A hybrid dynamic motion prediction method for multibody digital human models based on a motion database and motion knowledge

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Abstract

In this paper we present a novel method to predict human motion, seeking to combine the advantages of both data-based and knowledge-based motion prediction methods. Our method relies on a database of captured motions for reference and introduces knowledge in the prediction in the form of a motion control law, which is followed while resembling the actually performed reference motion. The prediction is carried out by solving an optimization problem in which the following conditions are imposed to the motion: must fulfill the goals of the task; resemble the reference motion selected from the database; follow a knowledge-based dynamic motion control law; and ensure the dynamic equilibrium of the human model, considering its interactions with the environment. In this work we apply the proposed method to a database of clutch pedal depression motions and we present the results for three predictions. The method is validated by comparing the results of the prediction to motions actually performed in similar conditions. The predicted motions closely resemble the motions in the validation database and no significant differences have been noted either in the motion's kinematics or in the motion's dynamics.

Keywords

Human motion prediction, Digital Human Modeling, Dynamic motion prediction, Data-based motion prediction, Knowledge-based motion prediction

1 Introduction

Digital Human Models (DHMs) are more and more frequently employed to test virtual products in the early stages of product design [1-4]. To simulate the interaction of DHMs, representing different user populations, with a variety of environments, human motion prediction is an interesting and useful tool to reduce the cost and time-to-market of new designs.

Motion prediction aims at predicting within a reasonable accuracy the motion that a subject would perform to accomplish a specific goal. Due to the redundancy of degrees of freedom (DoFs) in the human body, generally there are infinite sets of values of the DoFs which fulfill the goals of the motion. Of all these sets of values, only some can be defined as realistic, and may be grouped into the various strategies and styles adopted by subjects while carrying out the task.

In contrast with animation [5], which essentially guides a particular subject with a specific user-defined motion, motion prediction focuses on representing the motions that a generic specimen of a population would perform to accomplish a given task. While the requirement for an animated motion is to *look* realistic, the challenge for motion prediction is to generate motions that *are* realistic, as well as representative of the behavior of a population rather than of a specific individual.

Motion prediction methods can be classified into data-based and knowledge-based methods, according to whether they rely or not on a database of captured motions. Data-based methods may be divided according to whether they use the data to supply a reference motion to the prediction or whether they perform a regression analysis of the data. Methods which rely on a reference motion [6-9] consist in obtaining, among the motions which compose the database, the most appropriate one to be taken as reference and in modifying it in order to fulfill the new motion constraints. Defining with the term “scenario” the combination of a subject and an environment, the motion in the new scenario (a new subject in a new environment) is predicted starting from a real motion carried out in a reference scenario (a reference subject in a reference environment). Methods based on a regression analysis of the data [10-13] obtain regression functions for the variables of the motion and apply them to the new scenario to carry out the prediction.

The main advantage of data-based methods lies in the intrinsic realism of the motions in the database, which should be maintained during the modification process. Furthermore, a database of captured motions allows to identify the various strategies and styles [6, 8] which the subjects adopt during the fulfillment of the considered task. Each identified strategy and style may then be predicted, hence representing the variety of behaviors encountered in the population. The main drawback of data-based methods is the restriction of being able to reasonably predict only tasks which are present in the database: to predict a different task, first a corresponding database of motions must be generated.

On the other hand, knowledge-based methods [4, 14-18] do not rely on a database of captured motions and confer realism to the motion through the identification of an appropriate performance measure, representing the underlying motion control law that drives the motion. Several performance measures have been proposed in the literature: some are purely kinematic, taking into account the joint displacement with respect to a neutral pose [19, 20], whereas others are dynamic and generally are energy-related functions [14, 16, 21].

Although knowledge-based methods are theoretically applicable to any task, their drawback lies in the difficulty of identifying the most adequate performance measure. In fact, some authors [19, 22] have adopted multi-objective optimization, in which a combination of several performance measures is considered, in order to generate more realistic predictions. It must also be mentioned that knowledge-based methods are currently employed to predict relatively simple motions, such as lifting or walking; more complex motions (such as a vehicle ingress-egress motion) may require different performance measures across the motion as the various sub-goals of the motion are accomplished.

For specific task-driven motions, as those involved in the virtual testing of products, data-based methods may be considered the most suitable option. However, current data-based motion prediction methods are only kinematic and for certain applications, such as ergonomic studies, a dynamic prediction may be required. Moreover, while data-based methods may provide sound predictions for similar configurations to those present in the database, they may not be able to perform realistic extrapolations to more extreme configurations.

Two different hybrid methods have been proposed in the literature, one by Xiang et al. [23] and one by Pasciuto et al. [24-27], seeking to combine the advantages of both data-based and knowledge-based methods. The method proposed by Xiang et al. modifies the knowledge-based framework of predictive dynamics [4, 21, 22] by including the condition that specific DoFs in the model should resemble experimental values; on the other hand, the method proposed by Pasciuto et al. modifies the data-based framework of kinematic predictions [6-8] by including a knowledge-based dynamic performance measure in the prediction. The method we present in this paper is an improved method based on the previous works of Pasciuto et al. [24-26], and is hereafter described.

1.1 Approach outline

The hybrid dynamic motion prediction method that we present on the one hand relies on a database of captured motions, and on the other introduces knowledge in the prediction, in the form of a performance measure that represents the motion control law. Dynamics are included in the prediction both in the definition of the performance measure and in the compliance of the dynamic equilibrium equations of the DHM.

The method is composed of three main stages, shown in Figure 1, which are outlined hereafter and described in detail in the following sections. First, a multibody model of the system is defined, with which captured motions are reconstructed in order to generate a database of experimental motions. Among the motions in the database, a reference motion is selected to be resembled during the prediction. The reference motion is subsequently modified, through velocity-proportional or acceleration-preserving methods [28], to match the new global position of the model and the end-effector trajectory. Finally an optimization problem, comprising both data-based and knowledge-based approaches, is defined to carry out the prediction.

The method is applied to the prediction of clutch pedal depression motions. The clutch pedal depression presents the advantage of being a relatively simple task (it may be regarded as a dynamic reach motion) while containing all the relevant features for testing a dynamic motion prediction method: it is task oriented and it intrinsically requires interaction between the subject and the environment.

2 Multibody modeling

This section presents the multibody models adopted to describe the system, composed of the human subject and the environment it interacts with, and the equations governing its motion.

2.1 Human model description

The multibody model used to describe the human body is an approximation of its skeletal system: the body segments are considered as rigid bodies and the complex articulations connecting the segments are represented as lower kinematic pairs (revolute, universal or spherical joints). The position and orientation of each link in the resulting kinematic chain is described by the relative angles at the joints. Moreover, to account for the global position and orientation of the kinematic chain, we consider the 6 DoFs of the root element. The vector of the DHM DoFs $\mathbf{q}$ is composed of *nDoFs* elements.

2.2 Equations of motion

To obtain the equations governing the kinematics and dynamics of the human model, a recursive Newton-Euler method is adopted [29]. The method performs two iterations across the kinematic chain: the first starts from the root element of the chain and, moving outwards, it obtains the bodies' kinematics; the second starts from the distal bodies and, moving inwards, it obtains the forces and moments at the joints. Along with the vector of DoFs $\mathbf{q}$, its first and second order time derivatives $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ constitute the set of variables which appear in the equations of motion and characterize the system.

