Bio-Inspired Motion Control of the Musculoskeletal BioBiped1 Robot Based on a Learned Inverse Dynamics Model

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***Abstract*—Based on the central hypothesis that a humanoid robot with human-like walking and running performance requires a bio-inspired embodiment of the musculoskeletal functions of the human leg as well as of its control structure, a bio-inspired approach for joint position control of the BioBiped1 robot is presented in this paper. This approach combines feed-forward and feedback control running at 1 kHz and 40 Hz, respectively. The feed-forward control is based on an inverse dynamics model which is learned using Gaussian process regression to account for the robot's body dynamics and external influences. For evaluation the learned model is used to control the robot purely feed-forward as well as in combination with a slow feedback controller. Both approaches are compared to a basic feedback PD-controller with respect to their tracking ability in experiments. It is shown, that the combined approach yields good results and outperforms the basic feedback controller when applied to the same set-point trajectories for the leg joints.**

I. Introduction

Today the leg design of many humanoid robots is still based on chains of rigid links and actuated, rigid rotary joints and the control system is often based on a cascade of one-dimensional joint feedback controllers. Whereas walking, running, and hopping appear as natural and quite easy tasks for humans, yet for today's humanoid robots they still impose big challenges. Biomechanics research has revealed that a bipedal spring-mass template model can reproduce both, the elastic stance-leg behavior found in running and also the stance dynamics observed in walking [1].

However, in conventional robot systems joint elasticity is an unwanted property, as it increases the complexity of the model and its control system. But for bio-inspired bipedal robots like the BioBiped1 [2], elasticity is an essential property necessary to achieve versatile and energy-efficient motions. Furthermore the highly elastic coupling between the robot's joints through the series elastic actuators has a high potential to inherently help the robot to compensate for external disturbances, like uneven ground or slip.

The quest for a robot that implements human-like locomotion does not only involve the development of a human-like embodiment of the motor system as [2] and [3]. It also requires different control structures and especially bio-inspired control approaches appear to be promising. The elastic, musculoskeletal bipedal robot motivates the investigation of learning and conventional control approaches and their comparison. In the presented paper some aspects of the human motion control and its technical practicability are investigated and combined with a basic, standard approach, forming a new kind of bio-inspired controller. In experiments the general suitability of such a bio-inspired controller is exposed.

As in animals and humans the feedback delay is much higher than in technical systems, feedback can typically not be used to control fast movements. But it is used to adjust and improve the learned feed-forward trajectory [4]. To allow for a feed-forward dominated control, a sufficiently accurate inverse dynamics model of the system and the external influences like ground contact is necessary. For a complicated motor system as in BioBiped1 it is very difficult to set up such an accurate model, including also all external factors. Therefore as an alternative to the cumbersome and highly elaborate process of developing a mathematical model, it is reasonable to use a learned model generated by a hardware-in-the-loop learning algorithm.

In the presented paper three different control concepts, namely a feedback PD-control, a learned model based feed-forward control and a biologically inspired combination of both are examined and analyzed with respect to their general applicability to elastic bipedal robots. Additionally a more detailed evaluation of their quality of tracking setpoint trajectories and the learning algorithm's prediction error is shown.

II. State of Research

The presented work investigates joint level control concepts for an elastic, musculoskeletal bipedal robot. Common control concepts used in stiff robots like PID-controllers can be applied directly, but the quality of the resulting movements is limited due to the complexity of the system dynamics. The focus of this work is on the lowest control level, not yet considering higher levels including postural stability during a step cycle.

Common control approaches can only handle effects of elasticity to a limited amount. As the robot used in this work features high compliance in its series elastic actuation, more sophisticated control approaches are required to handle the large deflection in joint angles [5]. One approach to control systems with induced elasticity is to apply a model based feedback control, e.g., [5] and [6]. Different compliant control strategies of otherwise stiff hydraulic actuators have been evaluated in [7]. In [3], [8] manually tuned feed-forward control of pneumatic actuators for muscular skeleton robots has been investigated.

