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A force-based approach for joint efforts estimation during the double support phase of gait

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Abstract

There is a growing interest in predicting the gait motion of real subjects under virtual conditions, e.g. to anticipate the result of surgery or to help in the design of prosthetic/orthotic devices. To this end, the motion parameters can be considered as the design parameters of an optimization problem. In this context, determination of the joint efforts for a given motion is a required step for the subsequent evaluation of cost function and constraints, but force plates will not exist. Therefore, a force-based approach is proposed to estimate the joint efforts during the whole gait, including the double support phase.

Keywords: gait; ground reactions; force contact model; double support; stochastic optimization

1. Introduction

A great effort has been done by the biomechanics community to analyze the gait of real subjects [1]. Usually, the procedure starts with the capture of the subject's motion by means of an optical system, and the measurement of the ground reactions through force plates. Then, the obtained positions of a number of markers serve to calculate the histories of the coordinates defining a computer model of the subject. These data are processed to minimize the errors and differentiated to yield the histories of the coordinates at velocity and acceleration level. At this point, the equations of motion of the model are set in some way (forward or inverse dynamics) and the muscle forces that produce the joint efforts are estimated through

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optimization techniques due to their redundant nature. It can be said that today this whole process has reached a high degree of maturity, although the obtained values of the muscular forces are not always reliable. The results of this kind of analyses are a good help for medical applications.

However, in the last years, the biomechanics community is attempting to go one step further: the prediction of the gait motion of real subjects under virtual conditions [2-4]. If this problem was successfully solved, it would be extremely useful for the medical world, e.g. to anticipate the result of surgery or to help in the design of prosthetic/orthotic devices.

Multibody dynamics is a suitable tool to address the mentioned challenge. In fact, the dynamic behavior of many complex machines has been simulated for a long time thanks to this discipline, by stating and solving the so-called forward dynamics problem. The human body can be also considered a multibody system and, hence, its motion can, in principle, be simulated in the same way. There is, however, a key difference between the simulation of machines and the simulation of the human body: in the latter case, the inputs to the system, i.e. the motor actions, are the result of the neuro-muscular actuation and, hence, they are unknown. Consequently, forward dynamics cannot be applied as in man-made machines. Instead, two approaches can basically be followed: a) to state an optimization problem, so as to find the most likely motion or muscular forces according to some objective function under the corresponding constraints; b) to replicate the neuro-muscular system by means of an intelligent algorithm [5], like the smart drivers do in the automotive case. Up to now, the multibody community has chosen the first approach, as closer to its experience in mechanical problems.

The present work is part of a project aimed to simulate the gait motion of incomplete spinal cord injured subjects wearing active orthoses. The objective is to simulate the gait of real and specific patients when wearing orthoses that have not even been built. This is expected to serve for the design or adaptation and testing of subject-tailored ortheses in the computer, so that disturbance to patients is minimized.

To solve this problem, the plan is to follow the optimization approach indicated above. The design variables will be either the parameters defining the motion of the patient or the parameters defining the excitations of his muscles, while the objective function will be the total metabolic cost, whose calculation requires the histories of muscular forces to be known [6].

In the first case (motion parameters as design variables), the calculation of the muscular forces requires the joint efforts to be previously determined, which is not possible unless the ground reactions are obtained for the motion defined by the current value of the design variables. This last problem, i.e. to obtain the ground reactions for a given motion, is not such when only one foot is in contact with the ground, but its solution becomes undetermined during the double support phase. When actual captured motions are analyzed, the mentioned indeterminacy is overcome by the measurement of ground reactions by means of force plates, as explained at the beginning of this Introduction. However, force plates do not exist for the virtual motions generated during the optimization procedure. Therefore, the problem here is to calculate the ground reactions for a given motion, both during the single and double support phases, without making use of measurements coming from the force plates.

In the second case (excitation parameters as design variables), the muscular forces are straightforwardly obtained from the excitations defined by the current value of the design variables. However, a force contact model is required for the foot-ground contact, in order to obtain the motion resulting from the excitations by means of forward dynamics.