2.3 Environment model description

Often the task to be carried out requires interaction between the subject and the environment. This interaction may be purely geometric or dynamic. A purely geometric interaction imposes that a point in the human model be located at a specific point, curve or surface of the environment; a dynamic interaction additionally implies that a force is generated during the contact.
For what concerns the environment, we distinguish between mobile and fixed elements. Mobile elements are modeled as multibody systems and their geometric interaction with the human model is defined through constraints: the body in the human model which engages with the environmental element is constrained to follow the motion imposed by the latter's geometry. In dynamic interactions, the resulting external force acting on the human model is due to the engagement of the mobile element, which reacts to the interaction.

For what concerns fixed elements, a constraint is imposed to the position of a point in the human model in the case of a purely geometric interaction. However, if the interaction is dynamic, no constraint is imposed and the interaction is modeled exclusively through contact forces. To model a contact between rigid bodies, we consider the interference between the geometry representing the human model and the environmental element. Depending on the value and the velocity of their mutual penetration, a reaction force is evaluated by characterizing the contact through stiffness and damping curves.

3 Obtaining the reference motion

In order to obtain a reference motion for the prediction, a database of captured motions must be first generated and structured. The reference motion is then selected among the motions in the database and modified to meet the new targets imposed to the motion to be predicted. Each of these steps is hereafter described in detail.

3.1 Structured database generation

In motion prediction, a structured database is a database which is organized according to the relevant features of the considered task, the subjects performing the task and the environments it is performed in. Once the captured motions are reconstructed (using the same human model later to be used in the prediction), they must be analyzed to classify each motion composing the database.
The first descriptors that may be used for motion classification are related to the motion scenario, which is composed of the subject carrying out the task and the environment it is carried out in. For what concerns the subjects, descriptors such as the gender, age, height and weight may be taken into consideration. The relevant characteristics of the environment usually depend on the task, and can be, for instance, the position and orientation of the elements with which the subject interacts, and the location and dimension of obstacles.
Other descriptors related to the actual motions may be defined. One of the most common features adopted in describing task-oriented motions is the definition of key-frames in the motion. Key-frames are frames in which a relevant event occurs (e.g. a target is reached), and their identification defines the goals that characterize the key events in the motion. Moreover, the structured database should account

for the variability with which humans carry out a given task by identifying the strategies and styles adopted during the experiments. Strategies are defined when the end-effector displacement is mainly due to the action of different DoFs in the model [6, 30], whereas styles represent less evident differences in the motion which are nevertheless relevant in the classification.

3.2 Motion selection

The choice of which motion in the structured database is the most adequate to be considered as reference for the prediction, depends on the new scenario (new subject in a new environment) to be predicted, called "prediction scenario". Park et al. [8] and Monnier [31] establish thresholds (α_i) according to which motions are considered similar. Denoting with the subscript *Ref* quantities evaluated in the reference scenario or motion and with the subscript *Pred* quantities referred to the prediction scenario or motion, a motion is adequate to be selected as reference if:

$$\left|x_{i_{\mathrm{Pred}}} - x_{i_{\mathrm{Ref}}}\right| \leq \alpha_i \quad (1)$$

where i is the index which loops over the conditions to be set and x_i represents magnitudes associated to the subject (such as its stature) or to the environment (such as the target position). All the motions in the database which satisfy the conditions imposed by Equation (1) are retrieved and considered adequate to be used as reference. The user must then select among them the one reference to be employed in the prediction.

Wang [9] on the other hand obtains the reference motion with functional regression methods applied to the experimental database. The predictions obtained with the functional-regression-reference are similar to actually performed motions. However, adopting directly a motion from the database as reference yields better results, probably due to the fact that the latter has actually been performed, whereas the former is an averaged motion, not a real one.

Pasciuto et al. [24] compare the results of the dynamic predictions obtained using as reference a motion in the database or a motion obtained through prior kinematic prediction. The prior kinematic prediction is performed using as reference a motion in the database and modifying it in order to meet the goals in the prediction scenario. No significant differences are noticed when either reference is employed, suggesting that a prior kinematic prediction does not improve the dynamic prediction results.

In this work, the motion we consider as reference is an actually performed motion belonging to the database, which is selected as the motion which minimizes the following weighted squared sum:

$$\min \sum_i w_i \left(x_{i_{\mathrm{Pred}}} - x_{i_{\mathrm{Ref}}}\right)^2 \quad (2)$$

The conditions included in Equation (2) are the following: gender, age, stature, weight, position of the target with respect to the root element, range of motion (RoM) of the environmental elements and their orientation.

Equation (1) may retrieve one motion, several motions or no motions at all, depending on the values of the user defined thresholds (α_i). Equation (2) on the other hand only retrieves one reference motion: the one performed in the scenario which is most similar to the prediction scenario.

3.3 Motion modification

Once the reference motion is selected, it is modified to meet the new goals in the prediction scenario.

On account of the similarity between the reference and the prediction scenarios, we consider that all temporal features of the reference motion are maintained during the prediction: hence both the duration and the key-frames distribution in the predicted motion are the same as in the reference motion.

On the other hand, other features of the reference motion may require modification, such as the global position and orientation of the human model or the trajectory followed by the end-effectors.

In this study, the DoFs representing the global position and orientation of the human model are modified by adding a constant offset to the reference DoFs profiles in order to place the model of the prediction subject in the desired global configuration with respect to the prediction environment.

For what concerns the end-effector, generally the trajectory followed in the reference motion does not lead to the accomplishment of the task in the prediction scenario. To meet the new goals in the prediction, the end-effector reference trajectory must be modified. We distinguish between two types of modification depending on whether the motion is free or constrained by the motion of the environmental elements with which the end-effector interacts. Both modification methods rely on the similarity between the reference and prediction scenarios.

3.3.1 Free end-effector

When the end-effector's motion is free, the data required to perform the modification are the desired initial and final position of the end-effector in the predicted motion. Two modification methods are proposed in the literature [28]: velocity proportional (VP) and acceleration preserving (AP). In our work, we use VP to impose that the velocity profile of the end-effector along the modified trajectory $\dot{\mathbf{x}}_{Mod}$ must be proportional to that of the reference motion $\dot{\mathbf{x}}_{Ref}$:

$$\dot{\mathbf{x}}_{\text{Mod}}(t) = \mathbf{c}_1\dot{\mathbf{x}}_{\text{Ref}}(t) \ \rightarrow \ \mathbf{x}_{\text{Mod}}(t) = \mathbf{c}_1\mathbf{x}_{\text{Ref}}(t) + \mathbf{c}_2 \qquad (3)$$

AP instead imposes that the acceleration profile of the end-effector along the modified trajectory must be the same as in the reference motion:

$$\ddot{\mathbf{x}}_{\text{Mod}}(t) = \ddot{\mathbf{x}}_{\text{Ref}}(t) \ \rightarrow \ \mathbf{x}_{\text{Mod}}(t) = \mathbf{x}_{\text{Ref}}(t) + \mathbf{c}_1 t + \mathbf{c}_2 \qquad (4)$$

Generally both methods yield very similar results, nonetheless VP is favored in this study as it presents the desirable feature of maintaining the zero-velocity conditions of the end-effector. However, VP fails to generate a reasonable trajectory when the initial and final positions of the end-effector are very close to each other, since numerical problems arise. In this case, AP is applied instead.