In animal and human motion, further approaches for similar problems can be found. For accomplishing fast and robust movements, humans use a complex control structure combining several controller concepts including reflexes [9]. The

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presented paper focuses on the role of feed-forward control and feedback control, since these play a central part in animal motor control [10], and shows an approach for a bio-inspired combined solution. In order to provide accurate signals for controlling a specific motion, the part of the brain that is responsible for movement control called cerebellum requires a sufficiently accurate description of the respective inverse dynamics. To keep the model of the time-variant human motor system and its operational conditions up to date new data is collected and learned continuously [4].

Different learning algorithms have been used to obtain inverse dynamic models of various robotic systems already. As shown in [11] the non-parametric Gaussian process regression (GPR) offers a promising approach to fast and accurate learning of complex mechanisms. Preceding studies on applying learning algorithms to robots were focusing on stiff or backdrivable mechanisms as the SARCOS arm or the Barrett WAM [12]. These robotic arms utilize compliance for reasons of safety in human-robot interaction and revealed a significant improvement in accuracy when controlled with a model based feedback control using GPR for model generation.

III. Properties and Technical Details of BioBiped1

BioBiped1 is the first of a planned series of bio-inspired, elastic, musculoskeletal robots with successively enhanced designs and capabilities. It aims at the longterm realization of human-like three-dimensional stable running, walking and standing in a humanoid robot by transferring biomechanical concepts and insights from human locomotion analysis to robotics [2], [13]. Therefore, aside from the control aspects touched upon in this paper, a main focus of the design of BioBiped1 was placed on the mechanical implementation of the key properties of the human leg: (1) segmentation and (2) elastic leg behavior resulting from musculoskeletal, series elastic actuation.

As shown in Fig. 1(c), each leg consists of three segments corresponding to the human foot, shank and thigh. It has three joints, two degrees of freedom (DoF) in the hip for the pitch and roll movement, and one DoF in each ankle and knee for the pitch movement. Whereas the pitch axes enable operation of BioBiped1 in the sagittal plane, the roll axes shall allow for lateral leg placement.

Elastic leg behavior is enabled by the integration of muscle-tendon-like structures. Fig. 1(a) displays the leg muscles that take on essential tasks during human locomotion. The muscle pairs *Tibialis Anterior* (TA) - *Soleus* (SOL), *Popliteus* (PL) - *Vastus* (VAS), and *Gluteus Maximus* (GL) - *Iliopsoas* (ILIO) in ankle, knee and hip joint belong to the group of monoarticular muscles, spanning only one joint, and are mainly responsible for power generation [14]. Transfer of energy and coordination of joint synchronization are mainly ensured by the biarticular muscles *Rectus Femoris* (RF), *Biceps Femoris* (BF) and *Gastrocnemius* (GAS) [15], [16]. These muscles span two joints and extend and flex the coupled joints in coordination.

The above introduced structures are integrated either active- or passively in the legs of BioBiped1 (cf. Fig.1(b)). The muscle pair in the hip is represented by a bidirectional series elastic actuator [17]. Extensors of the knee and ankle joint are integrated by unilateral structures, each consisting of a geared rotary electric direct-current motor in series with a cable including an extension spring. All other structures are passive, so the forces exerted by them depend on the joint angles which are influenced by the active structures and external influences such as ground contact. Note that the interplay of the passive and active structures are no yet fully investigated. As the functionality of the structures GL, RF, BF and GAS was not required to achieve the desired motions they were not attached during the experiments described in this paper.

The dimensions of the robot are given in the table of Fig. 1 and approximate scaled human properties. The lengths of the segments have the same ratios as in average human adults. As the focus lies primarily on the bipedal locomotion at this stage of the project, the trunk was chosen to have only one DoF for tilting for- and backwards. The trunk will be extended further in subsequent robot prototypes.