The problem of determining the ground reactions for a given motion when force plates are not available has previously been addressed by other authors. For example, Ren et al. [7] introduce the concept of *Smooth Transition Assumption* (STA), which basically consists of adjusting a smooth function for the double support phase between the uniquely determined values of the ground reaction components of the single support phase. However, this approach may not be applicable when the duration of the double support phase represents a relevant part of the full gait period, as in some cases of pathological gait. Therefore, the solution proposed in this paper is different, and serves for the problems arisen in the two optimization options considered in the previous paragraphs. Given the motion, the inverse dynamics allows for the calculation of the ground reaction forces and moments during the whole period. Then, the parameters of a force contact model in both feet are considered as the design parameters of an optimization process. The objective function to be minimized is defined as the difference between the ground reactions obtained through inverse dynamics and the ground reactions yielded by the force contact model. Moreover, a null value of the reaction is imposed to each foot when it is not contacting the ground. The proposed method is applied to the captured motion of a real healthy subject, and the resulting ground reactions are compared with those measured by force plates, in order to assess their accuracy.

The proposed method shows some similarities with the work by Millard et al. [4], who address the problem of obtaining a foot-ground contact model that may be used within a predictive optimization scheme based on forward dynamics analyses. However, these authors define a planar model, not a 3D one, and try to tune the contact model parameters to reproduce the normal and tangential forces, but do not consider the reaction moments. Moreover, they measure the real contact forces by means of force plates instead of calculating them from the captured motion through an inverse dynamics analysis, which is consistent with the objective they were pursuing.

The paper is organized as follows. Section 2 describes the experiment, the measurements carried out, the computational model of the subject, the applied signal processing, and the inverse dynamics formulation. Section 3 explains the force contact model and the optimization process performed. Section 4 shows the obtained results and their discussion. Finally, Section 5 gathers the conclusions of the work.

2. Experiment, measurements, model, signal processing, and formulation.

A healthy adult male of age 37, mass 74 kg and height 180 cm, has been dressed with a special suit where 37 passive reflective markers have been attached, as illustrated in Fig 1a. For the experiment, the subject walks on a walkway with two force plates (AMTI, AccuGait) embedded, located in such a way that each plate measures the ground reactions of one foot during a gait cycle. The motion is captured by an optical system composed by 12 cameras (Natural Point, OptiTrack, FLEX:V100) and its software, which provides the 3D trajectories of the markers.

A 3D computational model of the subject has been developed in mixed (natural + relative) coordinates. The model, shown in Fig. 1b possesses 18 bodies and 57 degrees of freedom, and it is defined by 228 dependent coordinates. Unlike the 3D models proposed by several authors [2,3], the present model does not use the Head-Arms-Trunk (HAT) simplification. The reason is that it is expected that the upper limbs play a relevant role in the gait of incomplete spinal cord injured subjects, who are the final target of the project. All the body segments are connected by spherical joints in the model, so as to circumvent the problem of determining the rotation axes. Each foot is defined by means of two segments. Following the picture in Fig. 1b, the coordinates of the system are composed by the three Cartesian coordinates of all the points at the spherical joints plus the points at the centers of mass of the five distal segments (head, hands and forefeet), the three Cartesian components of two orthogonal unit vectors at each body (red and green vectors in Fig. 1b), the three angles that define the pelvis orientation with respect to the inertial frame, and the 51 (3x17) angles that define the relative orientation of each body with respect to the previous one in the open chain system with base in the pelvis.

The geometric parameters of the model are obtained, for the lower limbs, by applying correlation equations from a reduced set of measurements taken on the subject and, for the upper part of the body, by scaling table data according to the mass and height of the subject. Regarding the inertial parameters, they are obtained, for the lower limbs, by a correction, based on data coming from densitometry if available, of the method already indicated for the geometric parameters; for the upper part of the body, the scaling method is used again, but a second scaling is applied in order to adjust the total mass of the subject.

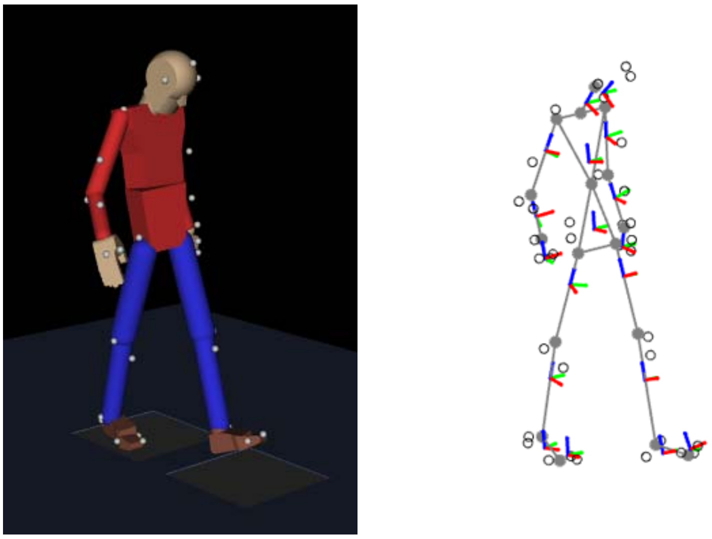

Fig. 1. (a) Markers location; (b) Computational model.