3.3.2 Constrained end-effector

When the end-effector interacts with a mobile element of the environment, its trajectory is constrained to follow the motion of the environmental element.
The motion of the environmental element in the prediction scenario may be obtained by modifying its motion in the reference scenario. For this, the initial and final values for each DoF θ_i of the environmental element in both the reference and prediction environment must be known. To obtain the new motion of the environmental element, we use a similar modification to the one applied to the free end-effector (Section 3.3.1), with the difference that in this case the modification is applied to the element's DoFs.
The formulation for the VP modification is:

$$\dot{\boldsymbol{\theta}}_{\text{Mod}}(t) = \mathbf{c}_1\dot{\boldsymbol{\theta}}_{\text{Ref}}(t) \ \rightarrow \ \boldsymbol{\theta}_{\text{Mod}}(t) = \mathbf{c}_1\boldsymbol{\theta}_{\text{Ref}}(t) + \mathbf{c}_2 \qquad (5)$$

If the initial and final values of any of the θ_i are very close to each other, numerical problems may arise in the VP modification. In such cases, the following AP modification is used instead:

$$\ddot{\boldsymbol{\theta}}_{\mathrm{Mod}}(t) = \ddot{\boldsymbol{\theta}}_{\mathrm{Ref}}(t) \ \rightarrow \ \boldsymbol{\theta}_{\mathrm{Mod}}(t) = \boldsymbol{\theta}_{\mathrm{Ref}}(t) + \mathbf{c}_1 t + \mathbf{c}_2 \qquad (6)$$

Once the new motion of the environmental element is obtained, the new trajectory for the end-effector must be calculated. The end-effector must follow the trajectory described by the contact point in the environmental element, which is obtained by applying forward kinematics to the element with the $\boldsymbol{\theta}_{Mod}$(t) values of its DoFs.

4 Motion prediction through optimization

In this study, a constrained nonlinear optimization problem is defined to obtain a realistic set of DoFs values which fulfill the task in the prediction scenario.
Given the high nonlinearity of the problem, the Jacobian and Hessian matrices for the objective function and the constraints are evaluated analytically to improve the solver's convergence. Both the first and second order derivatives with respect to the variables $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ are obtained combining the derivatives of the equations of motion, generated with the creation of the model (Section 2.2).

4.1 Objective function

The objective function represents the criterion that is selected to confer realism to the predicted motion. In our work we adopt a criterion that comprises more than one objective, as several features of the reference motion must be resembled and additional dynamic conditions are included. A multi-objective optimization may be solved by combining the objectives in a single function to be minimized [32].
We choose to combine the objectives in a weighted sum of squares:

$$f = \frac{1}{2} \, \boldsymbol{\Psi}^{\mathrm{T}} \, \mathbf{W} \, \boldsymbol{\Psi} \qquad (7)$$

where $\boldsymbol{\Psi}$ is a vector of objectives and $\mathbf{W}$ is a diagonal matrix containing the weights associated to each objective.
To combine non-homogeneous objectives, these are normalized using an upper-lower-bound transformation [33] as shown in Equation (8) below, where the superscripts *Max* and *Min* refer to the maximum and minimum values respectively of the quantity Ψ_i evaluated in the reference motion:

$$\Psi^N{}_i = \frac{\Psi_i - \Psi_i{}^{Max}}{\Psi_i{}^{Max} - \Psi_i{}^{Min}} \quad (8)$$

Hence the objective function is actually evaluated as:

$$f = \frac{1}{2}\, \boldsymbol{\Psi}^{N\,\mathrm{T}}\, \mathbf{W}^{\boldsymbol{N}}\, \boldsymbol{\Psi}^{N} \quad (9)$$

This choice does not guarantee that the normalized objectives are contained in the range [0, 1] but ensures that they present the same order of magnitude. Normalization not only reduces the numerical problems that may arise solving a nonlinear optimization problem, but also allows to use dimensionless weights $\mathbf{W}^N$ which reflect the relative importance of each objective.

4.1.1 DoFs profiles

The objective considered for the DoFs profiles is that of resemblance to the reference, either in terms of DoF values, Eq. (10), or in terms of DoF velocities to maintain the same profile shape as the reference motion, Eq. (11):

$$\forall t \in [t_0, t_T] \quad \boldsymbol{\Psi}_{\mathrm{DoFs}} = \mathbf{q}(t) - \mathbf{q}_{\mathrm{Ref}}(t) \qquad (10)$$

$$\forall t \in [t_0, t_T] \quad \boldsymbol{\Psi}_{\mathrm{D\dot{o}Fs}} = \dot{\mathbf{q}}(t) - \dot{\mathbf{q}}_{\mathrm{Ref}}(t) \qquad (11)$$

4.1.2 End-effector

During the time intervals of the motion in which the end-effector trajectory must resemble the modified trajectory, rather than match it exactly, the following objective is set:

$$\forall t \in [t_A, t_B] \quad \boldsymbol{\Psi}_{\mathrm{EndEffTraj}} = \mathbf{x}(\mathbf{q}, t) - \mathbf{x}_{\mathrm{Mod}}(t) \qquad (12)$$

When the orientation of the end-effector body depends on the environment, the direction of a vector $\mathbf{r}$ belonging to the end-effector body should resemble the direction of a vector $\mathbf{r}_{Env}$ belonging to the environment:

$$\forall t \in [t_A, t_B] \quad \boldsymbol{\Psi}_{\mathrm{EndEffOrient}} = \mathbf{r}(\mathbf{q}, t) - \mathbf{r}_{\mathrm{Env}}(t) \qquad (13)$$

4.1.3 Performance measure

A commonly employed dynamic performance measure [4, 15, 21, 22, 34] seeks to minimize the motion’s dynamic effort, defined as the sum of the squared joint torques $\boldsymbol{\tau}$ across the motion. Given the quadratic form of our objective function f in Equation (7), this objective is defined as:

$$\forall t \in [t_0, t_T] \quad \boldsymbol{\Psi}_{\mathrm{DynEff}} = \boldsymbol{\tau}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, t) \qquad (14)$$

On the other hand, Ren et al. [16] proposed an energy-related performance measure that seeks to minimize the mechanical energy expenditure across the motion:

$$\forall t \in [t_0, t_T] \quad \boldsymbol{\Psi}_{\text{MechEn}} = \boldsymbol{\tau}^{\mathrm{T}}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, t)\boldsymbol{\omega}_{\text{Rel}}(\mathbf{q}, \dot{\mathbf{q}}, t)\Delta t \qquad (15)$$

This condition is also included in the performance measure proposed by Kim et al. [14] who consider not only the mechanical but the whole metabolic energy, i.e. the chemical energy required by the muscles which is transformed into mechanical, heat and basal metabolic energy.

4.2 Constraints

The predicted motion should minimize the objective function f defined in the previous section while fulfilling a set of equality and inequality constraints, $\boldsymbol{\Phi}^{EQ}$ and $\boldsymbol{\Phi}^{IN}$ respectively. These constraints are normalized to avoid numerical problems using the same upper-lower-bound transformation reported in Equation (8) for the vector of objectives.

