A Test Bench to Study Bioinspired Control for Robot Walking

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Abstract: Test bench to study robot walking within the predicted structures of biological control systems is discussed. Physical system is briefly presented with components. Kinematic model and evolutionary way of gait generation for the leg structure in test bench is discussed. Different forms of gaits can be found by genetic optimization using patterns formed by central pattern generators.

Keywords: bioinspired control structure, central pattern generator, robot walking, evolutionary gait generation

1. INTRODUCTION

Legged locomotion offers a striking way of motion for designers in robotic field to design robots that can move on an irregular terrain (Arikawa, Hirose, 2007). Motion in multi direction, ability to overcome obstacles, and the ability to orient the body on irregular surfaces are some of the advantages of the legged locomotion. Producing the coordinated movement of the legs allowing robot motion is the elementary step of the robot walking. Gait generation can be produced in different ways considering engineering software, mathematical tools, etc. As an alternative to these approaches, there are other means of gait generation based on the inspirations from nature. In other words, legged robotics may receive assistance from nature's legged locomotion. In literature lots of recent studies present that optimal solutions to legged locomotion are real sources of inspiration for engineers (Alexander, 1996; Alexander, 2003; Binder, 1999; Ijspeert, 2003; Dillmann, et al. 2007; Pfeiffer, Inoue, 2007).

In biological systems, control system architecture is based on the brain, central nervous system, neurons, muscles, intelligence, and so on. Multi level architecture exists. In the bottom level, fast reflex loops exist. In the top level, offline processing such as motion planning appear. Cerebellar control exists in between (Bekey, 2005; Cruse, *et al.* 2007; Kuo, 2005; Mergner, *et al*. 2003; Paulin, 2005; Ruan, *et al.* 2006; Tahboub, 2009).

In nature almost all locomotion types preserve rhythmic behaviors. (Büschges, 2005; Büschges, *et al.* 2008; Chiel, *et al.,* 2009; Cruse, *et al.* 1998; Ekeberg, *et al.* 2004; Ijspeert, 2008; Loeb, *et al.* 1990; Nolfi, Floreano, 2000; Wermter, *et al.* 2005). In legged locomotion each leg is controlled by distinct neuronal network special to itself. Each joint receives corresponding torque depending on the rhythmic signals generated by central pattern generators. Coordination between limbs and legs are also determined by neural networks. In literature many studies exist that propose certain mathematical models for the neuronal central pattern generators (Amrollah, Henaff, 2010; Ijspeert, 2008).

It is desired to implement bioinspired control structures on robotic systems in our laboratory. To reach that vision a test bench is designed. It includes both hardware and software components. Software part includes simulation software, optimization algorithm, and the real time control architecture. Hardware part consists of a legged body, sensors, actuators, and data acquisition hardware. Multi level control architecture similar to the one in biological systems systems can be implemented and researched on the test bench. The aim of this test bench is to implement the control structures inspired from biology and find optimal parameter sets that are used within the bioinspired control structures for legged locomotion. As the experience gained on this bench, it can be extended to study various types of locomotion, such as flapping wings, by changing the physical structure of the system.

This system is studied at the Cognitive Robotics Laboratory of Mechatronics Engineering Department of Atılım University (www.mechatronics.atilim.edu.tr/CRL). Besides the system of concern in the paper, robot arms mimicking the human reaching motion in the cerebellar control structure and robot head to track targets mimicking human head are the other research subjects.

In this paper, test bench is presented and the evolutionary gait generation on the kinematic model is briefly discussed. In section 2, test bench is explained. Section 3 expresses the kinematic model used for simulations and gait design. Central pattern generators to get rhythmic patterns are given in section 4. Section 5 includes the evolutionary way of finding optimal walking gaits and finally section 6 discusses the future work on test bench.

2. TEST BENCH

Physical test bench is shown below in Fig. 1 and 2. Motion in vertical axis is constrained by using horizontal beams in parallel to guide the walking system. Body slides through the beams by the aid of linear bearings (Çengeloğlu, *et al*. 2007).

Test bench includes the legs with digital servo actuators, proximity and force sensors, data acquisition system, real time control system, and the off-line processing algorithm based on genetic algorithm to find and optimize various walking gaits. Matlab/Simulink is utilized as the software. Real Time Windows Target is employed to send angular references to servo motors and receive sensor measurements in real time. Humusoft MF 624 data acquisition board is used in the system. Fast response and high torque digital servo actuators are used. Proximity sensor is a Sharp GP2D2 type sensor that can measure in between 10 cm and 80 cm range. Force sensors are polymer thick film type resistors produced by Interlink Electronics. It shows a decrease in resistance as the applied force increases.

In Fig. 1 and 2, there exist two legs with 2 joints. However, simulations and genetic algorithm based optimizations are performed for a one leg system to reduce the complexity in the algorithm at the initial stage.

