that the estimations obtained from FDM and SGM are very similar, the concordance between SGM and muscular activity was verified over the reference muscles (vastus lateralis, VL, y vastus medialis, VM), using Spearman correlation coefficient.

Finally, the third level check consisted in the verification of the predictive capacity of the model. To do this, the trials with loading conditions L0 and L2 were used to establish a functional relation between the muscle forces estimated by the model, VL and VM muscles using SGM and the corresponding EMG observed signals (rms value). Then this functional relation was used to estimate the forces in the same muscles for loading condition L1, as a function of the corresponding EMG signals (rms) only. These new muscle estimates are denominated as FVL_{emg} and FVM_{emg}. For verification, they were compared with the same muscles values obtained by the model for the same loading conditions. The comparison was made using ICC and standard error of the mean SEM.

3. Results

Table (1) presents the median and the 95th percentile of the muscle forces of the major activation (VL and VM), estimated using the complete dynamic model (FDM), while figure (2) shows an example of rectus femoris muscle coefficients as a function of the considered generalized coordinates.

Table 1. Maximum (computed as 95th percentile) and median values (between parentheses) of the estimated muscle force using FDM at each loading level. All the values are in N.

	Load level		
Muscle	**L0** F_{max} (F_{median})	**L1** F_{max} (F_{median})	**L2** F_{max} (F_{median})
Vastint123	46,3 (14, 3)	53,1 (20,1)	56,7 (23,9)
VasMedInf12	15,7 (4,8)	18,0 (6,8)	19,2 (8,0)
VasMedMed12	80,7 (24,9)	92,6 (35,0)	98,9 (41,5)
VasMedSup34	96,4 (29,8)	110,6 (41,9)	118,2 (49,7)
VasLatSup12	424,9 (131,8)	487,3 (185,3)	520,7 (219,9)
VasInt456	46,5 (14,4)	53,4 (20,2)	57,0 (24,0)
VasLatInf4	16,0 (4,9)	18,4 (7,0)	19,7 (8,39

Table (2) shows the standard error associated with the differences between the estimates calculated by the FDM and SGM models for the different portions of the vastus femoris muscle. As can be seen, errors were lower than 1.0 N for all trials except for one muscle, which was lower than 2.0 N. In addition, the ICC was practically 1 in all cases. As a conclusion, almost no appreciable difference appears between FDM and SGM models.

Fig. 2: Rectus femoris muscle coefficients versus the relevant generalized coordinates.

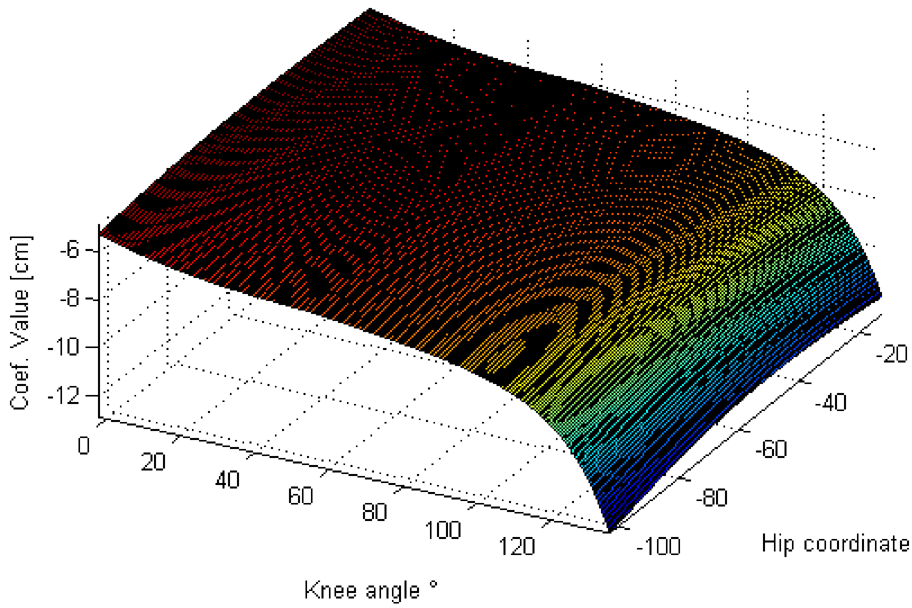

Table 2. Differences between the force estimations using FDM and SGM models.