To reduce the noise due to the motion capture process, the Singular Spectrum Analysis (SSA) filter is applied to the position histories of the markers, which are then used to calculate the histories of the model natural coordinates by means of simple algebraic relations. The values of these coordinates at each instant of time are not kinematically consistent due to the inherent errors of the motion capture process. Therefore, the kinematic consistency of the natural coordinates at position level is imposed, at each instant of time, by means of the following augmented Lagrangian minimization process [8],

$$\begin{gathered}\left(\mathbf{W}+\mathbf{\Phi}_{\mathbf{q}}^{\mathrm{T}}\alpha\mathbf{\Phi}_{\mathbf{q}}\right)\Delta\mathbf{q}_{i+1}=-\mathbf{W}\left(\mathbf{q}_i-\mathbf{q}^*\right)-\mathbf{\Phi}_{\mathbf{q}}^{\mathrm{T}}\left(\alpha\mathbf{\Phi}+\boldsymbol{\lambda}_i\right)\\ \boldsymbol{\lambda}_{i+1}=\boldsymbol{\lambda}_i+\alpha\mathbf{\Phi}\quad;\quad i=1,2,\ldots\end{gathered}\tag{1}$$

where $\mathbf{q}^*$ is the vector of the inconsistent natural coordinates, $\Delta\mathbf{q}_{i+1}=\mathbf{q}_{i+1}-\mathbf{q}_i$, $\mathbf{\Phi}$ is the vector of kinematic constraint equations, $\mathbf{\Phi}_{\mathbf{q}}$ is the corresponding Jacobian matrix, $\boldsymbol{\lambda}$ is the vector of Lagrange multipliers, α is the penalty factor, and $\mathbf{W}$ is a weighting matrix that allows to assign different weights to the different coordinates according to their expected errors.

From the consistent values of the natural coordinates, a set of independent coordinates $\mathbf{z}$ is calculated: the three Cartesian coordinates of the spherical joint connecting pelvis and torso, along with the three x, y, z rotation angles with respect to the fixed global axes, are used to define the pelvis position and orientation, while the joint relative coordinates are used to define the remaining bodies of the model in a tree-like structure.

Prior to differentiate the histories of the independent coordinates $\mathbf{z}$, the SSA filter is applied to them in order to reduce the noise introduced by the kinematic consistency. Then, the Newmark's integrator expressions are used to numerically differentiate the filtered position histories so as to obtain the corresponding velocity and acceleration histories [8].

Once the histories of the independent coordinates $\mathbf{z}$, and their derivatives, $\dot{\mathbf{z}}$ and $\ddot{\mathbf{z}}$, have been obtained, the inverse dynamics problem is solved by means of the velocity transformation formulation known as matrix-R [9], which provides the motor efforts required to generate the motion. However, since such motor efforts are obtained as an external force and torque acting on the pelvis and the corresponding internal joint torques, they are not the true ground reaction force and torque and the true joint torques, as long as the true external force and torque must be applied at the foot or feet contacting the ground, not at the pelvis. Anyway, a simple linear relation can be established between the two sets of motor efforts: it is obtained by equating the vector of generalized forces due to the set of force and torques with the pelvis as base body, and the vector of generalized forces due to the force/forces and torques with the foot/feet as base body/bodies.