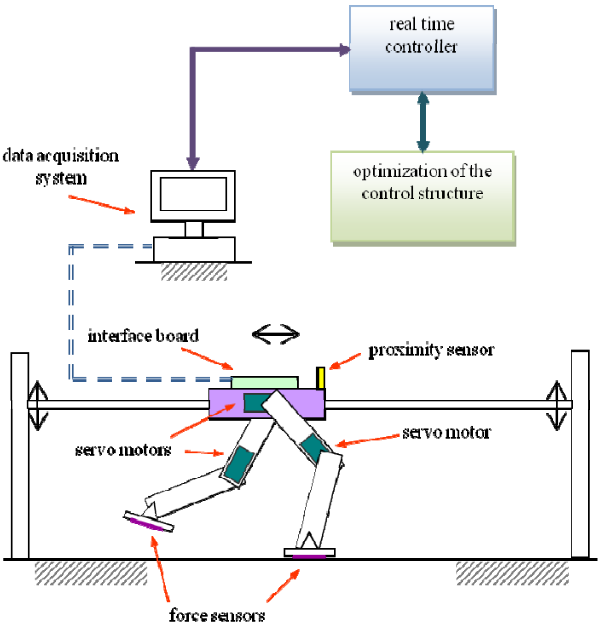

Fig. 1. Schematics of the Physical System

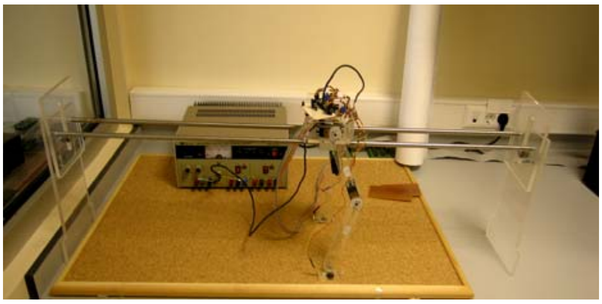

Fig. 2a. Photo of the Physical System

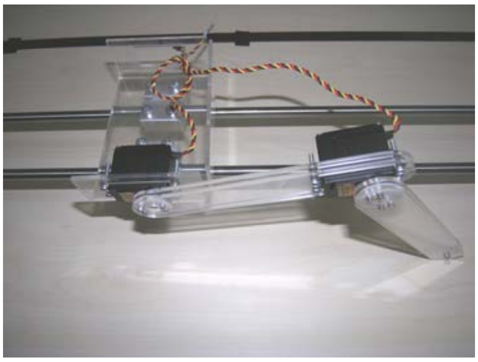

Fig. 2b. Closer view of acutators and single leg

3. KINEMATIC MODEL

Kinematic model is derived to perform basic analysis. Fig. 3 and 4 show the flight and stance modes of the leg structure.

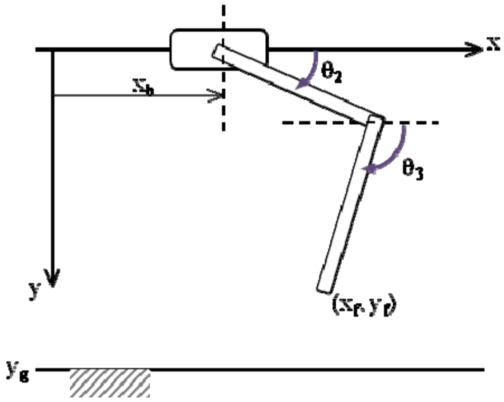

Fig. 3. Leg System in Flight Mode

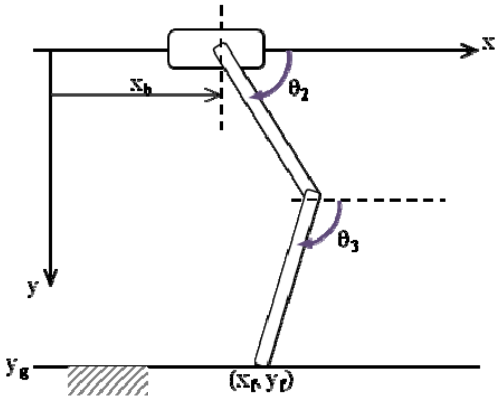

Fig. 4. Leg System in Stance Mode

It is assumed that, if the tip of the second link touches the ground, it behaves like a revolute joint. It means zero slip is assumed between the tip of the link and ground surface. Body can move along x-direction only in stance mode. In stance mode system is one degree of freedom. Hip joint angle, θ_2, is calculated with respect to knee angle, θ_3 which is determined by the central pattern generator.

In flight mode, degree of freedom of the leg system is equal to 2. Both hip and knee joint angles are determined by different central pattern generators in flight mode. Body of the leg system is assumed to be stationary in the flight mode. Under these assumptions and conditions, kinematic model is built up and is utilized in finding the walking gaits for the one legged structure.