Muscle	**SEM (N)** (maximun)
Vastint123	0.15
VasMedInf12	0.05
VasMedMed12	0.27
VasMedSup34	0.32
VasLatSup12	1.4
VasInt456	0.15
VasLatInf4	0.5

Spearman correlation coefficients between muscle forces estimated by SGM and EMG signals, for the muscles under consideration (Vastus lateralis y Vastus medialis), are shown in Table (3). In these results, data corresponding to flexion movement was separated from the extension one, for each loading condition.

Table 3. Spearman correlation coefficients between muscle forces estimated by SGM and the rms value of EMG signals. Mean (standard deviation) for all trials.

	Muscle	
Movement	**Vastus lateralis**	**Vastus medialis)**
Extension	0.940 (0.030)	0.928 (0.026)
Flexion	0.939 (0.015)	0.920 (0.035)

Finally, the concordance between the muscle force estimations for vastus medialis and lateralis muscles under L1 loading conditions is shown in figure (3). Solid lines correspond to the forces estimated by SGM, (FVL_{SGM} and FVM_{SGM} respectively), while the markers represent those estimated through the EMG signals of L1 and the force-EMG signal calibration curves obtained from the other two loading conditions L0 and L2 (FVL_{EMG} and FVM_{EMG}).

As can be seen, the agreement between the two estimates is excellent for both muscles. The SEM was 9.1 and 45.8 for the vastus medialis and lateralis muscles, respectively, and the ICC values are greater than 0.9 (0.953 and 0.937 for the vastus medialis and lateralis muscles, respectively).

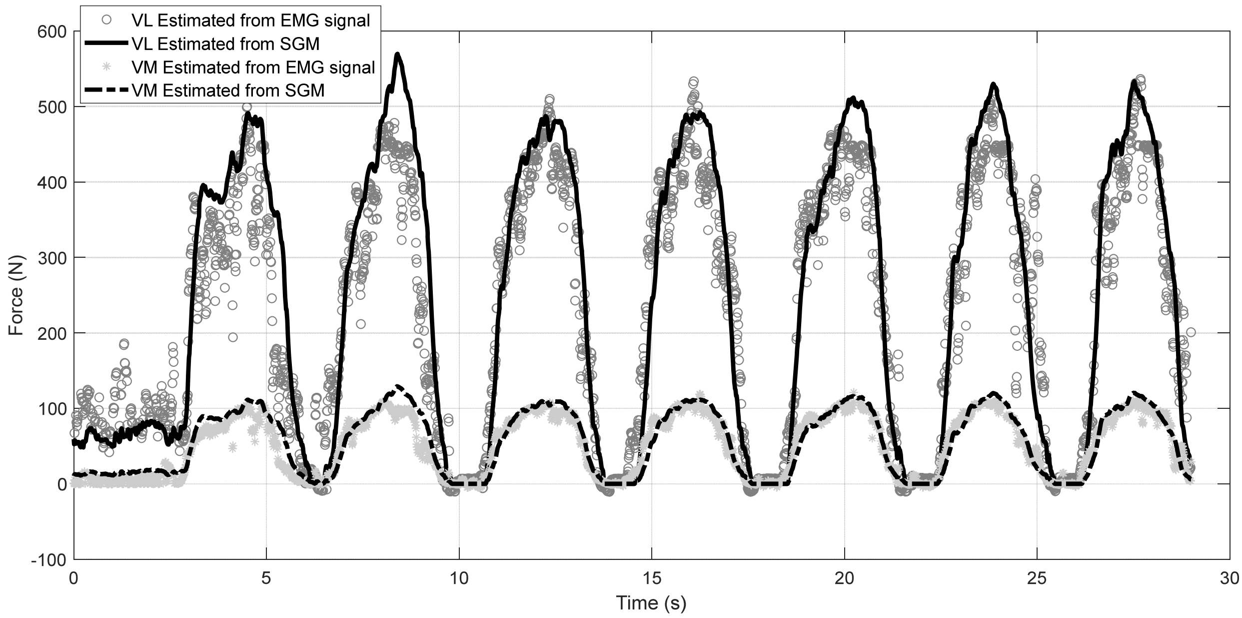

Fig. 3. Anatomical points inputs to the kinematic model

4. Discussion and conclusions

In this work, a simplified, accurate, and computationally efficient model for human lower limb was developed, which enables its future use in advanced based model control algorithms for knee rehabilitation using a low-cost parallel robot. This model, in comparison with more detailed and complicated ones, presents the advantage of being simple, subject adaptable, and able to work in real time control schemes. The model was obtained by assuming certain simplifications that will be discussed in this section.

