Adaptive posture control of a four-legged walking machine using some principles of mammalian locomotion

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Abstract

This paper presents an adaptive control scheme for the four legged walking machine BISAM. The task of the adaptive control is to learn sensor based reflexes for posture control. For this purpose, an incremental learning scheme is developed based on reinforcement learning. For the planned trajectory of the CoM the data taken from a goat are chosen as a basis, to investigate the transfer potential of biological locomotion to machine motion at this control level.

1. Introduction

Online learning methods for legged robots are investigated to enlarge the flexibility and the adaptivity to different environments, but their use on real walking machines is very complicated due to the high complexity of such robots and only in a few approaches realized. In [8] the leg coordination of a simple six legged walking machine is learned, in [5] the coordination of different behavior controllers for a four legged walking machine is learned. [1] and [7] show two approaches for online learning of biped robots are presented in which the control architecture consists of periodic central pattern generators and peripheral controllers for behaviors like posture control. All these approaches show that an appropriate representation of the control problem is crucial for an efficient and succesful learning process a point that also account the security requirements of real robots.

2. The Walking Machine BISAM

BISAM (Biologically InSpired wAlking Machine) consists of one main body, four equal legs and a head (figure 1). The main body consists of four segments, which are connected by five rotary joints. With the five active degrees of freedom of the body, namely rotation of shoulder and hip, the body supports the stability and higher flexibility in uneven terrain. Each leg consists of four segments, that are connected by three parallel rotary joints and attached to the body by a fourth. The joints are all driven by DC motors and ball-screw gears. The height of the robot is 70 cm, its weight is about 23 kg. A more detailed description of the mechanical construction and the hardware architecture can be found in [2].

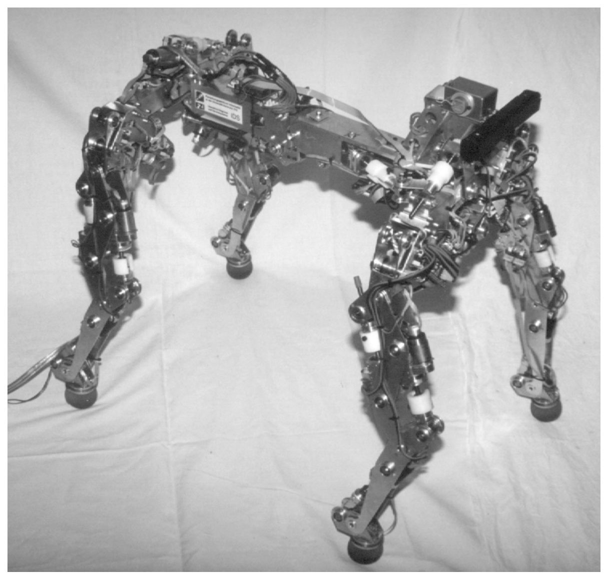

Figure 1: Photograph of the quadrupedal walking machine BISAM in mammal-like position. Due to the five active degrees of freedom in the trunk and the ability to rotate the shoulder and pelvis, the machine realizes key elements of mammal-like locomotion.

3. Control Approach

Based on a classical robotic approach, to determine the joint trajectories by inverse kinematics and pregiven body motion and foot trajectories a statically stable walk ($\beta = 0.8$) and a dynamically stable trot ($\beta = 0.6$) is realized. Special charateristic of the motion is the hip and shoulder movement, which realize an increasement of the step length.

By analysing this movements following problems have been identified:

- Because of the small feet of BISAM the ZMP-Criterion [9] is not fully adequate for the optimization of movements.
- The movements of BISAM are highly dependent of the load on the machine (camera head, internal PC) and the initial position of CoM.
- In dependency of the machine configuration all working points have to be tuned manually

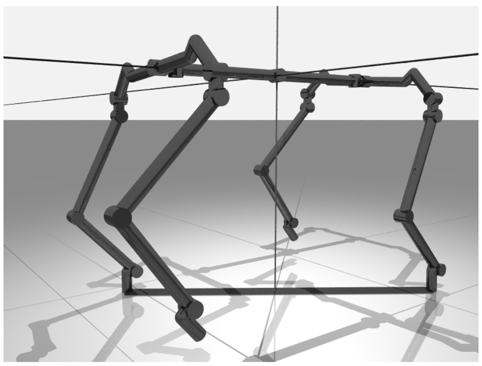

Figure 2: Small Support Area for dynamically stable movements of BISAM.