4.2.1 End-effector

The constraints regarding the end-effector trajectory are defined in the same way as their analogous objectives, reported in Equations (12) and (13). During the time intervals in which the end-effector trajectory or orientation must be constrained, the following equations apply:

$$\forall t \in [t_A, t_B] \quad \boldsymbol{\Phi}^{\text{EQ}}_{\text{EndEffTraj}} = \mathbf{x}(\mathbf{q}, t) - \mathbf{x}_{\text{Mod}}(t) = 0 \qquad (16)$$

$$\forall t \in [t_A, t_B] \quad \boldsymbol{\Phi}^{\text{EQ}}_{\text{EndEffOrient}} = \mathbf{r}(\mathbf{q}, t) - \mathbf{r}_{\text{Env}}(t) = 0 \qquad (17)$$

4.2.2 Joint range of motion

To ensure that the predicted DoFs do not exceed the natural RoM allowed by the human articulations, the values of $\mathbf{q}$ are restricted to a range delimited by the DoFs lower and upper limits $\mathbf{q}_L$ and $\mathbf{q}_U$:

$$\begin{aligned} \forall t \in [t_A, t_B] \quad \boldsymbol{\Phi}^{\text{IN}}_{\text{RoM}} &= \mathbf{q}_L - \mathbf{q} \le 0 \\ \boldsymbol{\Phi}^{\text{IN}}_{\text{RoM}} &= \mathbf{q} - \mathbf{q}_U \le 0 \qquad (18) \end{aligned}$$

4.2.3 Obstacle avoidance

Obstacle avoidance is treated as an inequality constraint set to a specified point in the human model $\mathbf{x}$. For spherical obstacles of center $\mathbf{x}_{Center}$ and radius a, the condition imposed to the point in the human model is:

$$\forall t \in [t_A, t_B] \quad \boldsymbol{\Phi}^{\mathrm{IN}}_{\mathrm{SphObstacle}} = a - \|\mathbf{x}(\mathbf{q}, t) - \mathbf{x}_{\mathrm{Center}}(t)\| \leq 0 \qquad (19)$$

For planar obstacles, defined with a point $\mathbf{x}_0$ and a normal vector $\mathbf{n}_{Plane}$, the condition to be met by the point $\mathbf{x}$ in the human model is:

$$\forall t \in [t_A, t_B] \quad \boldsymbol{\Phi}^{\mathrm{IN}}_{\mathrm{PlanObstacle}} = -\big(\mathbf{x}(\mathbf{q}, t) - \mathbf{x}_0(t)\big) \cdot \mathbf{n}_{\mathrm{Plane}} \leq 0 \qquad (20)$$

4.2.4 Dynamic equilibrium

To balance the forces in the human model with the forces due to the interaction between the human model and the environment, the condition of dynamic equilibrium is imposed. This condition is defined in terms of both forces and torques through inequality constraints:

$$\begin{aligned} \forall t \in [t_0, t_T] \quad \boldsymbol{\Phi}^{\mathrm{IN}}_{\mathrm{F\,Balance}} &= \mathbf{F}_{Root}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, t) - \boldsymbol{\varepsilon}_F \leq 0 \\ \boldsymbol{\Phi}^{\mathrm{IN}}_{\mathrm{F\,Balance}} &= -\mathbf{F}_{Root}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, t) - \boldsymbol{\varepsilon}_F \leq 0 \end{aligned} \qquad (21)$$

$$\begin{aligned} \forall t \in [t_0, t_T] \quad \boldsymbol{\Phi}^{\mathrm{IN}}_{\mathrm{M\,Balance}} &= \mathbf{M}_{Root}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, t) - \boldsymbol{\varepsilon}_M \leq 0 \\ \boldsymbol{\Phi}^{\mathrm{IN}}_{\mathrm{M\,Balance}} &= -\mathbf{M}_{Root}(\mathbf{q}, \dot{\mathbf{q}}, \ddot{\mathbf{q}}, t) - \boldsymbol{\varepsilon}_M \leq 0 \end{aligned} \qquad (22)$$

where $\mathbf{F}_{Root}$ and $\mathbf{M}_{Root}$ are obtained by summing all forces and torques acting on the pelvis, including the seat reactions.

The tolerances $\boldsymbol{\varepsilon}_F$ and $\boldsymbol{\varepsilon}_M$ according to which the equilibrium is considered satisfied depend on the accuracy with which the contact model is defined: the unfulfillment of the exact balance is assumed to be due to the approximate nature of the contact model, not to an inaccuracy of the resulting predicted motion.

4.2.5 Initial and final conditions

Conditions may be set to specify the velocity and acceleration conditions at the initial and final frames of the motion, in the form:

$$\begin{aligned} t = t_0, t = t_T \quad \boldsymbol{\Phi}^{\mathrm{EQ}}_{\mathrm{DoF\,Vel}} &= \dot{\mathbf{q}} = \dot{\mathbf{q}}^* \\ \boldsymbol{\Phi}^{\mathrm{EQ}}_{\mathrm{DoF\,Acc}} &= \ddot{\mathbf{q}} = \ddot{\mathbf{q}}^* \end{aligned} \qquad (23)$$

4.3 Design variables

Unlike kinematic prediction, which may consider only $\mathbf{q}$ as design variables, a dynamic prediction requires that the derivatives $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ be design variables as well. What the velocities and accelerations do is relate the values of $\mathbf{q}$ at a frame with its values at the previous and following frames. Hence, although kinematic predictions may be carried out one frame at a time, a dynamic prediction must be performed considering the motion as a whole. Instead of using the DoFs in each frame as design variables, as in spacetime methods [35-37], in this work we chose to parameterize the motion, using a B-Spline representation of the DoFs' profiles.

4.3.1 B-spline parameterization

B-spline curves are defined as a linear combination of independent p^{th} order piecewise polynomial functions N, called basis functions, through coefficients called control points (CPs). The basis functions only depend on the independent variable of the problem (in this case, time t) and are non-zero only in certain intervals. The control points instead are defined in the dependent variables space (in this case, the DoFs $\mathbf{q}$). Each DoF profile q_j is represented in B-spline form as a combination of nCP_j basis functions, as shown in Equation (24):

$$q_j(t) = \sum_{i=1}^{nCP_j} N_i^p(t)\, CP_{j_i} \quad (24)$$

The time derivatives of the DoF profiles are easily obtained as:

$$\dot{q}_j(t) = \sum_{i=1}^{nCP_j} \dot{N}_i^p(t)\, CP_{j_i}$$

$$\ddot{q}_j(t) = \sum_{i=1}^{nCP_j} \ddot{N}_i^p(t)\, CP_{j_i} \quad (25)$$

The advantages of using B-spline curves are several: they are a flexible parameterization, which fits the most general kind of data; they provide local support, given that each basis function is equal to zero during intervals of the motions; they ensure smoothness and continuity up to the p-1$^{\text{th}}$ derivative; and they are able to describe the whole motion with a relatively small number of variables. In fact, B-splines are a common motion parameterization employed in knowledge-based prediction methods [14, 22, 34, 38]. However, in these mentioned works, the number of CPs required to adequately represent the motion is decided *a priori*, considering how many extreme or inflection points the DoF profiles are expected to present.

In this study the assumption is made that the number of CPs which adequately describes the DoF profiles in the reference motion is also suitable to describe the profiles in the predicted motion. This assumption relies on the expected similarity between the reference and predicted motions: not only the reference scenario is the closest to the prediction scenario, but resemblance conditions to the reference motion are imposed in the prediction. To obtain the number of CPs which yield an appropriate representation of the motion, B-splines are adapted to the normalized DoF profiles of the reference motion and the smallest set of CPs which approximates the profiles to a specified tolerance is selected. This process is known as global approximation and is described in [39].