The first simplification was the consideration of quasi-static model. As rehabilitation exercises are carried out at low velocities and accelerations of the different parts of the lower limb, the resulting inertial forces will present negligible effect on the dynamic model, in comparison with the external and gravity forces. This assumption was verify in this paper, and also it was taken into consideration and applied in many previous works under the same conditions [8, 27, 28].

Another important factor that has a high computational cost in the dynamic model, preventing its application in real time tasks, is related to the method to deal with the redundancy problem of the actuating muscles, and the calculation of muscle coefficients, or moment arms. More precisely, for the first part, minimizing the sum of stresses in all muscles was found acceptable for producing a distribution of the generalized force between muscles [29]. The traditional solution of this problem was the use of a high computational cost numerical optimization procedure. In this work, this problem was completely solved by replacing the optimization procedure by an equivalent direct, linear, and analytical equation that relates each muscle force magnitude to the net generalized force at the knee, see equation (10). This conversion was accomplished using

Lagrange multipliers. The constant of the relation of each muscle, ε_i in equation (10), was found dependent on the muscle coefficient, or moment arm, and its area.

Afterwards, a simulated model was put forward to reproduce offline the motion of the subject in the considered rehabilitation task, from which muscle coefficients were calculated and so the corresponding values of ε_i. Finally, these values were stored as a function of the discretized generalized coordinates. Then, in the actual rehabilitation experiment and according to the current value of the generalized coordinates, the values of ε_i was retrieved using linear interpolation from which muscle force magnitude was determined.

Another aspect that distinguish this model in comparison with previous ones is the method in which the kinematics of the knee is represented. Here, a crossed links four-bar mechanism obtained by a synthesis process was used. This mechanism better reproduces the knee joint than conventional revolute joint [29, 32]

To validate the proposed procedure, a pilot test was conducted with a subject that carried out a squat exercise of different loading conditions by monitoring muscle activity using conventional EMG device. This exercise was selected because it imposes high flexion moment at the knee and, as a result, produces a relatively high muscle and contact forces, in comparison with normal gait exercise [28].

Results of the previous experiment show that the difference between the complete dynamic model and that one without inertial forces is negligible, supporting the hypothesis that a quasi-static model is eligible to be used. For this type of model position data inputs is required only. Since the computation of velocities and accelerations can be omitted , there will be no need to measure the position with high accuracy. As a result, low-cost position capturing devices can be used.

In addition, these results shows that the estimated force activity levels are similar to those obtained in other works of similar experiments [27]. In addition, high correlation was found between the estimated forces and measured EMG signals in all the considered trials. Finally, the proposed model showed an excellent predictive capability of muscle activation, at both activation level and timing. To prove this, a functional relation between predicted muscle force estimation and EMG signals was extracted. Then, it was used to predict the EMG signals for other loading conditions experiment starting from the estimated muscle forces. High level of concordance was found.

Although the verification carried out in this experiment does not constitute a validation in the strict sense, since the internal forces have not been measured directly, the proposed model allows to obtain estimates of the distribution of forces coherent with muscular activity.

Despite the fact that the comparison made in this study is not a validation for its capability of estimating internal forces. Still its good capability of estimating muscle's activation, level and timing, enables its future use in model based control algorithms forrehabilitation robots. These estimations could be used in the control of rehabilitation robots, thus improving the one currently used, which is based generally on kinematic criteria, forces registered by the robot sensors or on the generalized forces in the joints calculated using simple models [8, 10]. For future work, this model will be compared with other commercial more detailed models. Experimental data size will be amplified considering more subjects and experiments related to human knee rehabilitation and strengthening exercises.

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