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Human Kicking Motion Using Efficient Forward Dynamics Simulation And Optimization

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Abstract— **The problem of finding and predicting muscle activations for free goal oriented or measured human motion is one of the basic problems in biomechanics. While currently inverse dynamics approaches are most commonly used for their computational efficiency, they can not handle the problem in its most general form. We here present computational methods that increase the computational efficiency of the forward dynamics approach by two orders of magnitude. Results are presented for a time optimal kicking motion and the analysis of a measured kicking motion. Current work includes investigation of a jumping motion and finding optimal walking motions for a robot that is driven by artificial muscles.**

Keywords— **human kicking motion, efficient forward dynamics simulation and optimization, direct collocation, goal oriented motions, analysis of measured motion**

I. Introduction

Biomechanical systems are very complex due to the absence of a unique assignment of actuation and resulting motion: one joint is driven by more than one muscle and there are muscles that span and influence more than one joint. Furthermore, a certain motion goal like reaching a certain position may be realized by an infinite number of joint motions. The subject of this paper is how to overcome these two redundancy problems and calculate muscle activations for measured or free (goal oriented) human motions efficiently using general biodynamical human models, where the latter in fact means prediction of human motion.

II. Biomechanical multibody systems

The human body is modeled as multibody system in two or three dimensions including mass, center of mass and inertia of all limbs, position and orientation of the joints and boundary constraints for the joint angle range. The dynamic behavior of the multibody system is described by the well known differential equations of second order:

$$\mathbf{M}\ddot{\mathbf{q}} = \boldsymbol{\tau} - C(\mathbf{q},\dot{\mathbf{q}}) - G(\mathbf{q}) + \mathbf{J}_c^T\mathbf{f}_c,$$

where $\mathbf{q}$ are the joint angles, τ are the total torques, $\mathbf{M}$ is the mass matrix, $C(\mathbf{q},\dot{\mathbf{q}})$ are the Coriolis and centrifugal forces, $G(\mathbf{q})$ are the gravitational forces, and $\mathbf{J}_c^T\mathbf{f}_c$ are the contact forces. The equation is solved for $\ddot{\mathbf{q}}$ by the Articulated Body Algorithm, cf. Section IV.A.

The muscles are modeled in a Hill-type way[12]; force-velocity-(FV) and tension-length-(TL)-relations describe the functional capabilities of the muscles. Muscle paths are modeled to get the right working range of the FV- and TL-relation and to get the right line of action and point of actuation of the muscles. The muscles may not exert their forces instantaneously but the force generation follows certain chemical processes: muscle activation leads to an increased concentration of calcium ions which then results in the force generation. To include the muscle activation dynamics into our model, we use the following differential equation:

$$\dot{\gamma} = c_1(c_2 u - \gamma),$$

where u is the muscle activation (which will be a control of the optimal control problem) and γ is the calcium ion concentration (which will be a state in the optimal control problem). Properties of tendons and ligaments are taken into account by passive torques.

Several general merit functions for distribution of the total joint torque to the muscle forces are of interest, e.g. minimization of the sum of all muscle forces, where each of the forces may be scaled by diameter of the muscle or by the torque to be applied to the joint.

With our approach all general merit functions may be investigated. The models are validated by comparing the optimization results with data of real human data such as EMG measurements or joint angle trajectories. Once having validated the model and having found which merit function applies in human motion, it is possible to predict motions.

III. Forward vs. inverse dynamics simulation

The problem to be solved may be stated as: minimize a suitable merit subject to the multibody system and muscle activation system of differential equations and nonlinear and boundary constraints. Two generally different approaches exist for solving it: inverse and forward dynamics calculations. While inverse dynamics calculation directly concludes from the joint motion to the muscle activations by some specific assumptions on the model only [6], forward dynamics approaches solve the optimization problem of adjusting the muscle activations so that the resulting motion (here the forward dynamics calculations are involved) best fit the given (measured) motion.

Inverse dynamics approaches currently are the most efficient numerical methods but they have the drawback that they are directly applicable only to the problem of analyzing a given motion; forward dynamics approaches also can handle the problem of optimizing goal oriented motions (i.e. predicting human motion) for validated models. The assumption of specific merit functions in inverse dynamics approaches does not allow considering general merit function of interest as it is the case with forward dynamics.

