Preprint of a paper which appeared in
Breitner, Denk, Rentrop (eds.): From Nano to Space.
Springer-Verlag, Berlin, Heidelberg, 2008, pages 175-192 and 337.

Walking, Running and Kicking of Humanoid Robots and Humans

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Summary. In this paper key aspects and several methods for modeling, simulation, optimization and control of the locomotion of humanoid robots and humans are discussed. Similarities and differences between walking and running of humanoid robots and humans are outlined. They represent several, different steps towards the ultimate goals of understanding and predicting human motion by validated simulation models and of developing humanoid robots with human like performance in walking *and* running. Numerical and experimental results are presented for model-based optimal control as well as for hardware-in-the-loop optimization of humanoid robot walking and for forward dynamics simulation and optimization of a human kicking motion.

1 Introduction

A large variety of bipedal motions are known from humans whereas today's humanoid robots can only realize a small fraction of them. All motions on two legs have in common that maintaining stability and balance is a critical issue and that there are redundancies in the actuation of the respective system. For typical humanoid robots actuation redundancies lie in the level of joint angles: One overall locomotion goal (i.e., a certain walking trajectory and contact situation history of the feet during walking) usually may be achieved by an infinite number of joint angle trajectories. For humans, an additional level of redundancy must be considered in comparison with today's humanoid robots which usually have one actuator per rotational joint in the leg: Even for given joint angle trajectories, the involvement of the various muscles which actuate the respective human joints is not uniquely defined.

A widely accepted hypothesis in biomechanics is that for trained leg or whole body motions among all possible muscle actuation strategies the one is selected which minimizes or maximizes a certain objective [NH99]. Selecting the best possible walking trajectories is also mandatory for *autonomous* humanoid robots which must carry not only all of their actuators but also onboard computing, additional sensors and energy supplies.

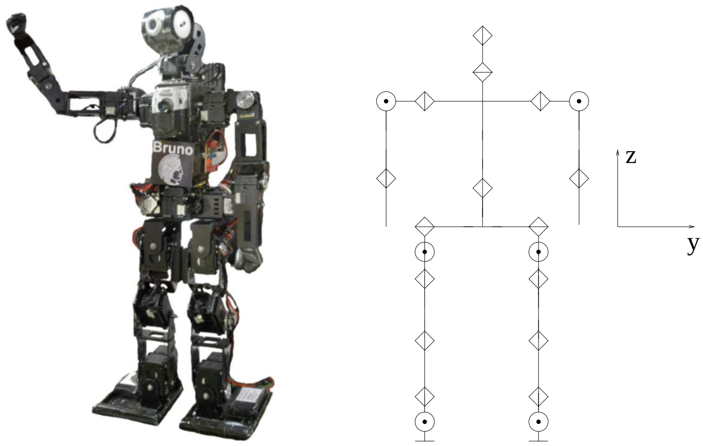
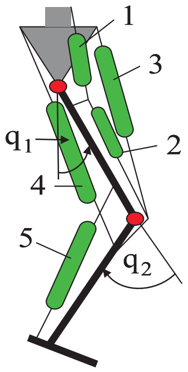


Fig. 1. The 55 cm tall, autonomous humanoid robot Bruno developed at TU Darmstadt (left) and its kinematic structure with 21 servo motor driven joints (right).

The research presented in this paper has been inspired by Roland Z. Bulirsch in manifold ways. For example, mathematical models of the locomotion dynamics of humanoid robots and humans result in medium to large systems of nonlinear ordinary or differential-algebraic equations. The determination of optimal control variable trajectories lead to large-scale nonlinear optimal control problems which can only be solved numerically. Bulirsch had already in the 1960s during his affiliation with the University of California, San Diego, pioneered one of the very first numerical methods for solving such problems, the so-called indirect multiple shooting method (in the terminology of [vSB92]). This method enabled to solve trajectory optimization problems in aeronautics and astronautics numerically in a satisfactory manner which had not been possible before. A variety of efficient numerical methods for solving optimal control problems which nowadays are used all over the world has directly evolved from his pioneering work, e.g., [BK94]. Furthermore, Bulirsch has always emphasized strongly that numerical methods must be mature enough to enable the treatment of real-world problems and not only simplified academical problem statements. However, this requires significant efforts for deriving a sophisticated and validated mathematical model of the problem in question.

2 Kinematical Leg Design

During the last decade significant advances in humanoid robotics concerning autonomous walking and hardware and software design have been achieved. The humanoid robot *H7* (137 cm, 55 kg, 35 degrees of freedom (DoF)) [NKK$^+$04] is able to execute reaching motions based on the implemented whole body motion control. Footstep planning and balancing compensation is



1. Ilio Psoas group
2. Vastus group
3. Rectus Femoris
4. Hamstring group
5. Gastrocnemius group

Fig. 2. Kinematic structure of a planar human leg model with five muscle groups actuating the hip and knee joints.