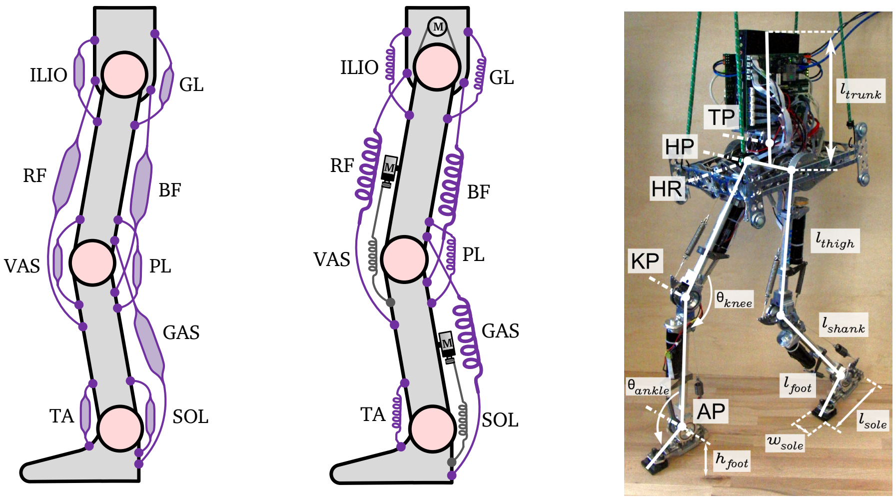
For the purpose of monitoring, evaluating and analyzing the robot's motions, a number of sensors have been included. An Analog Devices inertial measurement unit ADIS16364 is mounted on the hip of the robot and has six DoF, measuring angular speed and linear acceleration in all three axes. The sensor will be used to calculate the robot's posture and to control its postural stability. Each joint is equipped with two position sensors: one 12-Bit Hall encoder directly in each joint measuring the absolute joint angular position and one incremental encoder at each of the electrical actuators. In order to measure vertical and horizontal ground reaction forces (GRF), each foot has three force sensors: at the heel and forefoot to measure forces perpendicular to the foot sole and in the middle to measure forces exerted parallel to the forward axis of the foot.

To enable autonomous operation, the robot carries an on-board computer (Intel Atom processor) in its trunk. Sensors and motors are connected to two custom-made microcontroller boards which communicate with the on-board computer via an EtherCAT bus system at high speed and low latency. The robot's software is based on the Orocos Real-Time Toolkit [18] as an abstraction layer for the real-time functionality. To facilitate network communication with the developed graphical user interface, we utilize the Robot Operating System (ROS) [19]. Currently, instead of the onboard computer an external laptop is used for both software development and testing.

IV. Controllers Investigated

Three different control approaches are applied and evaluated in experiments (Sect. V) on the BioBiped1 robot, a basic feedback control, a feed-forward control based on a learned inverse dynamics model and a combination of both.

For the feedback controlled execution of target trajectories, a conventional proportional-derivative controller (PD-control) for joint position with a control frequency of 1 kHz is applied. In preceding studies [2] it was demonstrated, that a basic PD-control is sufficient to realize hopping motions on this



(a) (b) (c)

Dimensions	
h_{trunk}	269 mm
l_{thigh}	330 mm
l_{shank}	330 mm
l_{foot}	122 mm
h_{foot}	67 mm
l_{sole}	168 mm
w_{sole}	40 mm
Masses	
total mass	9.2 kg

Fig. 1. Up to nine main muscle-tendon groups of the human leg (a) can be mimicked by active and passive series elastic cable-spring structures (b) in the BioBiped1 robot (c) (during the experiments described in this paper the following muscle-tendon groups were not attached: GL, RF, BF and GAS). Weight and link lengths of the robot are given in the table.

musculoskeletal robot at the advantage of low implementation effort. Since no optimal tracking of the desired trajectory is required for learning, the controller gains are manually tuned to produce good results for the examined motions.