During animal-like motions with extended excursions not only of the limbs, but with also intense movements of the spine, no simple stability-criterion is definable taking into account the influences of load distribution and initial posture effects. The virtual-leg-mode does not yield closed solutions. A dynamic forward model of the machine at present lacks sufficient informations on the non linear-effects describing the behavior of drive and sensors.

Caused by the described problems we choose the strategy to determine a planned trajectory for the CoM and to learn adaptive reflexes which realize the corrections of the guidance of CoM based on the signals of the foot sensors.

For the modelling of the planned body trajectory, we do not use an analytical optimization criterion but we investigate the use of pregiven CoM-trajectories, which are observed from mammals.

4. Analysis of CoG Trajectory

The CoG Trajectory is analysed in to components on the base of the foot sensors according equations 1, 2 and figure 3.

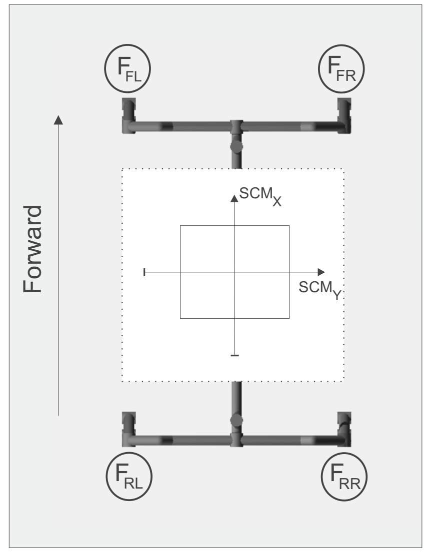

Figure 3: Illustration of the parameters SCM_X and SCM_Y for the sensor based measurement of the COG based on the foot sensors.

$$SCM_X = \frac{F_{FL} + F_{FR} - (F_{RL} + F_{RR})}{\sum_{F_{xy} \in \mathcal{F}} F_{xy}} \quad (1)$$

$$SCM_Y = \frac{F_{FR} + F_{RR} - (F_{FL} + F_{RL})}{\sum_{F_{xy} \in \mathcal{F}} F_{xy}} \quad (2)$$

A typical CoG-Trajectory for a trot with β=0.6 is shown in figure 4.

The description and adaption of the gait on the hand of the CoG-Trajectory have two main advantages:

- The description and of the gait on the hand of the CoG-Trajectory is apprpiate, because the movement experiments show that a right position of the CoG is an fundamental requirement for executing accurate movements
- This representation allows small input and output dimension for the neural networks presented in the next section

5. Learning of reflexes for posture control

For the online learning of the sensor based reflexes for posture control a reinforcement learning method [6] based on an actor/critic approach similar to the SRV-Algorithm [4] is used. This algorithm consists of a critic element which renders an internal evaluation of