used for adaptive walking. The German humanoid robot *Johnnie* (180 cm, 40 kg, 17 DoF) [LGP03] can walk with a maximum speed of 2 km/h. The control and computational power is onboard, whereas the power supply is outside of the robot. In the Japanese Humanoid Robot Project the robot *HRP-3* (160 cm, 65 kg, 36 DoF) has been developed with special skills for water and dust resistivity. It can walk with a maximum speed of 2.5 km/h [KKK$^+$04]. The Korean robot *KHR-2* (120 cm, 54 kg, 41 DoF) [KPL$^+$05] walks with a maximum speed of 1 km/h. The robots *QRIO* (50 cm, 5 kg, 24 DoF) by Sony and *ASIMO* (120 cm, 52 kg, 26 DoF) by Honda are two commercial humanoid robot platforms. *QRIO* [NKS$^+$04] can walk stable, jump and "jog" (i.e., fast walking with small flight phases) including the transitions between them. It can also execute many special motions, among them coordinated dancing, squatting and getting up. *ASIMO* [HHTH01] is the humanoid robot with the currently highest walking speed of 6 km/h and the most costly development. The autonomous humanoid robot *Bruno* (55 cm, 3.3 kg, 21 DoF, Fig. 1 left) can play soccer and walks with more than 40 cm/s, almost 1.5 km/h, in permanent operation [FKP$^+$06, HSSvS06].

All of these humanoid robots which today can walk flexible, stable and reliably in repeatable experiments share the same basic kinematic leg structure: Six (sometimes seven) rigid, rotational joints per leg are connected with rigid links. Usually three joints are used in the hip, one in the knee and two in the ankle (cf. Fig. 1 right) to reach a general position and orientation with the foot within its range. A joint typically consists of an electric actuator with gear which are designed to be as rigid, powerful and lightweight as possible.

The human leg, however, does not have one rigid rotary actuator in each joint, e.g., the knee joint. Redundant, elastic linear actuators, i.e., the contracting muscles, antagonistically arranged around the leg joints result in a very compliant leg design. In general, in biomechanical motion systems each joint is often driven by more than two muscles. Also there are muscles that have effect on more than one joint, e.g., the rectus femoris, the gastrocnemius and the hamstring group (cf. Fig. 2).

3 Modeling and Simulation of Locomotion Dynamics

Current humanoid robots can be modeled as a kinematical tree structure consisting of rigid links and joints, e.g., Fig. 1 right, and changing contact situation of the feet with the ground during walking. The locomotion dynamics describes the relationship between the joint angles $\boldsymbol{q}^T = (q_1(t), \ldots, q_n(t))$ and the joint torques $\boldsymbol{\tau}^T = (\tau_1, \ldots, \tau_n)$. It is represented by a multibody system (MBS) dynamics model with contact constraints

$$\mathcal{M}(\boldsymbol{q})\,\ddot{\boldsymbol{q}} = \boldsymbol{\tau} - \mathcal{C}(\boldsymbol{q}, \dot{\boldsymbol{q}}) - \mathcal{G}(\boldsymbol{q}) + J_c^T \boldsymbol{f_c} \tag{1}$$

$$0 = \boldsymbol{g_c}(\boldsymbol{q}), \tag{2}$$

where $\mathcal{M}$ denotes the positive definite mass matrix, $\mathcal{C}$ the Coriolis and centrifugal forces, $\mathcal{G}$ the gravitational forces, and $J_c^T \boldsymbol{f_c}$ the contact forces. The ground contact constraints $\boldsymbol{g_c} \in \mathrm{I\!R}^{n_c}$ represent holonomic constraints on the system from which the constraint Jacobian $J_c = \partial \boldsymbol{g_c} / \partial \boldsymbol{q} \in \mathrm{I\!R}^{n_c \times n}$ may be obtained, while $\boldsymbol{f}_c \in \mathrm{I\!R}^{n_c}$ is the ground constraint force.

For formulating the second order differential equations (1) different methods exist ranging from recursive methods based on force-moment relations as Newton-Euler to energy based, analytic methods as Euler-Lagrange [Cra05]. For efficiently formulating these equations in case of a large number of joints n the recursive $\mathcal{O}(n)$ articulated body algorithm (ABA) [Fea87] has been shown to be an accurate, numerically stable and efficient algorithm which computes $\mathcal{M}, \mathcal{C}, \mathcal{G}, J_c$ in three, resp. five in case of contact forces, forward or backward iterations (sweeps).

An alternative formulation of the ABA has been derived which results in an $\mathcal{O}(n)$ closed-form expression for the inverse mass matrix [RKDJ91] (see also [HvS03] for details). This recursive approach is modular and flexible as it facilitates the exchange of submodels and the reuse of other model parts without having to reformulate the complete model as it is the case, e.g., with the Euler-Lagrange method. An object oriented implementation has been developed based on this formulation of the ABA (cf. Sect. 5.3 and [HSvS06]) which enables a flexible and efficient computation in different applications of the dynamics model (1), e.g., simulation, optimization or control. The method can be extended to an efficient recursive, computation of partial derivatives of the dynamics model which are required for optimal control and trajectory optimization (cf. Sect. 5.3) or optimal parameter estimation.

In contrast to humanoid robots the torques τ_i acting in human joints do not stem from a single actuator but from contracting muscle groups whose dynamic behavior must be considered in addition to the dynamics model (1) of the skeleton and the wobbling masses. For modeling of the dynamic motion and force behavior of muscles as contracting actuators with serial and parallel elasticities and active contractile elements a number of well investigated approaches have been developed. They describe the muscle forces in relation to muscle length, muscle velocity and muscle activation as the many models based on the fundamental approaches of Hill and Huxley, cf. [NH99, Pan01]. Almost all models from literature assume that the muscle forces act at a point. For non-punctual areas of force application the muscles are divided into several muscle models with single points of actuation. Several approaches exist for modeling the muscle paths as the straight line method (modeling the muscle path to connect the points of application in a straight line), the centroid line method (modeling the muscle path to connect the centers of mass of the muscle cross sectional areas) or the obstacle set method (modeling the muscle path to move freely sliding along the bones). A survey of these approaches may be found, e.g., in [Pan01].