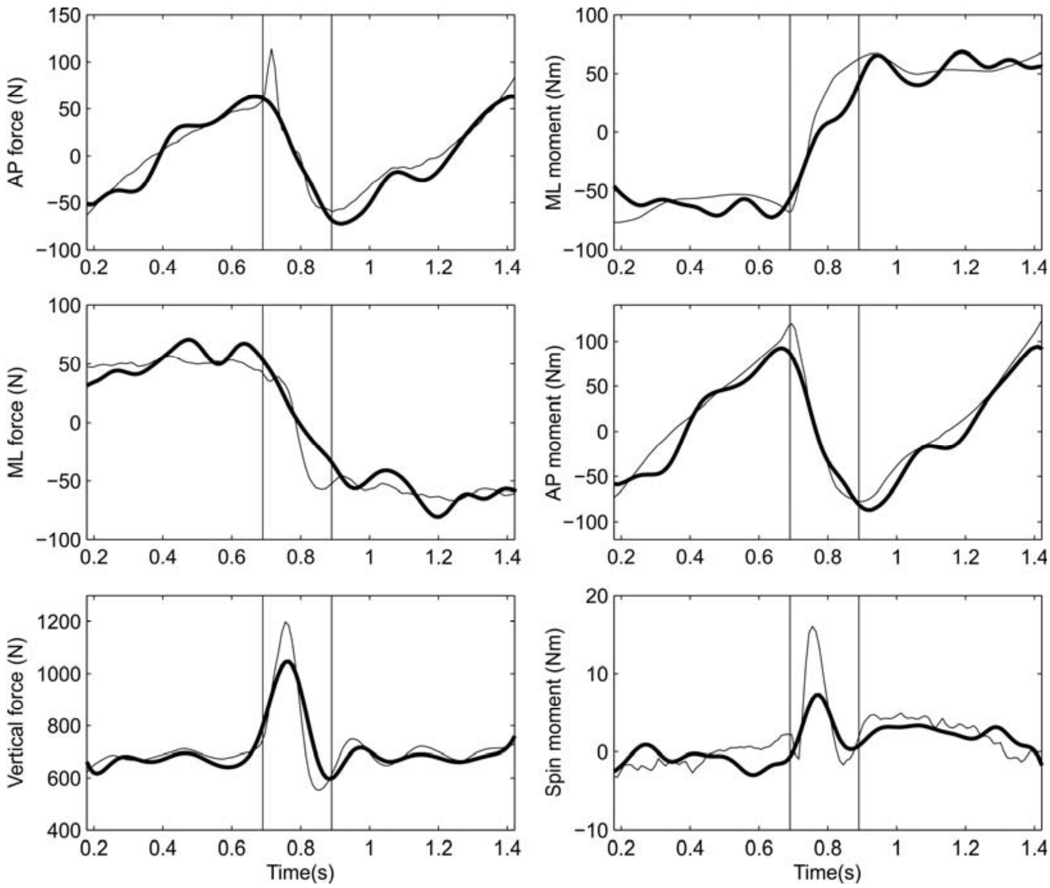

Fig. 2. Ground reactions calculated (thick line) and measured (thin line).

Fig. 2 shows the correlation between the ground reaction force and moment components calculated and measured. The reaction force and moment components coming from both plates have been added and the results plotted, so that they can be compared with the same terms obtained from inverse dynamics. The plots start at the toe-off of the right foot and finish at the heel-strike of the same foot. The two vertical lines delimitate the double-support phase, in which the inverse dynamics can only provide the addition of the force and moment components due to both feet. However, during the single support phase, the inverse dynamics provides the force and moment at the contacting foot.

3. Force contact model and optimization process

To model the foot-ground contact, a point force model that provides the contact force as function of the indentation between the two contacting surfaces is used. The total contact force is divided into the normal and tangential components. The normal component follows the model proposed by Lankarani and Nikravesh [10], while the tangential component is the bristle-type model proposed by Dopico et al. [11]. The corresponding parameters are design variables of the optimization process. The foot surface is approximated by several spheres, whose positions and radii are also design variables of the optimization process.

The objective is to adjust the position and size of the spheres and the contact force parameters, so that the ground reactions provided by the inverse dynamics are reproduced by the contact model. During the single-support phase, the contacting foot is responsible for providing the ground reaction force and torque obtained from inverse dynamics. However, during the double-support phase, both feet contribute to produce the total ground reaction force and torque obtained from inverse dynamics.

Therefore, the optimization problem is stated as follows: find the force contact parameters and the position and size of the spheres approximating the feet surfaces, so that the error between the ground reaction force and torque components provided by the inverse dynamics and the contact model is minimized. Upper and lower boundaries are set for each design variable. Moreover, a null value of the reaction is imposed to each foot when it is not contacting the ground. The introduction of this last constraint requires the transition times between single and double support to be determined, which has been done through the *Foot Velocity Algorithm* (FVA) [12].

Fig. 3. Feet models during the optimization process: right foot (blue solid line); left foot (blue dashed line).

To speed-up the optimization process, only the models of the two feet are used for each function evaluation, as illustrated in Fig. 3. Indeed, since the motions of the feet are known and the forces introduced by the contact model only depend on the indentation histories, dealing with the whole human body model is not required. The picture in Fig. 3 is a projection on the sagittal plane of the 3D feet models. For each foot, the red reference frames are rigidly connected to the heel and toe segments respectively: three spheres belong to the hindfoot and the fourth one is part of the forefoot.