Currently, forward dynamics approaches are based on control parameterization where only the controls are discretized; the states are obtained by numerical integration of the differential equations of motion[5]. Repeated evaluations are needed to obtain gradients for optimization which leads to high computational effort. Our approach is based on discretizing both the controls and the states and thus solving the differential equations of motion simultaneously to the optimization [8], which is more efficient.

IV. Dynamics algorithms and optimal control techniques

The two main numerical tasks with the forward dynamics approach are computing of the forward dynamics of the underlying multibody system and solving the optimal control problem to overcome the redundancies.

A. Efficient dynamics algorithm: Articulated body algorithm

For only few degrees of freedom, the systems of differential equations of motion may be stated in closed form. For larger systems, numerical methods are used. We use the Articulated Body Algorithm [1], which is a recursive algorithm of linear order w.r.t. the number of joints and is highly modular for different components of the model which allows an efficient object oriented implementation [3].

B. Numerical optimal control techniques

To be able to treat the problem of finding muscle activations for free or given human motions, it is necessary to consider the most general form of optimal control problems involving box constraints, boundary conditions and nonlinear inequality constraints. More precisely, the target is to find control vectors $\mathbf{u}(t)$ (and thus also state vectors $\mathbf{x}(t)$) that minimize some objective function

$$J = \varphi(\mathbf{x}(t_f), \mathbf{x}, t_f) + \int_0^{t_f} L(\mathbf{x}(t), \mathbf{u}(t), t)\,dt$$

which consists of a scalar part (which may involve the state at final time t_f, all states and the final time) and an integral part (which may involve all states and controls). This objective function is minimized subject to constraint, which may consist of a system of nonlinear ordinary differential equations

$$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}(t), t),$$

initial and final values

$$\mathbf{r}(\mathbf{x}(0), \mathbf{x}(t_f), t_f) = \mathbf{0},$$

and nonlinear state and control constraints

$$\mathbf{g}(\mathbf{x}(t), \mathbf{u}(t), t) = \mathbf{0},$$

where a special case of the latter are box constraints (simple lower and upper bounds for the states and controls).

The optimal control problem is solved using the direct collocation method DIRCOL [8]. Note that the differential equations of motion are of second order, while currently the optimal control technique used only treats differential equations of first order. Therefore the second order differential equations of motion are transformed into a set of differential equations of first order but double size.

Both the controls and the states are discretized by piecewise polynomials and thus the optimal control problem is transformed into a nonlinear constrained optimization problem (NLP). The NLP is solved using efficient SQP method SNOPT [2]. By this descretization of both the states and the controls, the system of differential equations is solved simultaneously to the optimization. SNOPT exploits the special structure of the discretization which results in an extremely efficient numerical method.

V. Applications

A. Time optimal kicking motion

As a first application of the method, the kicking motion from [9] was chosen. The task is to find a kicking motion, i.e. the motion of the leg from a given initial posture to a final posture in minimum time. The objective function is thus chosen to be:

$$J = t_f.$$

The planar leg model consists of two joints and five muscle groups, cf. Figure 1. The resulting optimal control problem comprises two states for each of the joint angles, two states for the joint angle velocities and five states for the calcium ion concentration in the muscles. The muscle activations of the five muscle groups are the controls. The complete state vector is thus given by:

$$x = \begin{pmatrix} q_1 \\ q_2 \\ \dot{q}_1 \\ \dot{q}_2 \\ \gamma_1 \\ \vdots \\ \gamma_5 \end{pmatrix} = \begin{pmatrix} \text{hip angle} \\ \text{knee angle} \\ \text{hip velocity} \\ \text{knee velocity} \\ \text{ca ion concentration muscle 1} \\ \vdots \\ \text{ca ion concentration muscle 5} \end{pmatrix}$$

and the control vector is given by

$$u = \begin{pmatrix} u_1 \\ u_2 \\ u_3 \\ u_4 \\ u_5 \end{pmatrix} = \begin{pmatrix} \text{activation of muscle 1} \\ \text{activation of muscle 2} \\ \text{activation of muscle 3} \\ \text{activation of muscle 4} \\ \text{activation of muscle 5} \end{pmatrix}.$$

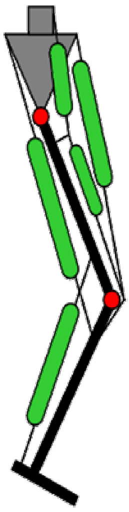

Figure 1: Kinematic structure of the leg.