4 Control and Stability of Bipedal Gaits

Several criteria have been established to ensure postural stability of a bipedal robot walking trajectory either during offline computation or online using feedback control. Two basic groups are distinguished: criteria for static and for dynamic stability. *Static stability* is present if the center of gravity (CoG) of the robot projected along the direction of gravity lies in the convex hull of the support area consisting of all foot-ground contact points. *Dynamic stability* is defined as a bipedal walking motion which is not statically stable but the robot does not fall over. This is the case for running, jogging and even medium fast walking of humans. Several constructive criteria are used to realize dynamic walking in humanoid robots, among them the nowadays widely used zero moment point (ZMP) [VB04] and the foot rotation indicator (FRI) [Gos99], an extension of the ZMP definition. Both indices for dynamic stability basically induce that no moments around the two possible axes that might lead to a falling of the robot occur while taking into account not only the mass distribution of the robot (as the static projected CoG criterion) but also dynamic effects, i.e., acting forces and moments.

For online evaluation of the stability indices for feedback control, the humanoid robot needs additional sensors to the standard joint angle position encoders. Usually accelerometers and gyroscopes are used in the upper body close to the CoG to determine the robot's pose and and force/moment sensors are used in the feet to measure foot-ground contact for ZMP-based stability control. In small to medium sized humanoid robots ZMP-based control can be implemented successfully also without ground contact force sensing, e.g., [FKP+06]. On the other hand for human-sized, high-grade humanoid robots in addition force/moment sensing in the joints is provided.

Commonly trajectory tracking control is applied in a hierarchical, decentralized scheme where the setpoints for the joint angles of the humanoid robot are updated in a constant frequency between 1 and 10 ms [HvS03]. The feedback control schemes of the joints, e.g., PD or PID, are usually operated independently of each other. Ideally, a nonlinear feedback control scheme would be applied based on a full nonlinear MBS dynamics model (1) of the hu-

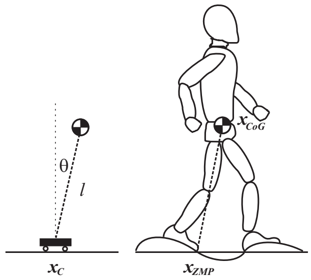


Fig. 3. The inverted pendulum model is used as a simplified model to describe walking properties of humanoid robots and humans.

manoid robot. However, this would require to evaluate such a model for at least 18 bodies and joints on an embedded processor and at least faster than the update frequency of the joint angle setpoints which is difficult to achieve.

Therefore, simplified motion dynamic models are used for stabilizing control schemes based on the ZMP or its precursor, the inverted pendulum (IP) model (Fig. 3), which was used in balancing control of the first bipedal walking robots. The IP model approximates the basic behavior of the whole walking robot and is easy to handle with low computational efforts [SNI02].

The IP model has also been used to describe slow human walking as balancing on stiff legs. Measured ground reaction forces are reproduced well. But this rigid model can not be extended to human running. A spring-mass system describes much better rebounding on compliant legs during running or jogging. Therefore, elasticities must be included in a robot leg design to describe dynamic walking and running as in Raibert's hopping robots [Rai86]. However, the latter can not be used for slow bipedal walking or even standing. Therefore, as the grand challenge in research of humanoid robot locomotion the question remains to be answered how humanoid walking and running can be realized well using *one* robot leg design.

An important difference between today's humanoid robots and humans is that any motion of a humanoid robot is under full feedback control at any time. To enable bipedal running using today's robot technology, the motors in the joints must be more powerful to enable higher joint velocities (like the wheels in a fast car). But the motion can only be as fast as the joint sensors are able to measure joint position and velocity to enable feedback control. This is not the case for many types of fast human motions. By suitable training, human motions can be generated feed-forward which are much faster than the internal sensing of an arm or leg but nevertheless are of high quality, e.g., a fast serve in tennis or fast piano playing. These fast motions make effective use of the elastic, compliant design of legs, arms and fingers like shooting an arrow with an elastic bow. From a robot control point of view, however, elasticity in a kinematical leg or arm design is avoided as much as possible because control becomes severely difficult. Compliant joint behavior is instead simulated using joint force/moment sensor and compliant control schemes.

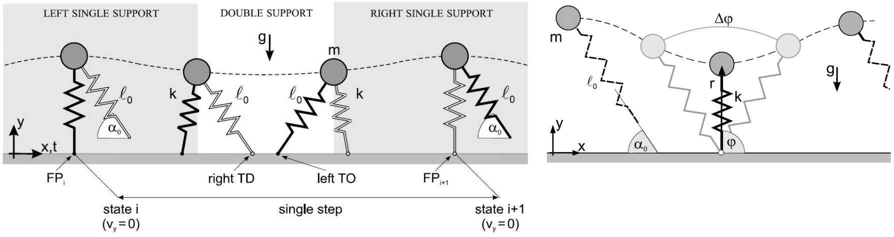


Fig. 4. A basic compliant leg model exhibits properties of both human-like walking (left) and running (right) in the same mechanical design (due to [Gey05]).