The evolutive optimization method known as *Covariance Matrix Adaptation Evolution Strategy* (CMA-ES) [13] has been applied. A Matlab function containing the implementation of the algorithm has been downloaded from www.lri.fr/~hansen/. Being an evolutive optimization method, it does not require that function evaluations are sequentially executed, thus enabling the process to be parallelized. Consequently, the CMA-ES function is prepared to simultaneously send several sets of design variables (arranged as columns in a matrix) for their respective values of the objective function to be calculated. A Matlab function has been developed by the authors that receives a matrix with as many columns (sets of design variables) as available parallel processors, and returns a row vector with the corresponding values of the objective function. This function makes use of the *Parallel Computing Toolbox* through the *parfor* statement, in order to perform the multiple function evaluations in parallel. Each function evaluation is carried out by a Fortran code packed into a MEX-file, that calculates the ground reactions due to the contact model and obtains the error with respect to the inverse dynamics results.

The method described so far is a general approach. However, to begin with, a simpler version has been implemented in this work. Four spheres have been considered for each foot. The design variables are the following five parameters for each sphere: x and y local position of the sphere center for a given z (blue vectors in Fig. 1b), sphere radius r, stiffness K and restitution coefficient c_e of the Lankarani-Nikravesh normal contact force model [10]. This makes a total of 40 design variables. Regarding the objective function, only the RMS errors due to the discrepancies between the normal force and the longitudinal and lateral moments provided by inverse dynamics and the force contact model are taken into account, this being equivalent to adjust the normal force and the center of pressure. All the three mentioned terms of the objective function are affected by weighting factors (1,5,5), in order to balance their different scales. The null value reaction at each foot when it is not contacting the ground is imposed by returning a Not-a-Number (NaN) value of the objective function when this condition is violated, as required by the CMA-ES algorithm.

4. Results and discussion

The results obtained from the optimization process are shown in Fig. 4. Fig. 4a plots the total normal contact force provided by inverse dynamics, the two normal contact forces yielded by the contact models of the feet, their addition, and the normal contact forces measured by the force plates during the experiment. The plots start at the toe-off of the right foot and finish at the heel-strike of the same foot. The two vertical black dashed lines delimitate the double-support phase, in which the inverse dynamics can only provide the addition of the normal forces due to both feet. Fig. 4b plots the mediolateral and anteroposterior moments provided by the contact model and the inverse dynamics.

It can be seen that the total normal force obtained from inverse dynamics is well reproduced by the total normal force obtained as the addition of the normal forces provided by the feet due to the optimized contact model. Moreover, the normal force at each foot measured by the force plates during the experiment is well adjusted too by the normal force at each foot due to the optimized contact model. On the other hand, an acceptable agreement is also observed between the results obtained by the inverse dynamics and the contact model for the two horizontal components of the reaction moment.

It must be said that modeling the foot as two segments proved to be relevant: a single-segment foot model was also tested but it led to notably higher errors.

The discontinuitites shown by the force and moments yielded by the contact model are presumably due to the fact that the motion is imposed and, hence, the forces and torques at the contact are not influencing the subsequent motion. Moreover, there is a notable error in the captured positions of the markers at the feet, which further amplifies the mentioned problem.

Regarding efficiency, the optimization process that led to the presented results took a wall-clock time of around 4 min on an Intel Core i7 950 computer, and roughly required 12,000 function evaluations, being these figures representative of the general trend observed during the study.

At the view of the results and the computational effort required by this optimization process, it is clear that the proposed method is not suitable to be applied at each iteration of a predictive optimization process having the motion as design variables, as long as the required computation times would be too high. Instead, it seems more reasonable to use this technique to obtain a foot contact model that could be applied on a predictive optimization process, having either the motion or the excitations as design variables. In such a context, it would be expected that the observed discontinuities in the reactions produced by the contact model vanished: in the first case, the optimizer would move away from motions causing discontinuities, due to their high metabolic cost; in the second case, forward dynamics would be run at each function evaluation, thus yielding a smooth profile of the contact reactions.