To make the model perform a kicking motion, the initial and the final value of the hip and knee angles are enforced as boundary conditions for the starting time t_0

$$q_1(t_0) = 0.1,$$
$$q_2(t_0) = 0.15$$
$$\dot{q}_1(t_0) = \dot{q}_2(t_0) = 0$$
$$\gamma_1(t_0) = \ldots = \gamma_5(t_0) = 0$$

and for final time t_f

$$q_1(t_f) = 0.8$$
$$q_2(t_f) = -0.05$$
$$\dot{q}_2(t_f) = 0.$$

Inequality constraints are imposed to the states and controls to model geometric constraints and the box constraints on the activation rates and calcium ion concentrations:

$$0 \le q_1 \le 1.5$$
$$-0.05 \le q_2 \le 1.5$$
$$0 \le u_i, \gamma_i \le 1, i = 1, \cdots, 5.$$

As a starting solution, linear interpolation of initial and final value are used if known and 0 otherwise. More details may be found in [7,10].

Discretization of the states and controls on a grid of 60 grid points leads to a NLP with 531 variables and 829 nonlinear constraints which is solved in about 6 sec on a 1700 MHz+ Athlon computer, which is two orders of magnitudes faster than current methods for forward dynamics optimization for exactly the same problem [11]. Computation times and details on the size of the resulting nonlinear optimization problem are shown in Table 1. The resulting joint motions match those observed in real human kicking very well (cf. Figure 2). The activations may be found in Figure 3.

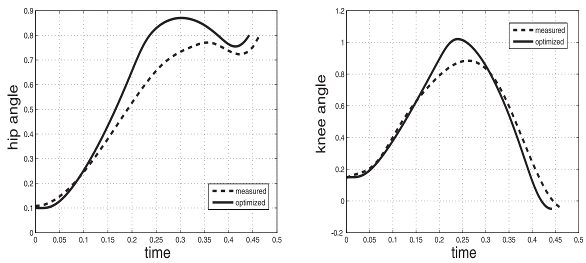

Figure 2: Joint motion of the hip (left) and the knee (right). Solid line is obtained from optimization, dashed line a measurement of real human kicking.

Table 1 Details about the size and calculation times for time optimal kicking motion

Grid points	10	60
Nonlinear constraints	81	829
Nonlinear variables	129	531
Computing time (1700 MHz+)	1.2 s	6.3 s

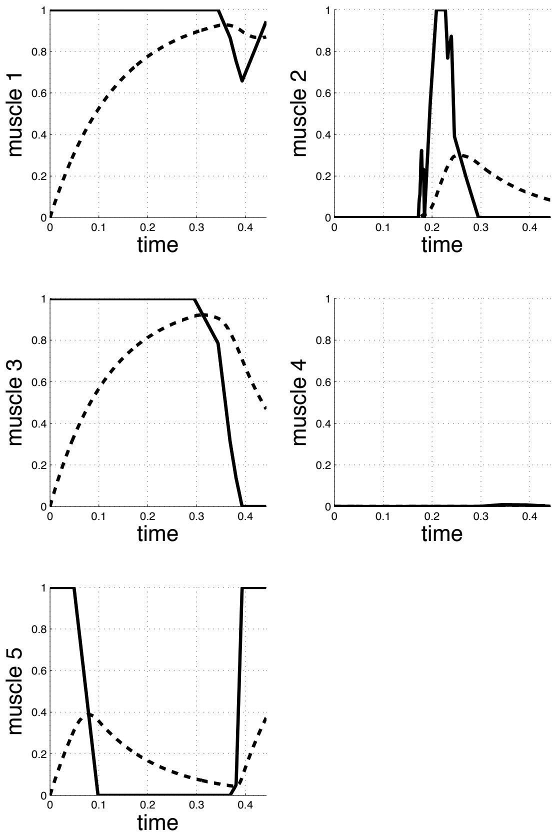

Fig. 3: Computed muscle activations (solid line) and calcium ion concentrations (dashed line) for the five muscle groups (time optimal kicking)