Recent results in biomechanics showed that by adding suitable elasticities to the most simple bipedal leg model properties of both fast, elastic running and slow, stiff walking can be represented quite well (Fig. 4) [Gey05, GSB06]. In numerical simulations bipedal locomotion using such basic compliant leg models has demonstrated to be quite robust against external disturbances like uneven terrain. This motivates to investigate bipedal walking machines with compliant, three-segmented legs like the ones of Sect. 5.2 as a step towards solving the grand challenge problem of humanoid robot locomotion. However, it remains yet unsolved how an elastic, possibly underactuated, bipedal leg design can be stabilized under different walking and running conditions.

In this context, passive dynamic bipedal walking should also be mentioned which has recently gained much interest. Low powered bipedal walking machines have demonstrated stable bipedal locomotion on flat terrain with low or even no actuation and therefore claimed a highly energy-efficient and natural way of walking [CRTW05]. A closer inspection reveals that the kinematical leg design consists of two-segmented, rigid legs with thigh and shank only. There is no need for an articulated foot with ankle joints. A foot point contact or knob-like foot and a rolling motion along the foot knob's surface during stance phase of the leg is sufficient when the bipedal walkers swing over a straightened knee joint. Moreover, such leg designs only enable a certain constant walking speed. A larger variation in walking speed is not possible, not even mentioning running. Passive dynamic walkers share these properties with current passive above-knee prostheses. It is very difficult using them to walk at very different speeds or to use them in uneven or steep terrain.

5 Methods and Case Studies

5.1 Forward Dynamics Simulation of Human Kicking Motion

There are approximately 650 skeletal muscles in the human body which are anchored by tendons to bone and affect skeletal movement such as locomotion. Considering the many individual muscles involved in locomotion and a mathematical model of locomotion dynamics and the redundancy in joint actuation by muscles involved (Sect. 3) then the secret of human biodynamics is explained in N.A. Bernstein's words (1935): "As in orchestra, each instrument plays its individual score, so in the act of human walking each joint reproduces its own curve of movements and each center of gravity performs its sequence of accelerations, each muscle produces its melody of efforts, full with regularly changing but stable details. And in like manner, the whole of this ensemble acts in unison with a single and complete rhythm, fusing the whole enormous complexity into clear and harmonic simplicity. The consolidator and manager of this complex entity, the conductor and at the same time the composer of the analyzed score, is of course the central nervous system".

A widely accepted hypothesis in biomechanics is that for trained motions among all possible actuation strategies of the many muscles involved the one is selected which minimizes or maximizes a suitable objective [NH99]. Such an actuation strategy must then essentially coincide with the much more simpler compliant leg model depicted in Fig. 4 which describes well the observed overall leg behavior in human locomotion but cannot explain the behavior of the many individual muscles involved. The modeling and numerical solution of optimization problems for the system dynamics to reliably predict system behavior and motion is nowadays well established for vehicle and robot dynamics. It is a grand challenge in human biodynamics research to develop such methodologies for the human musculoskeletal system and requires the development and validation of assumptions, models and methods.

The central problem statement addressed in this section is to find the activations $\boldsymbol{u}(t) = (u_1(t), ..., u_{n_m}(t))^T$ of each of the n_m muscles involved so that the resulting calcium ion concentration γ_i caused by the activation u_i of each muscle i leads to forces F_i, $i = 1, \ldots, n_m$, which cause a motion of all n joints (i.e., joint angle trajectories $\boldsymbol{q}(t) = (q_1(t), ..., q_n(t))^T$, $0 \leq t \leq t_f$) which

1. is equal or as "close" as possible to the kinematic and/or kinetic data of a human body motion measured in experiments (inverse problem), or
2. best fulfills some motion goal like maximum jump height or width or fastest possible walking or running (forward problem).

While in the first case only the redundancy of the muscles must be considered, the second case incorporates also the additional level of redundancy with respect to the overall motion. "Close" in the first case may be measured by an objective function, e.g., the integral over the difference of measured and calculated joint angle trajectories. The goal achievement in the second case can be measured by a suitable objective function as time or energy required.

Generally, the two different approaches of forward and of inverse dynamics simulation exist [SvS06]. The *forward dynamics simulation* of a human motion leads to high dimensional, nonlinear optimal control problems. Current approaches in this field are usually based on direct shooting techniques [BK94, vSB92] with finite difference gradient approximations. They require even for problems with reduced models of the whole human body computa-

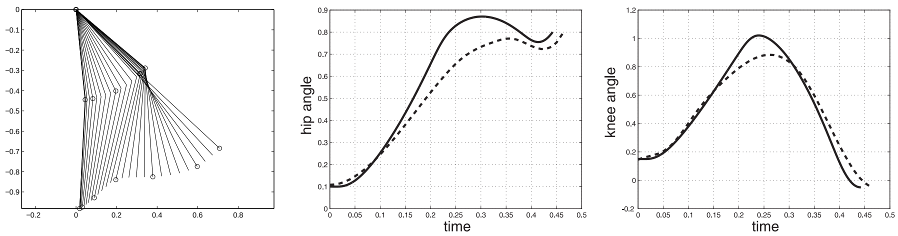


Fig. 5. Numerical results for the minimum time kicking motion: Visualization in phase space (left), measured (dashed line) and optimized (solid line) joint angle trajectories of hip (middle) and knee (right).

tional times of days or weeks on workstations, cf. [AP99, SKG99]. Forward dynamics simulation based on a validated dynamics model and model parameters has the important potential of *predicting* certain motions.