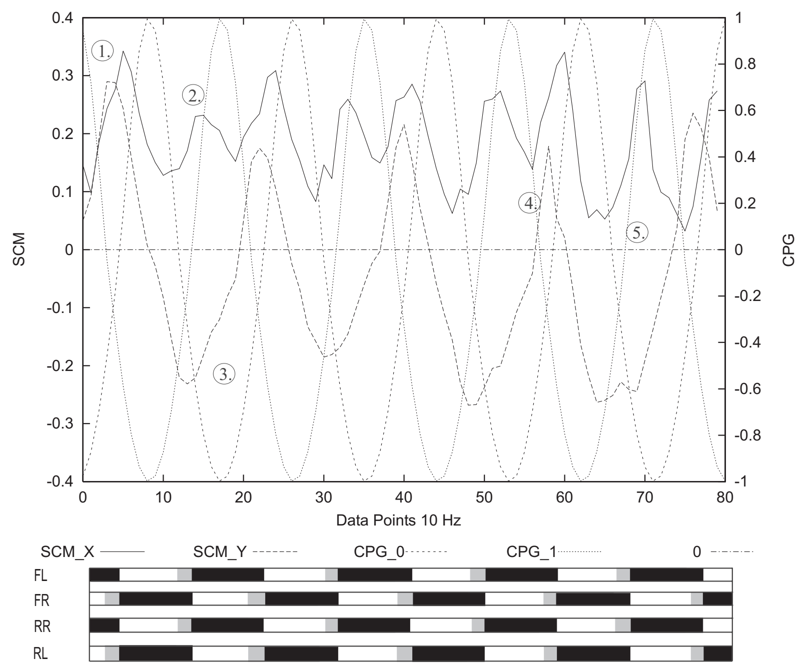

Figure 4: Illustration of a CoG-Trajectory gained by executing a trot with β=0.6. The CoG-Trajectory with the components SCM_X and SCM_Y in dependence of the gait phases can be seen.

the actual state and action elements which determines the next control values. In each control step an adaptation of both components by the TD(λ)-algorithm takes place.

The state space representation used by the learning method is incrementally constructed with self-organizing RBF-networks. The RBF-net builds localized receptive fields which divide the input space into regions of limited size thus allowing localized learning of a function within the boundaries of such a region. This property makes RBFs a suitable tool for online function approximation. In [6] a method is described by which the topology of the RBF network can be constructed according to the learning task.

A critical aspect for online learning processes is the problem modelling with the state and action space. We choose the the level of posture control to realize an adaptive component,

Based on this learning method a learning architecture for incremental learning of the following posture control aspects is developed (Figure 5).

- search for appropriate initial positions
- defined translations of CoM
- adaptive posture reflexes

6. Outlook

Our future work is analyse, in which way the CoG-Trajectories of BISAM can be compared with trajectories of small and medium-sized mammals. Another interesting question is, to which extend rules can derived from the analyses of the mammals for the locomotion of BISAM.

The biological paragon is derived from a huge kinematical and dynamic data base taken on 14 species of small and medium-sized mammals [3]. Techniques applied to determine kinematics were cineradiography (150 frames/sec), high-speed-video (up to 1.000 frames/sec) and marker-based motion analysis (up to 1.000 frames/sec). Ground-reaction forces GRF were taken using Kistler force-plates. The trajectory of CoM in several gaits was derived by two methods:

- ”’balancing”’ of a multi-segmental model fitted into the outlines of the animal. The triangular finite elements were weighted by mass data taken from dissected cadavers or CT-, MRI- or surface-light laser scans.
- Integration of GRF.

After matching of these data representative points for CoM could be derived. Since the deformations of the body stem are the less the larger the animal is, as a paragon for the control of BISAM the trajectories of

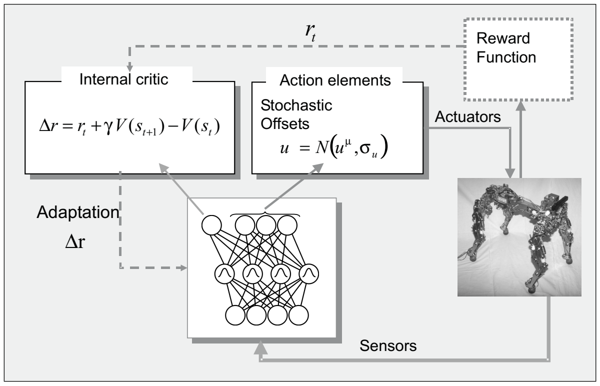

Figure 5: The concept of the adaptive component. The network generates the internal evaluation and prototypical actions. For exploration purposes, stochastic offsets are added to these actions. The stochastic offsets are generated using a normal distribution. The variance of this distribution is determined by the current performance of the net. The executed action sequence caused an external reward. The adaption of the internal evaluation and the action units are based on the successive external and internal evaluations.