As mentioned in Sect. II GPR offers a suitable approach for acquiring an inverse dynamic model from recorded motion data. The process of implementing a feed-forward trajectory on the robot requires additional preparation steps ahead of the actual execution.

A. Recording of Motion Data

First, a joint angle trajectory is executed on the robot using the feedback controller mentioned above, while recording the actual joint angle and corresponding motor voltages trajectories over time. In this step the information about the current configuration and the system specific dynamics is gathered.

B. Learning of Correlations

Next, GPR [20] is applied off-line using the numerical computing software MATLAB. The GPR utilizes a Bayesian kernel approach for solving a high dimensional regression problem, which is based on the recorded training data. The covariance matrix of the Bayesian kernel is defined by the squared exponential covariance function

$$k(x, x') = \sigma_f^2 \exp\left[\frac{-(x-x')^2}{2l^2}\right] + \sigma_n^2 \delta(x, x') \,. \qquad (1)$$

Here, the noise reduction factor σ_n^2 is set constant. The hyperparameters for horizontal length-scale l and vertical length-scale σ_f^2 are obtained by an optimization process maximizing the marginal likelihood over the training dataset.

Since the recorded data do not include joint velocities or accelerations explicitly, which are essential for a complete description of the robot's inverse dynamics, a new concept of parameter management is introduced. Instead of approximating the missing information out of the given data, e.g., by filtered finite difference schemes, multiple time steps are delivered as additional parameters (see Fig. 2). Hence, possible inaccuracies through approximation are avoided. Note that the additional information does not necessarily describe the actual velocities or accelerations at the respective time step, but adds the required context to characterize the systems dynamics.

Each leg joint is actively actuated by a motor for which a voltage trajectory is computed. This is done for each motor individually, but to consider the complex correlations of the highly non-linear dynamics of the musculoskeletal robot and to improve the results despite using a low number of training datasets, the other joints' input data are added as additional parameters of the respective joint. Hereby, one single input dataset serves as training set for all joints and is associated with the respective output data.

C. Calculation of Control Input Voltage Trajectories

To follow a feed-forward set-point trajectory, the robot requires a corresponding voltage trajectory for each actuator. The set-point trajectory can in principle be chosen arbitrarily, but the quality of the respective output depends on the training data. The actual voltages are generated from this trajectory by applying the learned GPR model.

D. Execution of Feed-Forward Controlled Motions

Before applying the voltage trajectories to the robot, the robot needs to be set up using the basic feedback controller to reach the starting configuration on the actual robot which has also been used as start of the calculated trajectory. After assuming the startup configuration using feedback control, the input voltage trajectories are then executed on the robot in a feed-forward fashion.

E. Executing Movements with Bio-Inspired Control

In this controller setup the outputs of the feed-forward and feedback control are combined to leverage the advantages of both approaches. The sequence of voltages generated through the model for the feed-forward control are added to the voltages produced by the feedback control following the target joint angle trajectories and applied to the robot. To mimic a biological system, the robot's feedback control frequency is reduced to 40 Hz and a control signal delay of 25 ms is introduced. Additionally the controller gains are reduced to 10% of their original value.

During the execution of the trajectory feed-forward signals are sent to the robot with 1 kHz while the additional vestigial feedback control output described above is updated at only 40 Hz.

V. Experiments and Results

To evaluate the fitness of the GPR learned model for off-line generation of motor input voltage trajectories for feed-forward control of the BioBiped1 robot two experiments are conducted: One aiming at learning the inverse dynamics of the robot's leg without external disturbances and the other learning a combined model of the complete robot and its interaction with the ground (and the constraining mechanism).

In each of the experiments a given joint angle trajectory is being followed once using the PD-controller while recording time histories of motor voltages and actual joint values. The trajectories are designed to move the joints inside the angular areas involved in running, although the method can be transferred to more general motions. Based on this data an inverse model of the system dynamics is learned using GPR.