On the other hand, *inverse dynamics simulation* investigates given kinematic position and velocity trajectories of a human motion, e.g., obtained from measurements. Together with special approximate modeling approaches for the dynamics model and the objective it allows a comparatively fast numerical computation of the controls of each muscle group if restrictive assumptions on the underlying model like special objective functions for control of the muscles involved are made, e.g., [RDV01]. Inverse dynamics simulation for a measured human motion gives an *interpretation* of the acting forces and torques on the level of the single muscles involved.

To overcome the drawback of high computational burden an efficient forward dynamics simulation and optimization approach for human body dynamics has been suggested [SvS06]. It is based on an efficient $\mathcal{O}(n)$ modeling of the dynamics of the musculoskeletal system consisting of the MBS (1) and suitable models of the activation dynamics $\dot{\gamma}_i$, the force-velocity and tension-length and further muscle properties. Instead of using one of the direct shooting approaches which require feasibility with respect to the MBS dynamics constraints in each iteration of the optimization method a simultaneous approach for solving the MBS dynamics integration and optimization problems inherent in the optimal control problem is selected. In direct collocation [vSB92] the implicit integration for a sequence of discretization steps from initial to final time is included as a set of explicit nonlinear equality constraints in the optimization problem and the optimal control problem is transformed into a sparse and large-scale nonlinearly constrained optimization problem (NLP). Without the restriction to feasibility to the ODE constraints in each iteration as in direct shooting only the final solution of direct collocation iterations must satisfy them. Without the restriction to feasible iterates and with much easier computable gradients the solution may be obtained much faster.

As one first example, a time optimal kicking motion has been investigated, i.e., $t_f \to$ min!. Kinematic and kinetic data of the musculoskeletal system as

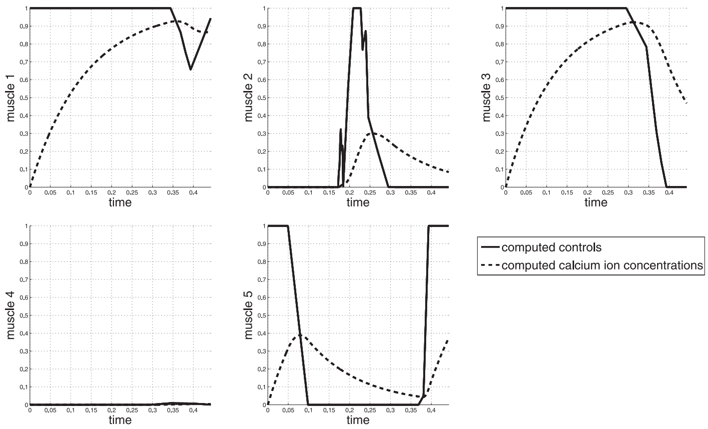


Fig. 6. Numerical results for the minimum time kicking motion: The control variables are the muscle activations (which correspond to EMG, solid lines) and the resulting calcium ion concentrations of the muscles (dashed lines).

well as muscle model parameters and measured reference data have been taken from [Spä98, SKG99]. The model consists of two joints, two rigid links and five muscle groups (Fig. 2). The problem is formulated as an optimal control problem with 9 first order state variables (hip angle q_1, knee angle q_2, the corresponding joint velocities and 5 calcium ion concentrations) and 5 control variables, i.e., the activations of the muscles. The muscle lengths and velocities that are needed for the force-velocity and tension-length relationship of the Hill-type muscle model are calculated according to [Spä98]. The resulting lever arms used for transforming the linear muscle force into joint-torques depend on the joint angle and are also taken from [Spä98], as well as the passive moments. Suitable boundary conditions at t_0 and t_f must be meet by q_i, $\dot{q}_i$, γ_j and box constraints are imposed on $q_i(t)$, $\gamma_j(t)$, $u_j(t)$ during $[t_0, t_f]$ [SvS06].

Compared to the data of the measured human kick (and the results of [Spä98, SKG99] which matched the measured data very well), our results show a shorter time t_f and larger maximum angles (Fig. 5). This is because in [Spä98] the maximum muscle forces were modified successively in a way that the computed minimum time for the motion matches the measured time closely. Now solving the same problem with our approach a better (local) minimum can be computed. But, the controls (Fig. 6) show the same characteristics. Time discretizations with, e.g., 10 resp. 60 grid points lead to NLPs with 129 resp. 531 nonlinear variables and 81 resp. 829 nonlinear constraints. The resulting computing time of SNOPT [GMS02] was 1.2 s resp. 6.3 s on an Athlon XP1700+ PC. The direct shooting approach of [Spä98, SKG99] for 11 grid points required hours on a workstation to compute the solution [Spä05]. Compared with our approach and considering how processor performance has progressed since 1996, we obtain a speed up of two orders of magnitude.

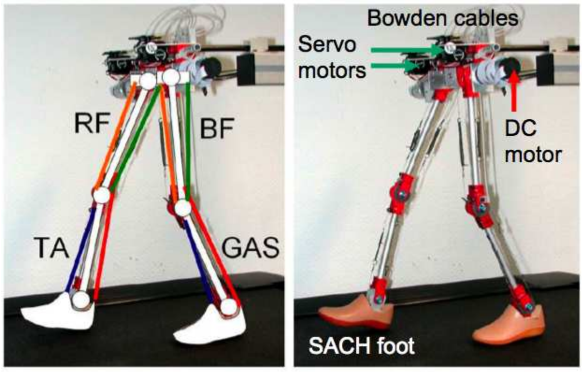


Fig. 7. The arrangement of adjustable elastic structures (springs) spanning the ankle, knee and hip joints in the JenaWalker II as a demonstrator for bipedal walking with three-segmented passively compliant robot legs [IMRS06, STS$^+$06].