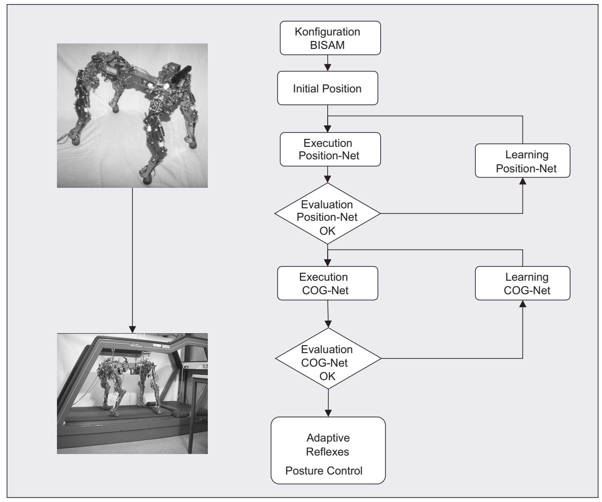

Figure 6: Concept of the incremental learning process for the posture control of BISAM. Based on networks which learn to optimize the initial position and the displacement of the CoM, adaptive reflexes are learned, which do sensor based corrections of the CoM.

CoM of two sub-species of goats were chosen. The kinematical data provided contained informations on the motions of the CoM and the hoofs in walk, trot and bound.

7. Conclusion

The aim of this work is to investigate, to which extend biological data on trajectories of the CoM from mammals can be used as basis for a four-legged walking machine. To adapt this planned motion to different circumstances, posture control reflexes are learned with an online learning method based on reinforcement learning.

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References

[1] H. Benbrahim and J. A. Franklin. Biped dynamic walking using reinforcement learning. *Robotics and Autonomous Systems*, 22(3):283–302, december 1997. Special Issue: Robot Learning - The New Wave.

[2] K. Berns, W. Ilg, M. Deck, J. Albiez, and R. Dillmann. Mechanical construction and computer architecture of the four-legged walking machine BISAM. *IEEE Transactions on Mechatronics*, 4(1):1–7, march 1999.

[3] M. S. Fischer and H. Witte. The Functional Morphology of the Three-Segmented Limb of Mammals and its Specialities in Small and Medium-Sized Mammals. In *Proccedings of the European Mechanics Colloquium : Biology and Technology of Walking . Euromech 375*, pages 10–17, 1998.

[4] V. Gullapalli. Learning control under extreme uncertainty. In *Advances in Neural Information Processing Systems 5*, pages 327–343. Morgan Kaufmann Publishers, San Mateo, California, 1992.

[5] M. Huber and R. A. Grupen. Learning to coordinate controllers. In *Proceedings of the 15th International Joint Conference on Artificial Intelligence*, 1997.

[6] W. Ilg, Th. Muehlfriedel, and K.Berns. A Hybrid Learning Architecture based on Neural Networks for Adaptive Control of a Walking Machine. In *IEEE International Conference on Robotics and Automation (ICRA'97)*, Albuquerque, 1997.

[7] A. Kun and W. T. Miller. Adaptive dynamic balance of a biped robot using neural networks. In *Proceedings of the IEEE International Conference on Robotics and Automation*, 1996.

[8] P. Maes and R. Brooks. Learning to coordinate behaviours. In *Proceedings of the 8th AAAI Conference*, pages 796–802. Morgan Kaufmann Publishers, San Mateo, California, 1990.

[9] M. Vukobratovic, B. Borovac, D. Surla, and D. Stokic. *Biped Locomotion*. Springer–Verlag, Heidelberg, Berlin, New York, 1990.