Two different control strategies for the multi-step forward-dynamic simulation of running gait

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Every year 65-80% of all runners suffer injuries, which represents a serious problem for the health care system. Nowadays, human running gait is an important topic of research aimed at improving the performance of athletes and reducing the number of running-related injuries. Dynamic simulations can be a useful tool to predict how a subject would move under different virtual conditions and, therefore, how these injuries could be reduced. While most existing work has focused on walking simulations, the simulations of whole-body running are relatively scarce in the literature; e.g., Chung [1]presented a non-linear optimization-based formulation for the prediction of 3D human running, Hamner et al. [2] presented a muscle-actuated simulation of human running, and Zhou and Przekwas [3] presented a control algorithm for running based on PD control.

Inverse Dynamic Analysis (IDA) is useful for analyzing human motion, usually captured during experimental testing. Conversely, Forward Dynamic Analysis (FDA) determines how a mechanical system will move due to the effect of external and internal forces without the need of experimentation, i.e., it is a predictive method. It is widely known that in the case of forward dynamic simulation of human motion, a control strategy must be applied in order to make the model move in a human-like manner.

Humans have a remarkable ability to control their motions, which involve the cooperation of the nervous and musculoskeletal systems. The most challenging aspect of FDA is the characterization and implementation of the control rules used to drive the model. An appropriate control to generate a forward dynamic simulation consistent with the locomotion task has not been clarified yet. The methods most frequently used to predict the human motion use optimization techniques, where the cost function can take into account different design variables: the parameters defining the motion, the parameters defining the drive efforts, or both types of parameters and including the relations among them, i.e., the equations of motion, as constraints of the optimization problem. Usually, these methods take into account the muscle forces responsible of the motion. These approaches demand a high-fidelity model; errors in the dynamic response of the model will affect the predicted muscle loads and thus the calculated metabolic cost. If the dynamic response of the model is not realistic, the simulated motion will not be reflective of how the subject would move. Therefore, a control to guarantee the reliability of the motion is highly important.

This study presents two closed-loop control algorithms to preserve the stability of a multi-step running gait simulation. An important aspect of this work is to maintain the stability of the model for a long simulation time containing multiple running gait cycles. We dynamically control the human model to track captured motion data, which inherently respect the kinematic and dynamic equations of the multibody system.

Most of the works on FDA of human locomotion only simulate a single step and most of them keep the foot fixed to the ground. In this study, a multi-step forward dynamic analysis is presented. For this reason, a running movement has been captured in the biomechanics laboratory by 18 optical cameras while the subject runs on a treadmill. Three different treadmill velocities have been considered: 8 km/h, 10 km/h and 12 km/h.

The 2D human model used consists of 12 anatomical segments: trunk, head, two arms, two forearms, two thighs, two shanks and two hindfeet. The segments are linked by ideal revolute joints defining a 14 degree of freedom model. The analysis is carried out using a set of $n = 14$ independent coordinates $\mathbf{z}$ (Fig. 1): the two Cartesian coordinates (z_1, z_2) of the right ankle joint, and the 12 angular variables $(z_3, \ldots, z_{14})$.

Using the kinematic information of the whole-body and combining the equations of motion of all the segments, the external foot-ground contact wrench (force and torque) and the internal joint torques can be calculated using multibody dynamics techniques. The inverse dynamics problem is solved by means of the velocity transformation

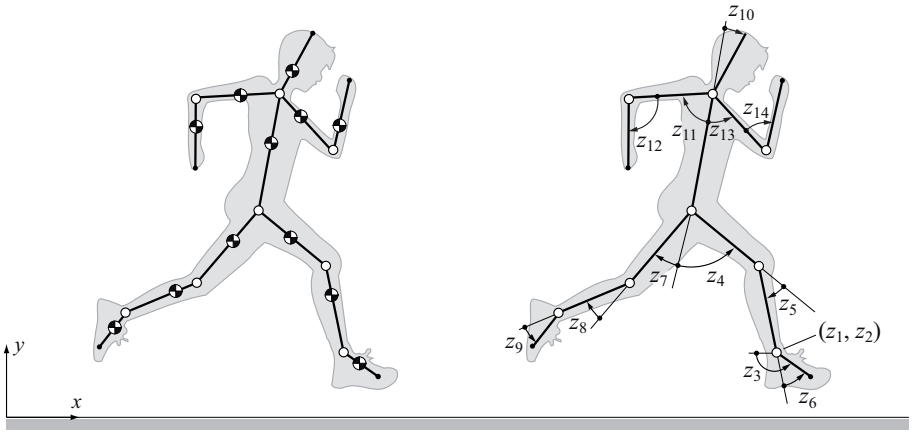

Fig. 1: Biomechanical model used with 12 anatomical segments and 14 degrees of freedom.

formulation known as matrix-R, which provides the required actuation in the form of generalized forces associated to the independent coordinates z [4]. The inverse dynamics results are used to guide the motion: the joint torques obtained from the IDA are used as input data of the FDA, and the movement captured at the laboratory is used to define the desired trajectories of the independent coordinates.

This study analyzes two different control strategies: a Proportional Derivative (PD) controller and a Computed Torque Control (CTC) with feedback linearization. The multibody system which needs to be stabilized is a nonlinear Multiple Input Multiple Output (MIMO) system. The nonlinear state space representation for a second order multibody system in matrix-R formulation can be described as:

$$\begin{cases} \dot{\mathbf{x}} &= \left\{ \begin{array}{c} \dot{\mathbf{z}} \\ \ddot{\mathbf{z}} \end{array} \right\} = \left\{ \begin{array}{c} \{\dot{z}_1, \ \ldots, \ \dot{z}_n\}^T \\ (\mathbf{R}^T\mathbf{M}\mathbf{R})^{-1}\left[\mathbf{R}^T(\mathbf{Q}_0 - \mathbf{M}\dot{\mathbf{R}}\dot{\mathbf{z}})\right] \end{array} \right\} + \left[\begin{array}{c} \mathbf{0} \\ (\mathbf{R}^T\mathbf{M}\mathbf{R})^{-1} \end{array} \right] \mathbf{Q}_{\text{in}} \\ \\ \mathbf{y} &= \mathbf{z} = \{z_1, \ \ldots, \ z_n\}^T \end{cases} \tag{1}$$

where $\mathbf{R}$ is the velocity transformation matrix, $\mathbf{M}$ is the mass matrix of the system, $\mathbf{Q}_0$ are the known generalized forces (in this case the gravitational forces), and $\mathbf{Q}_{\text{in}}$ is the input vector with the driving forces and torques provided by the IDA ($\mathbf{Q}_{\text{IDA}}$) and by the controllers ($\mathbf{Q}_{\text{Control}}$): $\mathbf{Q}_{\text{in}} = \mathbf{Q}_{\text{IDA}} + \mathbf{Q}_{\text{Control}}$. The gain parameters of the controllers are selected in order to follow the reference motion closely. The two control strategies are analyzed for the mentioned treadmill velocities and the numerical results are compared in terms of the differences between the obtained motions and the reference one, and the dynamic responses of the two controllers

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