5.2 Passively Compliant Three-Segmented Bipedal Robot Legs

For validating hypotheses in human locomotion [GSB06] and to overcome the limitations of current robot legs three-segmented bipedal robot legs have been developed by the Locomotion Laboratory of the University of Jena in cooperation with TETRA GmbH, Ilmenau [IMRS06]. Four major leg muscle groups (cf. Fig. 2) are represented in the leg by passive elastic structures: tibialis anterior (TA), gastrocnemius (GAS), rectus femoris (RF) and biceps femoris (BF) (Fig. 7). Only the hip joints are directly actuated by a central pattern generator through sinusoidal oscillations. The motions of the knee and the ankle is only due to gravity, foot-ground contact forces and the interaction by the elastic leg structure. The bipedal walker locomotes on a treadmill while its upper body is attached to a holder to avoid sidewards falling.

A computational model has been developed to optimize nine different parameters including parameters of the hip central pattern generator like frequency, amplitude and offset angle [STS$^+$06]. As derivatives of the solution of the computational model implemented in Matlab are not available, different methods for robust parameter optimization are investigated. In the first optimization study implicit filtering [GK95] was used as a robust, projected Newton-type method to maximize the walking speed. A final speed of 1.6 m/s was achieved which was about 60 % faster than the one achieved with a manually adjusted parameter set. Both speeds were below the estimated maximum walking speed of about 3 m/s which results from the product of the angular velocity of the hip joint multiplied by the leg length. The drawback is that the hip joint torque increases dramatically to 700 Nm for a robot model of assumed total mass 80 kg. Thus, in a second study the torques were bounded to be below 500 Nm. Nomad [Abr02] was used to optimize for walking speed w.r.t. to the torque constraint. A walking speed of 3.6 m/s was found which is remarkable for two reasons: the speed was increased after constraining the

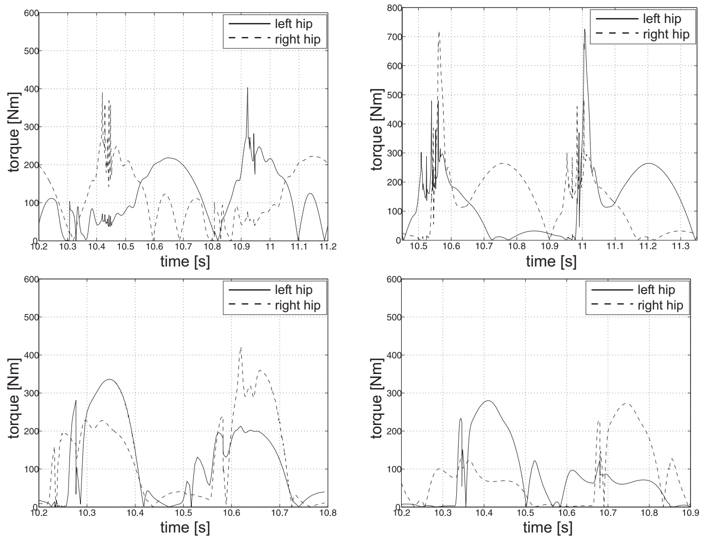


Fig. 8. Bipedal walking with three-segmented passively compliant robot legs. Resulting hip torque trajectories for different problem statements (from top left to bottom right): (0) initial guess, (1) maximum velocity, (2) maximum velocity with limited torque, (3) minimum torque with constrained minimum velocity.

problem (as a consequence, implicit filtering must earlier have gotten stuck in a local minimum) and the speed is even higher than the predicted maximum walking speed. Indeed, flight phases have been observed in the model that lead to a speed higher than achievable by walking. In a third study, the hip torques were minimized and the minimum walking speed was bounded to be $\geq 2\,\text{m/s}$. This problem formulation results in a reduction of the hip torques to less than 300 Nm. The resulting hip torques are displayed in Fig. 8. Experimental results have shown similar behavior like the simulation results which are visualized in Fig. 10. Also the flight phases can be observed.

5.3 Model-Based Trajectory Optimization and Control for Humanoid Robots

MBS dynamics models for humanoid robots are typically characterized by a high number of degrees of freedom, relatively few contact constraints or collision events, and a variety of potential ground contact models, actuator models, and mass-inertial parameter settings due to changing load conditions (cf. Sect. 3). Better suited for practical use in simulation, optimization and control than closed-form dynamical expressions of Eqs. (1) - (2) is an recursive modeling approach. The latter can be similarly efficient but permits in addition the easy interchangeability of joint types, parameters, and the introduction of external forces without repeated extensive preprocessing. Among the various, recursive, numerical algorithms which satisfy these criteria the ABA [Fea87] has been selected in the alternative formulation of [RKDJ91] (cf. [HvS03]). It can be implemented highly modular as all calculations and parameters can occur as an exchange of information between links.