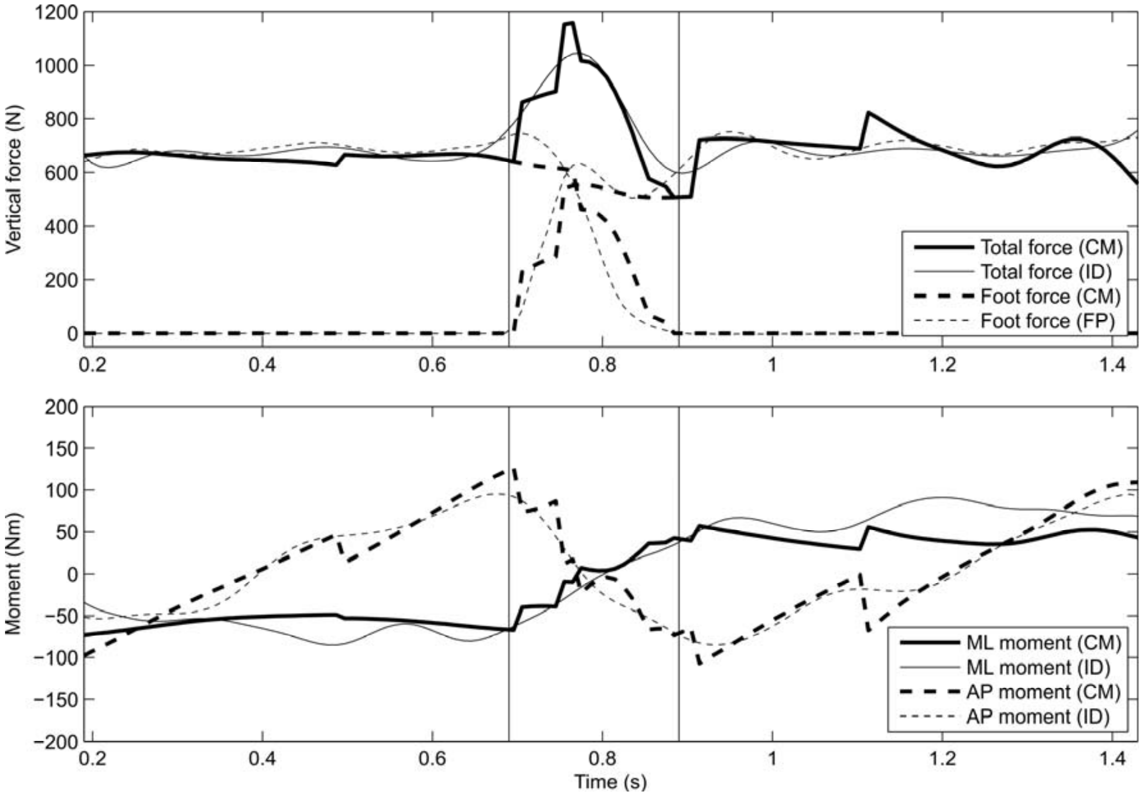

Fig. 4. Comparison among ground reactions from inverse dynamics (ID), contact model (CM) and force plates (FP): a) vertical force; b) horizontal moments.

For the use of the method in the abovementioned way, it would be advisable to set the same model for both feet. However, this has not been done in the present work, since the excessive inaccuracy in marker location led to non-satisfactory results. Therefore, more attention should be paid to marker location (especially in the feet) in the experiment. Also, it would be recommendable to carry out experiments at different gait speeds, as in [4], in order to adjust the model to all of them, or to seek a relationship between the contact model parameters and the gait speed. Finally, the method should be extended to the general case, thus including the parameters of the tangential force model among the design variables, and adding to the objective function the weighted RMS errors due to the discrepancies in tangential force and spin moment.

5. Conclusions

A force based approach has been presented that enables to estimate the ground reactions during gait from a given motion without the help of force plates, thus allowing to estimate the joint efforts that generated the motion. The difficulty of the problem comes from the ground reactions indeterminacy that occurs during the double support phase of gait.

Basically, the idea is to seek the parameters of a force contact model that produce the same reaction forces and moments than those estimated from inverse dynamics. In this work, only the contact surface and normal force parameters have been considered as design variables, being the normal reaction force and the horizontal components of the reaction moment the magnitudes whose error has been minimized.

The proposed approach has shown a good correlation with measurements taken from force plates, and the computational times required have been kept moderated (some minutes). Therefore, it could serve to generate foot-ground contact models to be used within optimization processes aimed at predicting the motion of real subjects under virtual conditions. This kind of tool would be of great help to anticipate the result of surgery or to help in the design of prosthetic/orthotic devices. However, for such an application, further work should be done in the future.

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