To execute the feed-forward control on the robot the model is applied to the target joint trajectories to produce motor voltages used as input for the robot in a second, pure feed-forward run. In a third run, the robot is controlled by the bio-inspired control concept described in Sect. IV-E.

A. First Experiment

In this experiment the robot's upper body is firmly attached to an external frame supporting the robot's weight, leaving both legs hanging freely above the ground. This allows to move the robot's legs without external disturbances from ground contact. The movement that was performed in this posture mimics the switching between retracted and touch-down position as it occurs during the flight phase just before touch-down of an alternate hopping motion which was performed in another series of experiments described in [2]. As in this setup the motions of both legs are not correlated, only the periodic motion of one leg between the two postures is investigated.

To generate the motor voltage trajectories for the feed-forward controlled motion the considered three leg joints in the sagittal plane are treated as three independent GPR problems, whose interdependencies are treated as described in Sect. IV. For each joint a covariance matrix is optimized using 220 samples from a single training data set as input. Every sample connects the motor voltage corresponding to one joint with a set of three times five joint positions as depicted in Fig. 2. Three being the number of joints and five the number

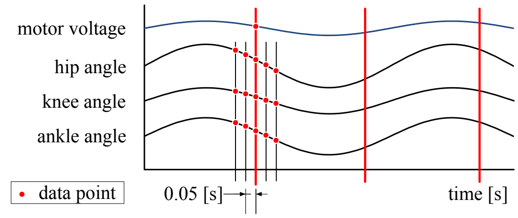


Fig. 2. Schematic visualization of the 16 data points (red dots) contained in one training data sample for one of the motors.

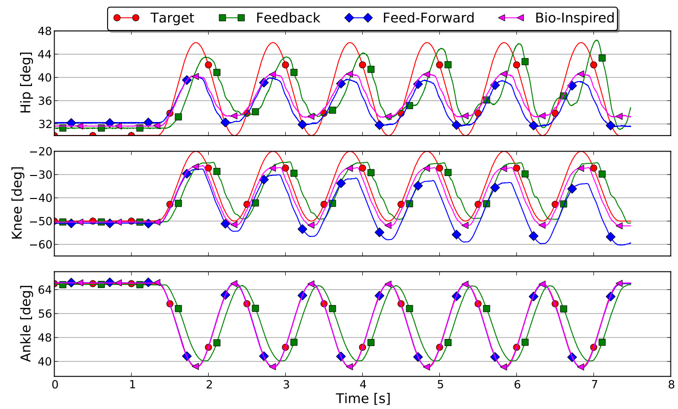


Fig. 3. Experiment 1: Target trajectories and resulting joint angle trajectories for feedback, feed-forward and bio-inspired control.

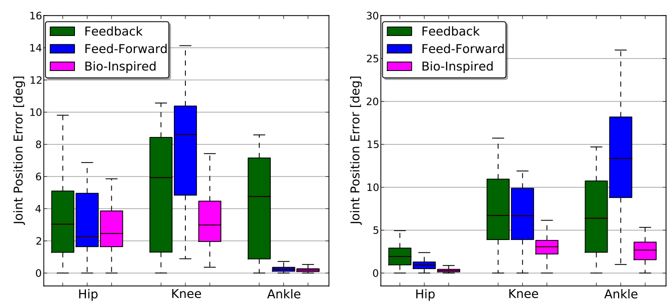


Fig. 4. Experiment 1 (left) and 2 (right): Joint position error for feedback, feed-forward and bio-inspired control.

of considered time steps to account for the velocities and accelerations of all joints. The time step length is 50 ms.

On a current laptop computer (CPU: Intel Core i7, 2.5GHz, RAM: 4GB) the optimization needs 12 s to complete. Calculation of the input voltage trajectories for the three target joint trajectories of 10 s duration requires additional 91 s.