To avoid the problem in industrial robotics of having to re-code the MBS dynamics model in different applications for different purposes like simulation during robot design, model-based trajectory optimization and model-based control an object-oriented modeling architecture has been proposed [HSvS04, HSvS06]. A central aim was to generate modular and reconfigurable MBS dynamics code for legged robots which can be used efficiently and consistently in different applications. In [HSvS04] it was demonstrated that using this approach a full, 3D MBS dynamics model of a humanoid robot consisting of 12 mechanical DoF for the torso and two legs and 1D drive-train models can be computed on a typical onboard computer in less than 1 ms. Thus, it is well suited for developing novel, nonlinear model-based humanoid robot control schemes.

Computing optimal locomotion trajectories is equally important for the design and operation of humanoid robots. The question of finding optimal trajectories of the n joint motor torques $\boldsymbol{\tau}(t)$, $0 \leq t \leq t_f$, w.r.t. to time, energy and/or stability leads to optimal control problems [HvS03]. A forward dynamics simulation and optimization approach analogous to the biomechanical optimization in Sect. 5.1 is applied. To improve the efficiency and robustness of the numerical optimization the contact dynamics of the DAE system (1)-(2) can be computed using a reduced dynamics approach. This is based on coordinate partitioning and results in an equivalent ODE system of minimal size by projecting the dynamics onto a reduced set of independent states. The approach requires solving the inverse kinematics problem for the dependent states which, in the case of legged systems, are generally the contact leg states. For most leg configurations, this problem is easily solved using knowledge of the relative hip and foot contact locations [HvS03].

Besides the system dynamics and the objective, further details must be considered in the optimal control problem formulation for humanoid robot locomotion. To determine optimal walking motions, only one half-stride has to be considered due to the desired symmetry and periodicity of the walking motion. Further constraints to be considered include a) box constraints on joint angles and control, b) symmetry resp. anti-symmetry of the joint angles at the boundaries of the half-stride, c) lift-off force equals zero at the end of a half-stride, d) stability (one of the criteria of Sect. 4), e) foot orientation and position, and f) avoidance of slipping (cf. [BHK+03, HvS03] for details). The object oriented modeling approach allows easy exchange of parts of the model as well as reuse of code, in this case for the differential equations as well as for different constraints.

Using the outlined approach a design study for optimal motor and gear selection for an 80 cm tall humanoid robot has been conducted [HvS03]. For the manufactured prototype optimal joint trajectories for walking have been computed which enabled the robot to perform stable walking experiments on level ground using only PID-control of the joint angle without using inertial sensors in the upper body and contact sensors in the feet for stabilization [BHK+03]. More flexible and stable walking motions however can be realized using the approaches based on additional sensors as outlined in Sect. 4.

5.4 Hardware-in-the-Loop Optimization of the Walking Speed of an Autonomous Humanoid Robot

Optimization based on simulation models for humanoid robot dynamics has many advantages. For example, the optimization process can be performed unsupervised, it can run overnight and there is no hardware deterioration. Nevertheless, it has a major drawback. The relevance of the optimization result for the application on a real robot depends critically on the quality and accuracy of the simulation model. For legged robots obtaining accurate kinetical data is difficult. This data may even vary from one robot to another of the same production. Moreover, effects like gear backlash, joint elasticity and temperature dependent joint friction as well as different ground contact properties are difficult and cumbersome to model accurately. All these effects may accumulate to a significant simulation model error.

The solution of an optimal control problem for maximizing walking speed or stability will utilize all "resources" available in the model. The numerical solution is then likely to be found in a region where the above mentioned modeling errors significantly affect the applicability of the numerically computed trajectories to the real robot. For obtaining best robot performance it is therefore advisable to use the robot itself as its best model and to perform optimization based on experiments which replace the evaluation of the simulation model. But then the optimization method must be able to cope with a noisy function evaluation as no walking experiment will give exactly the same results if repeated even in the same setting. Moreover, the method should use as few as possible function evaluations as every experiment may cause not only time for human operators, too many experiments will wear out the robot's hardware and make the results useless. A disadvantage which is often observed with evolutionary type optimization methods.

For optimization of the walking speed for the autonomous humanoid robot Bruno (Fig. 1), the distance the robot covers during a walking experiment for a certain walking parameter set is used as the objective function. The robot starts walking with a small step length and increases it linearly during the experiment until the robot falls or reaches a final step length. The distance obtained by a large, constant number of steps (e.g., 52) is then measured. The walking motion is generated by prescribing trajectories for the hip and the feet and solving the inverse kinematics for the joint angles. Thus, the walking motion is parameterized by a large number of parameters for the trajectories of hip and feet. By experimental investigation the most relevant parameters affecting walking performance have been identified: the relation of the distances of the front and of the rear leg to the robot's CoG, the lateral position, the roll angle and the height above ground of the foot during swing phase, and the pitch of the upper body. Starting from an initial, stable but slow walking motion these five parameters are varied in each iteration of the optimization method and a walking experiment is carried out. It should be noted that only lower and upper bound constraints on the parameters are applied. It is not needed to incorporate explicit constraints for maintaining walking stability as stability is implicitly included in the objective function.