Given that dynamics involve up to the second order derivative of the DoFs, to guarantee continuity in the accelerations, the basis functions must be at least cubic splines. In this study 5th order splines are adopted to ensure smoothness in accelerations as well.

4.3.2 Formulation of the optimization problem

The variables which define the dynamics of the system, $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$, all depend on the vector of control points $\mathbf{CP}$, as shown in Equations (24) and (25). Therefore, the control points of the B-splines are chosen as the design variables for which the optimization problem is solved.

Hence, the optimization problem can be formulated as:

$$\begin{gathered} \text{find } \mathbf{CP} \\ \text{to minimise } f = \frac{1}{2}\boldsymbol{\Psi}^{T}(\mathbf{CP})\ \mathbf{W}\ \boldsymbol{\Psi}(\mathbf{CP}) \\ \text{subject to } \boldsymbol{\Phi}^{\mathrm{EQ}}(\mathbf{CP}) = 0 \text{ and } \boldsymbol{\Phi}^{\mathrm{IN}}(\mathbf{CP}) \leq 0 \end{gathered} \qquad (26)$$

The set of control points obtained in the global approximation of the reference DoF profiles constitutes the initial approximation for the optimization.

To obtain the derivatives of the objective function and the constraints with respect to the design variables $\mathbf{CP}$, we calculate the derivative of the variables $\mathbf{q}$, $\dot{\mathbf{q}}$ and $\ddot{\mathbf{q}}$ with respect to the control points:

$$\frac{\partial q_j(t)}{\partial CP_{j_i}} = N_i^p(t)$$

$$\frac{\partial \dot{q}_j(t)}{\partial CP_{j_i}} = \dot{N}_i^p(t)$$

$$\frac{\partial \ddot{q}_j(t)}{\partial CP_{j_i}} = \ddot{N}_i^p(t) \qquad (27)$$

Defining **s** as the vector of variables **s**=[$\mathbf{q}$, $\dot{\mathbf{q}}$, $\ddot{\mathbf{q}}$]^T, the derivative of a generic function Ξ_i, representing either an objective (Ξ_i=Ψ_i) or a constraint (Ξ_i=Φ_i), with respect to the CPs is calculated as:

$$\frac{\partial \Xi_i}{\partial CP_j} = \frac{\partial \Xi_i}{\partial s_k} \frac{\partial s_k}{\partial CP_j} \qquad (28)$$

where the repeated index k implies summation. Denoting with the subscript ***s*** or ***CP*** the derivative with respect to **s** and **CP** respectively, the Jacobian of function Ξ_i may be rewritten in matrix form as:

$$\boldsymbol{\Xi_{CP}}_i^{\ T} = \boldsymbol{\Xi_s}_i^{\ T}\, \mathbf{s}_{\boldsymbol{CP}} \qquad (29)$$

where $\boldsymbol{\Xi_{CP}}_i^{\ T}$ is the i^{th} row of the Jacobian matrix $\boldsymbol{\Xi_{CP}}$ whose elements are defined by Equation (28). The second derivative is calculated as:

$$\frac{\partial^2 \Xi_i}{\partial CP_j \partial CP_k} = \frac{\partial \Xi_i}{\partial s_m}\left(\frac{\partial \Xi_i}{\partial s_l}\frac{\partial s_l}{\partial CP_j}\right)\frac{\partial s_m}{\partial CP_k} = \frac{\partial^2 \Xi_i}{\partial s_l \partial s_m}\frac{\partial s_l}{\partial CP_j}\frac{\partial s_m}{\partial CP_k} \qquad (30)$$

Hence, the Hessian of function Ξ_i may be rewritten in matrix notation as:

$$\boldsymbol{\Xi_{CP^2}}_i = \mathbf{s}_{\boldsymbol{CP}}^{\ \mathrm{T}}\, \boldsymbol{\Xi_{s^2}}_i\, \mathbf{s}_{\boldsymbol{CP}} \qquad (31)$$

where the squared subscripts denote the variable with respect to which quantities are derived twice.

The derivatives of the constraints are obtained directly from Equations (29) and (31), whereas the derivatives of the objective function are obtained as:

$$\boldsymbol{f_{CP}} = \boldsymbol{\Psi}^{\mathrm{T}}\, \mathbf{W}\, \boldsymbol{\Psi_{CP}}$$

$$\boldsymbol{f_{CP^2}} = \textstyle\sum_i w_i\left(\Psi_i\, \boldsymbol{\Psi_{CP^2}}_i + \boldsymbol{\Psi_{CP}}_i^{\ \mathrm{T}}\, \boldsymbol{\Psi_{CP}}_i\right) \qquad (32)$$

The vectors of objectives $\boldsymbol{\Psi}$ and constraints $\boldsymbol{\Phi}$ contain the functions defined in Sections 4.1 and 4.2 evaluated at several instants in time. At each instant t, the length of the vector of variables **s** which affect the dynamics of the system is 3×*nDoFs*. On the other hand, the number of control points of a B-spline must be greater than the order of the basis functions: given that accelerations must be at least continuous, this implies $p \geq 3$ and $nCP \geq 4$ for each DoF. Hence, the length of the **CP** vector must necessarily be greater than $4 \times nDoFs$. This implies that the Hessians which appear in Equation (31) have different sizes, being the Hessian with respect to **CP** always larger than the Hessian with respect to **s**. However, the rank of a matrix can never be increased through multiplication, hence the Hessian with respect to **CP** is always rank deficient. An explanation for this characteristic is that **CP** is a vector which represents the totality of the motion, whereas **s** only represents a specific instant in time. Due to the local support of B-splines, only a certain number of control points affects the dynamics of a specific instant *t* of the motion: at *t*, other control points have no influence at all, leading to zero derivatives.

This characteristic has a strong effect on the objective function *f*, which must ensure that all variables (**CP**) be controlled: a necessary condition for this is that the objectives must be evaluated at a minimum number of frames. Given a number of frames *nFrames* (each being represented by a vector of variables **s**), the number of variables which describe all frames is $nFrames \times (3 \times nDoFs)$. If the size of the **CP** vector were greater than this quantity, the evaluation of the objective function at all frames would not be sufficient to provide information for each CP, and some CPs would be uncontrolled. Hence we may obtain the minimum number of frames at which the objectives must be evaluated as:

$$n_{min} = \frac{nCP}{3\ nDoFs} \qquad (33)$$

Evaluating the objective function at a number of frames $nFrames > n_{min}$ however does not guarantee that each CP is controlled. For that, the frames must be spaced across the period of the motion in order to involve all basis functions in their non-zero interval.

4.3.3 Effect of the number of control points

According to the allowed tolerance with which the reference DoF profiles are approximated, the number of control points for each B-spline may range from a minimum value, given by $p+1$, to a maximum value, given by $nFrames-1$ (if the number of control points equals the number of data available the curve no longer approximates but interpolates the data). A larger number of control points on the one hand entails a finer approximation to the reference profiles, however on the other it increases the size of the problem. However, due to the particular construction of the basis functions [39], by increasing the number of control points, the intervals during which each basis function is equally zero are longer: each basis function controls a smaller portion of the motion. This implies that matrices get larger but sparser with the increase of the number of control points. Figure 2 shows the effect of the number of CPs on the Hessian matrix of the objective function. When the number of control points is close to the minimum, the matrix is relatively small but full (Figure 2a corresponds to a case in which the minimum number of CPs is adopted); as it increases (Figures 2b and 2c), the size of the matrix is larger but it becomes more sparse and with a characteristic multi-diagonal shape. Moving towards the right or the bottom of the matrix corresponds to moving across the motion in time: in Figures 2b and 2c it may be seen how the effect of the first control points (associated to the first basis functions) is nullified while the following control points start affecting the motion.