B. Second Experiment

Here, the robot is standing on the ground with both feet, supporting its own weight. To prevent the robot from falling over its upper body is constrained by an external frame to linear motion in vertical direction. The motion performed is a periodic, synchronous up and down swinging motion using both legs in a standing posture. The feet are in contact with

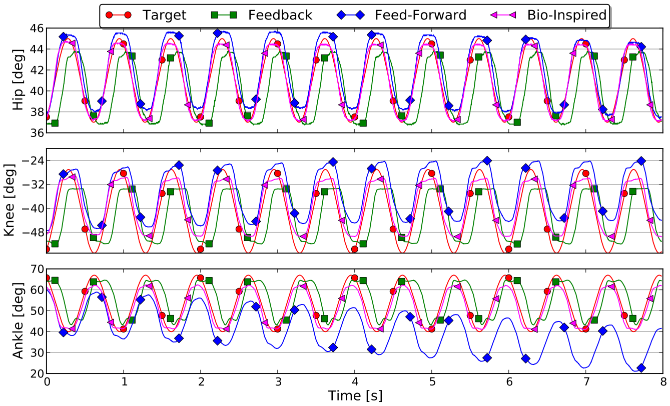


Fig. 5. Experiment 2: Target trajectories and resulting joint angle trajectories for feedback, feed-forward and bio-inspired control.

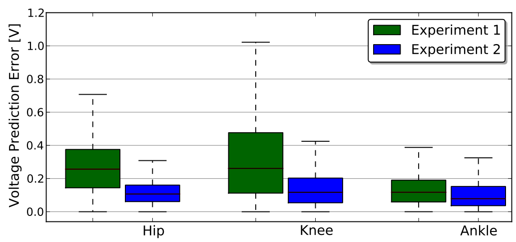


Fig. 6. Error of the voltage prediction of the GPR model for the two experiments and joints.

the ground only at the foot-tips allowing for some variation in the angle between foot and floor.

For this experiment, the control of each leg is seen as an independent problem, which is treated as in the first experiment. Also, the treatment of both legs together in a single problem has been considered, but with no significant improvements in this case.

C. Results

To examine the prediction error of the learning algorithm the correlations are learned and applied not to the target, but to the actually performed trajectory. In theory this should lead to the very same voltage trajectory the learning was based on, since the robot did actually perform this voltage to movement combination. As can be shown by subtracting the resulting voltages from the actual voltages recorded in the training data (see Fig. 6) there exists an error in the learned model. This rather small error is due to non-optimal choice or small number of training points.

In the experiments on the robot all three examined control approaches showed reasonable results as depicted in Fig. 3 for the first and in Fig. 5 for the second experiment. The PD-controller tracks the target with a small delay and displays an increasing oscillation especially in the first experiment in the hip joint. In the second experiment a clear overshot in the hip joint can be seen in Fig. 5. These are the expected problems for such a basic controller applied to such a complex robot dynamics with high elasticity.

The feed-forward approach on the other hand exhibits a drift, leading to an increasing joint position error over time (see Fig. 4. But it does not exhibit delays, oscillations or overshooting effects, which is quite advantageous compared to the performance of the basic PD-feedback controller.

The bio-inspired controller combines the advantages, as both Fig. 4 clearly show. The error plots depict an improvement of setpoint tracking in both experiments in all examined joints. Especially in the ankle in experiment 1 and the hip in experiment 2 the errors are reduced to nearly zero, as can also be seen in Fig. 3 and Fig. 5. The delay typical for feedback control is reduced to a minimum and the drift seen when using pure feed-forward control is avoided also.

VI. Conclusions and Outlook

In this paper, three joint level control approaches have been investigated for motions of the elastic, muskuloskeletal BioBiped1 robot whose highly nonlinear dynamic motor system is oriented towards the muscle functions of the human leg. A basic feedback controller implementing a cascade of PD-controllers per joint does not account for the specific system dynamics but has already demonstrated to produce synchronous and alternate hopping motions in previous work [2] and therefore is a valid candidate for comparison. The second approach is a feed-forward multi-variable controller based on a learned model of the system's inverse dynamics. The experimental results reveal the validity of this approach in showing a low divergence to the desired joint trajectory without exhibiting the usual weaknesses of a basic PD-controller as delay, overshooting or oscillation. A drawback of this approach is a drift away from the target trajectories over time in some joints.