B. Analysis of measured kicking motion

If not a free, goal oriented motion, shall be predicted and optimized but a measured motion is to be analyzed, the forward dynamics approach may be used in a similar way. The only difference lies in the objective function. Let φ_{hip} and φ_{knee} be the measured hip and knee angle trajectories. Then, to calculate the muscle activations that lead to the measured motion and take into account human motion control which is supposed to minimize the activation effort, the objective function is chosen to be

$$J = \int_o^{t_f} (x_1 - \varphi_{hip})^2 + (x_2 - \varphi_{knee})^2 + c\mathbf{u}^T\mathbf{u}dt,$$

where c is a weight factor for taking into account human motion control. Note that by minimizing the differences of measured and calculated joint angle trajectories, the optimization result must not exactly match the measured motion like it is the case when applying the inverse dynamics approach. Thus, measurement errors may be implicitly compensated for which avoids that small measurement errors lead to large errors in the computation results like with inverse dynamics simulation and optimization.

The calculated and measured joint angle trajectories now of course better match (cf. Figure 4). The results for the activations are given in Figure 5. Computation times are about only 20% of that of the free goal oriented motion from the previous section. The reason for this is, that as a starting solution for the joint states, the measured motion may be taken as it is known and involved in the objective function.

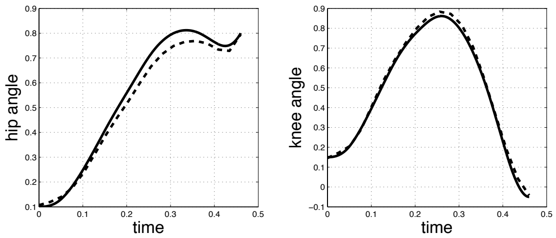

Figure 4: Joint motion of the hip (left) and the knee (right). Solid line is obtained from analysis, dashed line a measurement of real human kicking.

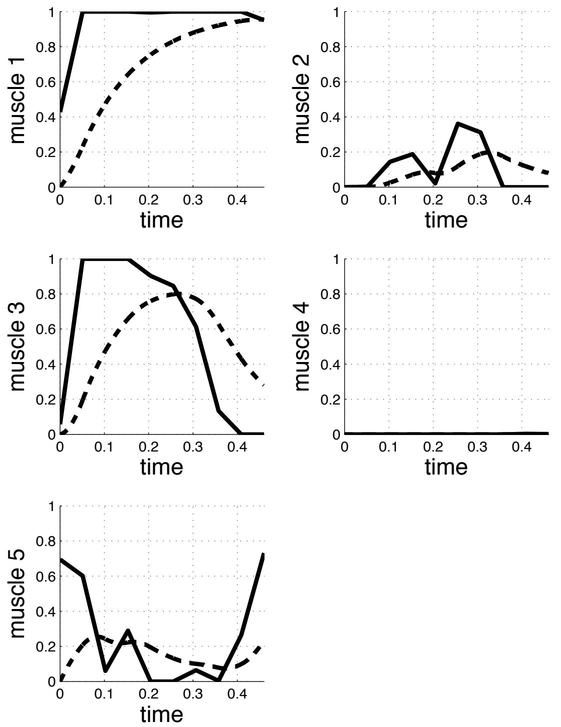

Fig. 5: Computed controls (analysis of measured kicking motion)

VI. Conclusions and outlook

Our approach for forward dynamics simulation and optimization reduces the computational effort by two orders of magnitude. We verified our approach and validated the model by a simple example for both optimization of a free, goal oriented motion (i.e. prediction of the kicking motion) as well as analysis of a measured motion. This gives rise to the hope that forward dynamics simulation and optimization can be used for actual problems in biomechanics.

Current work includes computation of the analyzing of human kicking on refined grids, the extension to more complex models such as for jumping, where contacts of the feet and the ground must be considered, and to motions where the upper body and wobbling masses must be considered. Furthermore, the method shall be applied to a humanoid robot driven by artificial muscles [4], where similar problems arise when a computational model of the robot shall be optimized for walking speed or energy consumption.

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