5 Application to clutch pedal depression

The motion prediction method proposed in this paper has been applied to clutch pedal depression motions. The specifics introduced by the particular motion being predicted are detailed hereafter.

5.1 Adopted human model

A three-dimensional human model has been generated following RAMSIS specifications (Human Solutions GmbH). Since the clutch pedal motion hardly involves any limbs other than the left leg, the complete human model is simplified to a 13 DoF model of the left leg, as shown in Figure 3. The left leg subject-specific parameters are estimated based on boney palpable markers [40]. Additionally the inertial properties of the upper body are estimated using regression equations [41] and included in the pelvis.

5.2 Structured database generation

The database is constituted by clutch pedal operation motions, recorded at IFSTTAR in the framework of the European Project DHErgo following the experimental protocol detailed hereafter. The motions have been reconstructed and the constituted database has been analyzed considering the features described in Section 3.1.

5.2.1 Experimental protocol

Four groups of five healthy subjects (Table 1) were asked to perform the motion in an adjustable vehicle mock-up, which could assume the configuration of five different commercial vehicles from BMW, Peugeot-Citroën and Renault. The subjects were asked to perform a clutch pedal operation in each vehicle, yielding an experimental database composed of 100 motions.

A total of 17 reflective markers were placed on the body parts described by the multibody model: 6 on the pelvis, 4 on the left thigh, 3 on the shank and 4 on the foot. Additionally, 6 markers were placed on the seat to establish its position and orientation and 8 markers were used to describe the motion of the clutch pedal during the task. The motion of the markers was recorded with a VICON optoelectronic system with 10 cameras. Moreover a 3D force sensor synchronized with VICON recorded the force applied by the subject on the clutch pedal.

5.2.2 Motion reconstruction

The kinematics of the captured motions was reconstructed using the Optimal Tracking Method proposed by Ausejo et al. [42-44]. A recursive Newton-Euler method was then applied to the reconstructed motions to solve the Inverse Dynamics problem and obtain the forces and torques at the joints.

5.2.3 Database analysis

The following key-frames were identified in the pedal depression motion: the frame at which the motion starts, called *StartMotion*; the frame at which the pedal is reached by the foot, called *StartDepression*; the frame at which the pedal is fully depressed, called *EndDepression*.

Analyzing the DoF profiles, no substantial variability was identified to claim that more than one strategy or style was adopted in the motions.

Hence, each motion in the database was characterized with the following descriptors: gender, age, height, weight, seat position, clutch pedal initial position and orientation, travel length and travel angle to reach the fully depressed position, and key-frames values.

5.3 Human-environment interaction characterization

We consider the interaction of the DHM with two elements: the seat and the clutch pedal. The pedal is characterized [27] through: a) a stiffness curve relating its normal reaction force F_n, directed as the unit vector **n** (Figure 4), to its angular position θ; and b) through a linear relationship between the normal force F_n and the radial force F_r.

To characterize the human-seat interaction [27], four spring-damper elements have been employed to relate the value and velocity of the mutual penetration between the pelvis and the seat. Since the clutch pedal depression motion is carried out mainly in the sagittal plane, the seat reactions taken into account are limited to the above-mentioned plane, assuming that all transversal forces in the interaction are negligible. The calculated seat reactions in the sagittal plane are included in the prediction to ensure the dynamic equilibrium with the inequalities reported in Equations (22) and (23), where the $\boldsymbol{\varepsilon}$ coefficients are chosen as:

$$\begin{aligned} \varepsilon_F &= 0.1 \cdot m_B \cdot g \\ \varepsilon_M &= \varepsilon_F \cdot b_{hMax} \qquad (34) \end{aligned}$$

where m_B indicates the body mass and b_{hMax} is the maximum hip width.

The coefficient for the torque (ε_M) is set to reflect the same tolerance associated to the force balance (ε_F) multiplied by a dimension (b_{hMax}) which characterizes the contact surfaces.

Finally, for what concerns the obstacle avoidance conditions, collisions between the left foot and a horizontal plane representing the vehicle floor are considered.

5.4 Reference and prediction scenarios

Three predictions (referred to hereinafter as “trials”) were carried out to validate the proposed method, focusing on the group of young females. Therefore, the motion database among which to select the reference motion is a subset of the experimental one (Section 5.2.1) and is composed of the 25 motions performed by the young females.

The characteristics of the three subjects considered in the predictions and the three subjects used as reference are reported in Table 2. For what concerns the environments, the prediction environment was the same in all three trials and the most similar environment in the motion database was selected as reference. The environmental characteristics are shown in Figure 4 and their values in both the prediction and reference environments are listed in Table 3.

In order to validate the method, a validation database was employed, composed of clutch pedal depressions performed by 5 young females in the prediction environment. Each subject performed three repetitions of the motion, yielding a validation database composed of 15 motions. Additionally, each prediction subject was chosen to match the anthropometry of a validation subject, therefore each trial represents the prediction of an actual experimental configuration, in which three motion repetitions were captured. Hence, for validation purposes, the results of each trial are compared to all the motions in the validation database, including these three specific repetitions, hereinafter referred to as “validation motions”.

5.5 Optimization problem definition

This section describes the characteristics of the optimization problem, presented in Section 4, applied to the prediction of clutch pedal depressions.

The motions selected as reference are approximated with B-splines with a tolerance of 2% of the range of values for each DoF (Section 4.3.1): each reference motion is characterized by 17 CPs describing the profiles of the rotational DoFs and 15 CPs for the translational DoFs.

The values of the 215 CPs in the predicted motion are obtained by imposing the following conditions:

Objectives:

- The reference values of the DoFs must be resembled, Eq. (10), throughout the motion. The weight assigned to this objective is relatively low (0.01) as its aim is to avoid that the predicted values stray from the reference values.
- The shape of the DoF profiles is instead expected to be maintained more accurately. Hence a higher weight (0.5) is assigned to the resemblance of all the reference DoF velocities, Eq. (11), throughout the motion.
- The left foot must follow the modified trajectory, Eq. (12): during the first part of the motion, in which the foot reaches the pedal, the weight is lower (0.1) than in the second part (1), since in the first part the modified trajectory must only be resembled whereas in the second the trajectory of

the foot must match the pedal trajectory. An equality constraint is also set during the pedal depression, as detailed later.

- The motion control law to be followed is that of minimum mechanical energy expenditure, Eq. (15), imposed with a weight of 0.1 as the aim of including knowledge in the prediction as a motion control law is that of fine-tuning the data-based solution.

Equality constraints:

- The left foot starts at a specific point on the vehicle floor at frame *StartMotion* and follows the trajectory of the clutch pedal between frames *StartDepression* and *EndDepression*, Eq. (16);
- The predicted motion starts and ends at rest: the initial and final values of the DoFs velocities and accelerations must be zero, Eq (23) with $\dot{\mathbf{q}}^* = \ddot{\mathbf{q}}^* = \mathbf{0}$.