The third examined approach reduces this drift by adding a feedback component and hereby yields the best trajectory tracking results. The bio-inspired control leverages the advantages of both feedback and feed-forward control: fast movements can be performed even with very little and delayed sensory feedback, resulting in strongly reduced requirements on signal processing and control frequency. This allows either control of complex systems with less performant electronics, or the use of more processing power for other tasks.

The GPR learning of the inverse dynamics model has successfully been enhanced by a new concept of handling the missing information about joint velocity and acceleration. For incorporating this essential information further time steps have been added as parameters to the regression problem.

Compared to the development of a mathematical model of the inverse dynamics by formulating a set of equations of motion and fitting the model parameters to the actual robot based on experimental evaluation, the advantages of the learning algorithm of the presented control approach are as follows. Not only is the GPR faster in generating the model, but also can it be more accurate in the learned areas, meaning ranges of angles, velocities and accelerations in particular, because it also accounts for effects which are very difficult to model. A further noteworthy aspect of the learned model approach is the potential inclusion of outer interferences, meaning especially the ground contact forces, that are usually very hard to model accurately. However, if the robot is operated in regions remote to the learned ones, the learning algorithm reveals its disadvantage by loosing quality and can even produce a zero function in areas not learned at all. Here an approach based on a mathematical model of the inverse dynamics offers a solution for the whole workspace of the robot, allowing to compute appropriate control voltage trajectories for every possible motion. Further advantages of the conventional, mathematical model are the ability to use it as transfer function for complex model based feedback control and the ability of exclusively varying particular system parameters without the need for hardware changes, assuming knowledge of the respective hardware properties. In case of hardware changes the presented learned model has to re-learn the updated hardware configuration by executing the learning algorithm again.

The work-flow described in Sect. IV takes only about three minutes and has potential for optimization or even online learning, allowing a combination of feedback and feed-forward motions for a) a GPR model based feed-forward execution of target trajectories in learned regions of angles, velocities and accelerations with all the presented advantages, b) a general feedback controlled tracking for moving in unlearned regions and for gathering training data and c) a GPR model based feedback control for high precision tasks, e.g., as in [12].

The results presented in this paper for bio-inspired controlled motions are a first step towards biologically inspired control of hopping and eventually running motions of the musculoskeletal BioBiped1 robot. Ongoing work investigates the applicability of this control approach to these motions with discontinuities caused by changing ground contact.

Furthermore, it is aimed at developing an integrated approach for controlling the bipedal robot for different tasks and requirements. Also, it is planned to compare the learned model to a mathematical inverse dynamics model derived from first principles. The mathematical model, with parameters calibrated based on experiments, is currently under development.

Beyond feed-forward control of fast, elastic robot motions, an accurate motion dynamics model is useful for multiple tasks, such as internal planning of the robots next step literally and in a metaphoric sense [21]. An internal model provided by a learning algorithm, that accurately describes the current state of a robot, could serve as basis for such a biologically inspired planning behavior and enhance the level of its artificial intelligence. Eventually, reafference, a biologically inspired controller concept for distinguishing external interferences from internally induced movements by means of an internal model [22], shall be examined in coherence with a learned model.

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References

[1] H. Geyer, A. Seyfarth, and R. Blickhan, "Compliant leg behaviour explains basic dynamics of walking and running." *Proc. Royal Society B: Biological Sciences*, vol. 273, pp. 2861–2867, 2006.

[2] K. Radkhah, C. Maufroy, M. Maus, D. Scholz, A. Seyfarth, and O. von Stryk, "Concept and design of the BioBiped1 robot for human-like walking and running," *International Journal of Humanoid Robotics*, 2011, in press.