To solve the arising non deterministic black-box optimization problem, where besides of a noise function value no further information, especially no objective gradient, is provided, a surrogate modeling approach has been selected. An initial set of experiments is generated around the initial motion by varying each parameter on its own. This set builds the basis points for the use of design and analysis of computer experiments, [SSW89], which is applied to approximate the original objective function on the whole feasible parameter domain. The sequential quadratic programming method [GMS02] is applied to rapidly compute the maximizer of the smooth surrogate function resulting in the current iteration. For this parameter set the corresponding walking experiment is performed. If the distance of a found maximizer to a point already evaluated by experiments falls below a defined limit, not the actual maximizer, but the maximizer of the expected mean square error of the surrogate function is searched, evaluated, and added to the set of basis points for approximation. This procedure improves the approximation quality of the surrogate function in unexplored regions of the parameter domain and avoids to get stuck in a local maximum. After a new point is added, a new surrogate function is approximated, and the optimization starts again. From our experience this approach for online optimization of walking speed is much more efficient than genetic or evolutionary algorithms which are usually applied to cope with the robust minimization of noisy functions.

After about 100 walking experiments in less than four hours a very stable and fast walking motion with a speed of 30 cm/s has been obtained for the first version of the humanoid robot. The distance the robot covered before falling down or reaching the end of the velocity slope is plotted in Fig. 9. A sequence of a resulting walking motion is depicted in Fig. 11. Later the robot has been modified to reduce weight in the upper body and the optimization procedure has been repeated resulting in an even further improved speed of 40 cm/s [HSSvS06]. This is so far the fastest walking motion of any humanoid robot of any size in the humanoid robot league of the RoboCup (www.robocup.de).

6 Conclusions and Outlook

In this paper, several methods and case studies on modeling, simulation, optimization and control of motion dynamics of humanoid robot and humans have been presented. They constitute steps towards the grand challenges of

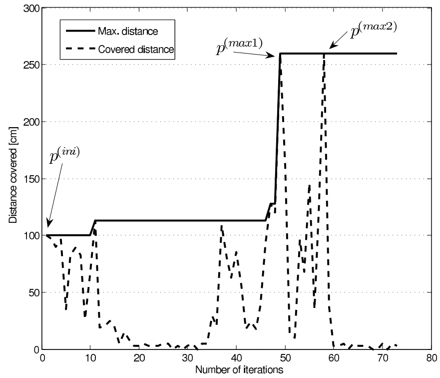


Fig. 9. Hardware-in-the-loop optimization of the walking speed of an autonomous humanoid robot: The distance the robot covers in each iteration.

understanding and predicting human biodynamics by numerical simulation and of developing humanoid robots being able to walk and run with human-like efficiency.

Acknowledgement. The successful investigation of the methods and case studies presented in this paper would not have been possible without the major contributions of the following coauthors whose most valuable contributions are deeply acknowledged: A. Seyfarth, R. Tausch, F. Iida, A. Karguth (Sect. 5.2 [STS+06]), M. Hardt, R. Höpler (Sect. 5.3 [HvS03, HSvS04, HSvS06]), Th. Hemker, H. Sakamoto (Sect. 5.4 [HSSvS06]).

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A Colored Figures

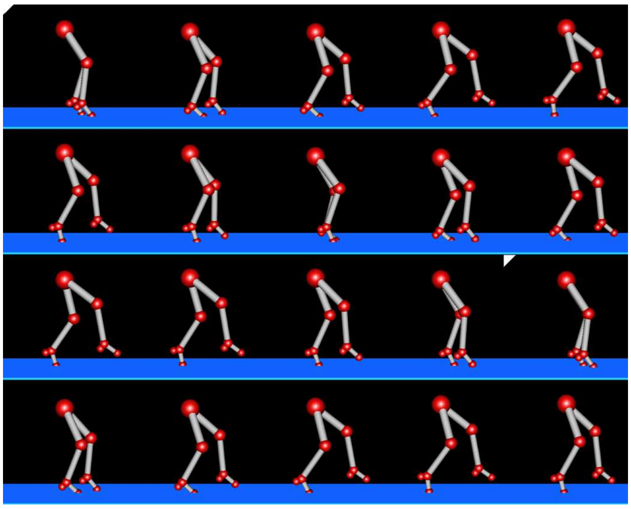

Fig. 10. Bipedal walking with passively compliant three-segmented legs: Resulting gait sequence for parameter set optimized for low hip torques and bounded minimum walking speed (page 12).

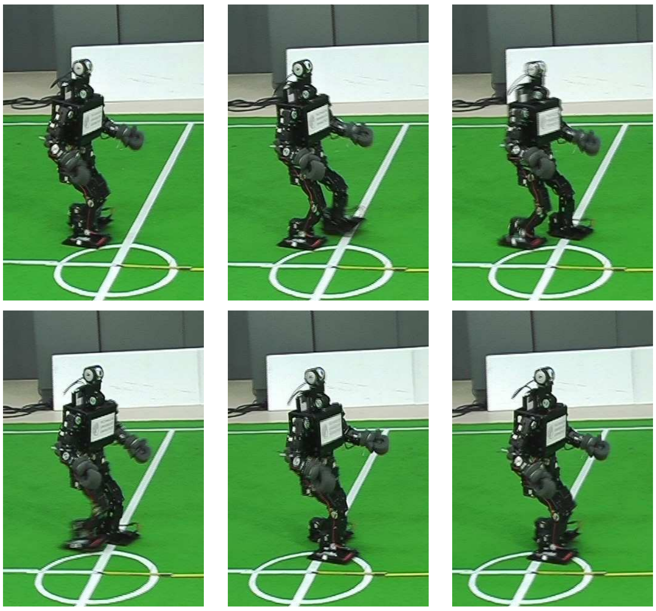

Fig. 11. Optimized walking of the autonomous humanoid robot Bruno (page 15).