Inequality constraints applied throughout the motion:

- The values of the DoFs must be within the joints' RoM, Eq. (18);
- The left heel must be above the vehicle floor, Eq. (20);
- The forces and the torque acting in the sagittal plane must be balanced, Eqs. (21) and (22), within the tolerances specified in Eq. (34).

A detailed evaluation of the effect of the relative values of the weighting factors associated to the objectives can be found in [27].

These conditions are not imposed at every frame. With the considered reference motions composed of about 150 frames, equality constraints are set every 20 frames, inequalities every 15 frames and the objective function is evaluated every 3. Equality constraints reduce the number of free variables, and imposing them more often leads to a motion which may no longer adapt to minimize the objective function. Note that to avoid significant deviations from the pedal trajectory in between the frames at which the foot is constrained, the condition that the foot must follow the pedal trajectory is also included in the objective function with a high weight, as detailed before. Inequality constraints do not reduce the number of free variables but strongly affect the computational cost of the algorithm and require greater memory storage. Finally, the objective function must be evaluated at a number n of frames so that $n \geq n_{min}$ (Section 4.3.2) and $n \leq n_{Frames}$. Ideally, evaluating at every frame leads the CPs to be controlled best; however the smoothness ensured by the B-splines parameterization makes a frame-by-frame evaluation unnecessary: we have found that, with the number of control points we employ, evaluating the objective function every 3 frames is a good compromise between computational cost and accuracy.

6 Results and validation

The results obtained for the three trials are presented and discussed in the following sections, along with the validation of the proposed method. An interior-point method has been used to obtain the results shown in Sections 6.1-6.4 and is compared in Section 6.5 to a sequential quadratic programming method.

6.1 End-effector trajectory

Figure 5 shows the trajectories followed in the sagittal plane by the point in the foot which comes into contact with the pedal in the three predictions (Trials 1, 2 and 3), including the reference, the modified and the predicted trajectories. During the first phase of the motion, in which the foot reaches the pedal, the modified trajectory is only resembled, whereas in the second phase the two trajectories match, since the foot is constrained to the pedal. Additionally, it can be seen that the employed motion modification methods (Section 3.3) succeed in generating a modified trajectory which resembles the shape of the reference trajectory.

6.2 Joint angle profiles

In this section, the results of the flexion-extension (FE) angle profiles of the hip, knee and ankle joints are presented (Figure 6), as they are the DoFs which mostly contribute to the clutch pedal depression. To validate the prediction method, the predicted joint angle profiles are compared to the profiles adopted in the validation database, represented through their mean profile μ and their variability $\mu \pm 2\sigma$, where σ represents the standard deviation. Assuming a normal distribution, only about 5% of the profiles should fall out of the area delimited by $\mu \pm 2\sigma$. The further the predicted profile is from the mean, the lower is the probability that the predicted motion may be considered as an element of the validation database. Additionally, each predicted motion is compared to its three validation motions through a root mean square error (RMSE) of the predicted and validation profiles with respect to the mean profile μ of the validation database (Table 4). The values in Table 4 do not aim to identifying the most realistic motions as those presenting a lower RMSE. On the contrary, we use Table 4 to compare the RMSE of the validation motions to the RMSE of the predictions: if a prediction presents a similar RMSE to the validation motions, it may be considered an equally realistic motion.

The values of the predicted DoFs are almost always contained within the $\mu \pm 2\sigma$ area (Figure 6). Comparing the RMSEs of the predicted and the validation motions, almost all predictions present lower RMSEs than their corresponding validation motions. The exceptions are the hip and knee profiles in Trial 2 and the ankle profile in Trial 3 (Figure 6d, 6e, 6i respectively). These RMSEs, nevertheless, are not larger than some RMSEs associated to the validation motions of other trials. For instance, considering the ankle profile of Trial 3 (Figure 6i), which seems not to fully extend during the depression, its RMSE is larger with respect to its validation motions, but an even larger RMSE is associated to the second validation motion in Trial 1 (Figure 6c). This leads to the conclusion that such profiles are not the most common but nevertheless are occasionally adopted. Finally, it may be noticed that the shapes of the predicted profiles strongly resemble the shape of the reference profile, which agrees with the high weight associated with this objective, Eq. (11).

6.3 Joint torque profiles

The predicted torques closely resemble the values in the validation motions (Figure 7), which may suggest that the motion control law that is actually followed during clutch pedal depressions is not very different from the condition of mechanical energy minimization. It must not be surprising that the reference torques are not always included in the $\mu \pm 2\sigma$ area, since the reference motions do not belong to the validation database.

The only case in which the prediction RMSE is larger than the validation motions (Table 4) is for the ankle FE torque in Trial 2. However, although the predicted torque differs from the mean more than the validation motions do (Figure 7), its value is actually smaller, in accordance with the adopted performance measure of minimum mechanical energy, Eq. (15). This result may suggest that a different criterion may also be followed unconsciously to guide the ankle FE motion during pedal depressions. The results in the prediction of the hip and knee FE torques on the other hand seem to suggest that mechanical energy minimization is an appropriate control law to guide their motion.

6.4 External forces profile

The shapes and values of all predicted pedal reaction forces (Figure 8) resemble the measured reaction forces in the corresponding validation motions. Additionally, the predicted profiles are contained within the $\mu \pm 2\sigma$ area, suggesting that the contact model employed to represent the human-pedal interaction is adequate.

For what concerns the seat reaction forces (Figure 9), the predicted reactions resemble the values in the validation motions, which are obtained through Inverse Dynamics. However the natural oscillations encountered in the validation motions are amplified in the predictions, which may possibly be due to the simplified contact model used to represent the human-seat interaction.

6.5 Comparison of optimization methods

Finally, we compare the results obtained with the interior-point method mentioned earlier with a sequential quadratic programming (SQP) method. The root mean square errors between the results obtained with the two methods are RMSE < 2º in the joint angles and RMSE < 1Nm in the joint torques, showing that the results of our method are not strongly affected by the employed solver. The main difference between the solvers lies in their computational performance: the SQP method, which requires a numerical evaluation of the Hessian, presents a CPU time of about 40-50 minutes, whereas the interior-point, which employs the user-provided analytical Hessian, only requires 10-15 minutes of CPU time.

7 Discussion

The aim of human motion prediction is to represent the motions that a generic specimen of a population would perform to accomplish a given task. Although the prediction scenario matches an actual experimental scenario, the goal of the prediction method is not to replicate the motion in the database, but to generate a new motion which reasonably may have been performed in such a scenario.

In Figures 6 and 7 it may be seen that the three validation motions present quite dispersed data. This dispersion is a measure of the internal variability with which subjects perform repetitions of the considered task. In such dispersion, the predicted motion should fit as an additional motion, not as an exact match of an actually performed motion.

The hybrid prediction method we present may also be adapted in the case in which the aim of the prediction were extended. If the prediction should not only represent a realistic motion, but also the variability encountered in the database, our method offers three paths to be followed. The first option is changing the reference motion, and instead of selecting the most similar scenario as reference, performing several predictions by using a different reference for each prediction. The second possibility is to change the relative weights assigned to the objectives in the optimization problem. An appropriate set of weights however is not easily obtained, and generally is the result of a trial-and-error procedure. Moreover, their effect on the resulting motion is not always known beforehand and is generally nonlinear [22,27]: changing the value of a weight may under certain conditions hardly affect the resulting motion or modify it significantly.

The third option to change the predicted motion is to include a different motion control law, or combining several [19] to obtain different realistic predictions. These three options lead to stating the flexibility of our hybrid method to generate different predictions, as the aspects related to both the data and knowledge may be modified.