[3] K. Hosoda, Y. Sakaguchi, H. Takayama, and T. Takumai, "Pneumatic-driven jumping robot with anthropomorphic muscular skeleton structure," *Autonomous Robots*, vol. 28, no. 3, pp. 307–316, 2010.

[4] M. Bear, B. Connors, and M. Paradiso, *Neuroscience: Exploring the brain*. Lippincott Williams & Wilkins, 2006.

[5] S. Klug, T. Lens, O. von Stryk, B. Möhl, and A. Karguth, "Biologically inspired robot manipulator for new applications in automation engineering," in *Proceedings of Robotik 2008*, ser. VDI-Berichte, no. 2012, 2008.

[6] B. Yoo and W. Ham, "Adaptive control of robot manipulator using fuzzy compensator," *IEEE Transactions on Fuzzy Systems*, vol. 8, no. 2, pp. 186–199, 2000.

[7] D. Bentivegna, C. Atkeson, and J. Kim, "Compliant control of a hydraulic humanoid joint," in *7th IEEE-RAS International Conference on Humanoid Robots*, 2007, pp. 483–489.

[8] T. Takuma, S. Hayashi, and K. Hosoda, "3D bipedal robot with tunable leg compliance mechanism for multi-modal locomotion," in *IEEE/RSJ Intl. Conf. on Intelligent Robots and Systems*, 2008, pp. 1097–1102.

[9] P. Zehr and B. Stein, "What functions do reflexes serve during human locomotion?" *Progr. in Neurobiology*, vol. 58, no. 2, pp. 185–205, 1999.

[10] E. Taub, I. Goldberg, and P. Taub, "Deafferentation in monkeys: pointing at a target without visual feedback," *Experimental Neurology*, vol. 46, no. 1, pp. 178–186, 1975.

[11] D. Nguyen-Tuong, J. Peters, M. Seeger, and B. Schölkopf, "Learning inverse dynamics: a comparison," in *Proc. European Symposium on Artificial Neural Networks*, 2008, pp. 23–25.

[12] D. Nguyen-Tuong and J. Peters, "Local Gaussian process regression for real time online model learning and control," in *Advances in Neural Information Processing Systems 22 (NIPS)*, 2008.

[13] BioBiped project website. [Online]. Available: www.biobiped.de

[14] A. V. Voronov, "The roles of monoarticular and biarticular muscles of the lower limbs in terrestrial locomotion," *Human Physiology*, vol. 30, no. 4, pp. 476–484, 2004.

[15] G. J. van Ingen Schenau, M. F. Bobbert, and R. H. Rozendal, "The unique action of bi-articular muscles in complex movements," *Journal of Anatomy*, vol. 155, pp. 1–5, 1987.

[16] R. Jacobs, M. F. Bobbert, and G. J. van Ingen Schenau, "Mechanical output from individual muscles during explosive leg extensions: The role of biarticular muscles," *Journal of Biomechanics*, vol. 29, no. 4, pp. 513–523, 1996.

[17] G. A. Pratt and M. M. Williamson, "Series elastic actuators," in *IEEE/RSJ Intl. Conf. Intelligent Robots & Systems*, 1995, pp. 399–406.

[18] "Orocos real-time toolkit," http://www.orocos.org/rtt.

[19] "Robot operating system (ROS)," http://www.ros.org/.

[20] C. E. Rasmussen and C. K. I. Williams, *Gaussian Processes for Machine Learning (Adaptive Computation and Machine Learning series)*. The MIT Press, November 2005.

[21] D. Wolpert and J. Flanagan, "Forward models," *The Oxford Companion to Consciousness*, pp. 294–296, 2009.

[22] B. Webb, "Neural mechanisms for prediction: do insects have forward models?" *Trends in Neurosciences*, vol. 27, no. 5, pp. 278–282, 2004.