Our hybrid method also overcomes some of the limitations of current motion prediction methods. Data-based methods [6-8] are currently only kinematic, hence may not be expected to reasonably predict motions in which dynamics play a relevant role. Our method is able to predict a clutch pedal depression operation, in which the forces arising from the interaction between the subject and the environment are taken into account. Moreover, the capabilities of extrapolation from the database are limited in purely data-based methods when the prediction scenario differs significantly from the scenarios present in the database. By including knowledge in the prediction, our hybrid method overcomes the data-based limitation and is able to extend the prediction to different scenarios, as discussed in [27].

On the other hand, the greatest challenge for current knowledge-based methods [4, 14-18] is to predict realistic complex motions. An appropriate performance measure is not always easily identified and often a combination of motion control laws is required to obtain a more realistic prediction. Recently, Xiang et al. [23] presented a hybrid method, which seeks to overcome the limitations of knowledge-based methods in terms of the realism of the predicted motion. The data included in the method however derived from one experimental motion, which may not be representative of the motions performed in similar scenarios. The reasons for this limited data contribution are to be found in the origins of this hybrid method, which is built on the framework of a purely knowledge-based method [4, 21]. The validation of Xiang's hybrid method is carried out by comparing the prediction results to the single experimental motion. It may be argued that this one-to-one comparison may not be sufficient to assert that the method is valid to predict realistic human motions.

On the other hand, the validation process carried out to assess the validity of the hybrid dynamic method we present in this paper, compares the result of three different predictions with a database of actually performed motions, along with three repetitions of the motion actually performed in the prediction scenarios. The general trends of the joint angle and torque profiles are identified and resembled by the predicted motions, which do not deviate with respect to the mean profile more than the actually performed motions.

8 Conclusions

In this paper we have presented a hybrid dynamic motion prediction method, which relies on a database of captured motions and includes knowledge in the prediction through the definition of a performance measure, which represents the motion control law that drives the motion. The method is dynamic since the system's dynamics are included both in the performance measure and in the condition that the dynamic equilibrium of the human model must be ensured. The equilibrium is obtained by balancing the internal and external forces acting on the human model, the latter being defined through appropriate contact models to represent the interaction between the human model and the environment.

The prediction is carried out by solving a constrained nonlinear optimization problem and is applied to the prediction of clutch pedal depression motions to demonstrate its validity. Three clutch pedal depression predictions are presented and discussed in the paper and the results are validated against actually performed motions in a similar scenario. The predicted motions closely resemble real motions in the trajectory followed by the end-effector, as much as in the joint angle profiles, the joint torque profiles and the external forces acting on the human model across the motion.

The presented results show that the proposed method is able to generate realistic predictions. The application to clutch pedal depression motions serves as example and not as a boundary to the applicability of the method. The generality with which the proposed method is defined allows it to be easily applied to different task-oriented human motions, as the constraints and the objectives remain valid and must not be reformulated. For the prediction of longer and more complex motions, the motion can be divided into time periods to be predicted separately, ensuring the continuity through the initial and final conditions presented in this work.

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Figure Legends

Fig. 1 Hybrid dynamic motion prediction method outline

Fig. 2 Objective function Hessian matrix with different numbers of control points. The blue dots represent the non-zero elements of the matrices

Fig. 3 Human model for the clutch pedal depression motions (13 DoFs)

Fig. 4 Environment characteristics

Fig. 5 End-effector trajectories in the longitudinal x axis and vertical z axis in the three trials. The grey dot-dashed curves represent the trajectories followed in the reference motions; the black dotted curves represent the modified trajectories, which must be followed during the prediction; and the black solid curves represent the predicted trajectories

Fig. 6 Flexion-extension angle of hip, knee and ankle joints. Values calculated in accordance to Kapandji [45], except for the ankle which presents a +90º offset. The black solid curves represent the predicted profiles; the thin black curves represent the database mean profile μ and the variability curves $\mu\pm2\sigma$; the black dashed curves represent the profiles of the validation motions; the grey dot-dashed curves represent the reference profiles

Fig. 7 Flexion-extension torques of hip, knee and ankle joints. The black solid curves represent the predicted profiles; thin black curves represent the database mean profile μ and the variability curves $\mu\pm2\sigma$; the black dashed curves represent the profiles of the validation motions; the grey dot-dashed curves represent the reference profiles

Fig. 8 Pedal reaction forces acting on the left foot along the radial and normal directions in the pedal. The black solid curves represent the predicted profiles; thin black curves represent the database mean profile μ and the variability curves μ±2σ; the black dashed curves represent the profiles of the validation motions; the grey dot-dashed curves represent the reference profiles

Fig. 9 Seat reaction forces acting on the pelvis along the longitudinal and vertical directions. The black solid curves represent the predicted profiles; thin black curves represent the database mean profile μ and the variability curves μ±2σ; the black dashed curves represent the profiles of the validation motions; the grey dot-dashed curves represent the reference profiles

Tables

	Group 1	**Group 2**	**Group 3**	**Group 4**
Gender	Female	Male	Female	Male
Age	25±5	28±7	69±3	72±6
Stature [cm]	165±5	176±7	159±6	172±3
Mass [kg]	61±4	68±13	64±8	82±6

Table 1: Characteristics of the subject groups for the clutch pedal depression experiment

SUBJECTS	**Gender**	**Age**	**Stature [cm]**	**Weight [kg]**
Prediction 1	Female	30	168.4	58.6
Reference 1	Female	21	168.2	57.2
Prediction 2	Female	23	163.9	63.7
Reference 2	Female	30	168.4	58.6
Prediction 3	Female	23	163.9	63.7
Reference 3	Female	21	168.2	57.2

Table 2: Characteristics of the subjects to be predicted and the reference subjects

VEHICLES	**Seat height [m]**	**Pedal rest position and orientation**				**Travel L [m]**	**Travel α [deg]**
		x [m]	**y [m]**	**z [m]**	**β_0 [deg]**		
Prediction	0.272	-0.766	-0.080	-0.130	65	0.157	8
Reference	0.256	-0.814	-0.060	-0.069	76	0.131	0

Table 3: Characteristics of the environment to be predicted and the reference environment

		Angles (Flex-Ext) [deg]			**Torques (Flex-Ext) [Nm]**		
		Hip	Knee	Ankle	Hip	Knee	Ankle
Trial 1	Pred	3.531	3.439	4.064	4.002	1.246	1.182

	Val 1	8.182	4.935	7.802	4.615	2.211	0.955
	Val 2	6.290	8.156	12.337	20.121	11.667	3.053
	Val 3	8.272	5.838	9.961	20.973	11.216	3.670
Trial 2	Pred	8.306	7.207	5.553	6.627	2.878	2.945
	Val 1	5.447	6.096	3.655	3.389	2.396	1.043
	Val 2	5.061	4.468	7.572	10.738	3.385	1.393
	Val 3	1.363	1.867	2.432	14.041	6.360	1.914
Trial 3	Pred	3.632	4.437	11.559	4.833	1.696	1.540
	Val 1	5.447	6.096	3.655	3.389	2.396	1.043
	Val 2	5.061	4.468	7.572	10.738	3.385	1.393
	Val 3	1.363	1.867	2.432	14.041	6.360	1.914

Table 4: RMSE of the prediction and validation profiles with respect to the mean profiles μ