4. CENTRAL PATTERN GENERATORS

In literature various forms of central pattern generators exist. In this study, central pattern generators based on Rowat-Selveston neuron model (Amrollah, Henaff, 2010) is employed. Central pattern generators act in the production of the relevant torque inputs to the joints. In our study, central pattern generator units are modified to generate required angular references for the hip and knee joints. Mathematical model of the generators are given below. Fig. 5 and 6 show the central pattern generator structures in Simulink.

$$\tau_m (dV/dt) = -F(V,\sigma_f) - q + I_{inj} \quad (1)$$

$$\tau_s (dq/dt) = -q + \sigma_s V \quad (2)$$

$$F(V,\sigma_f) = V - A_f \tanh(\sigma_f V/A_f) \quad (3)$$

V is the output of the central pattern generator and I_{inj} is the input as pulses. Certain forms of outputs are possible by changing the numerical values of parameters. One can refer to (Amrollah, Henaff, 2010) for more details about the employed central pattern generators in this study.

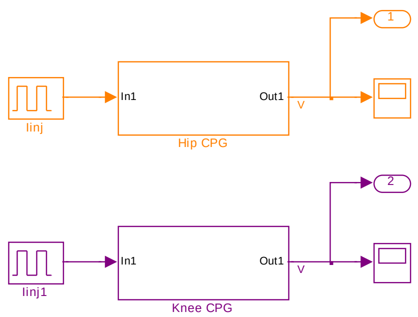

Fig. 5. Hip and Knee Central Pattern Generators

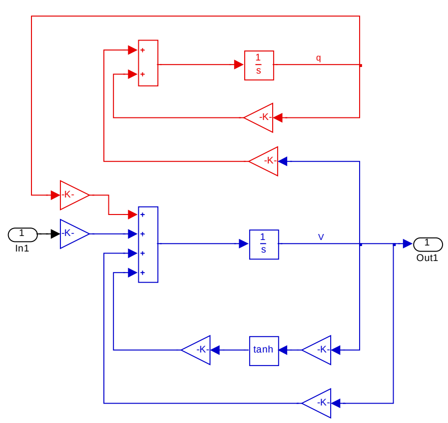

Fig. 6. Internal Dynamics of Central Pattern Generators

5. EVOLUTIONARY GAIT GENERATION

Each pattern generator outputs angular patterns for each joint. The question is simple in fact: How should θ_2 and θ_3 vary with time so as to generate motion along +x-direction (i.e. to increase x_b)? Answer is given by using central pattern generators for which we find optimal parameter sets.

Parameter set for each joint's central pattern generator is given below.

$p_i = \{A_i, A_{fi}, \tau_{si}, \tau_{mi}, \sigma_{fi}, \sigma_{si}\}$, i=2,3.

A_i is the amplitude of the pulse input to the central pattern generator. Pulse width and period of the input are set prior to the optimization algorithm run.

Optimal parameter sets for hip (joint 2) and knee (joint 3) joints are determined by genetic algorithm (Nolfi, Floreano, 2000).

Cost function to minimize is critical in the optimization of the gait. Different cost functions are utilized in this study. Initial one includes only the position, x_b, of the body.

$$J_1 = -\sum_{k=1}^{N} x_b(k) \quad (4)$$

N is number of elements of position vector in simulation.

Another cost function includes energy related terms in addition to position.

$$J_2 = -\sum_{k=1}^{N} x_b(k) + \sum_{k=1}^{N} \theta_2^2(k) + \theta_3^2(k) \quad (5)$$

This cost function aims to minimize the energy while changing position. This fact is also available in nbiological locomotion (Alexander, 1996).

Constraints for θ_2 and θ_3 are also shaped during the optimization. $\theta_2 > 0$ and $\theta_3 > 0$ are the stated constraints.

Figures below show some gaits as a result of evolutionary optimization technique.

Fig. 7 shows the resulting gait without any constraints for joint angles.

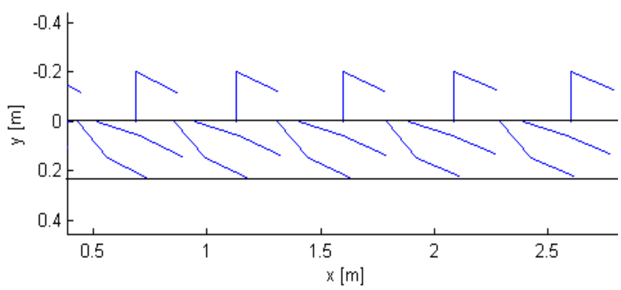

Fig. 7 Simulation of Walking Gait without any Constraints

Evolutionary optimization algorithm reveals the gait below in case of applied constraints for joint angles.

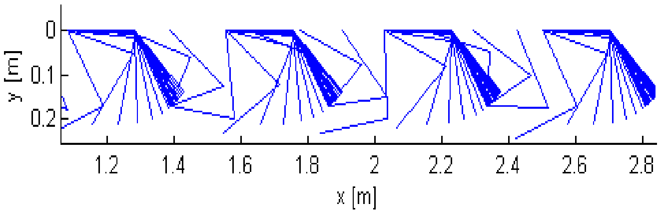

Fig. 8 Simulation of Walking Gait with Constraints

Displacement of the body with time is given below.

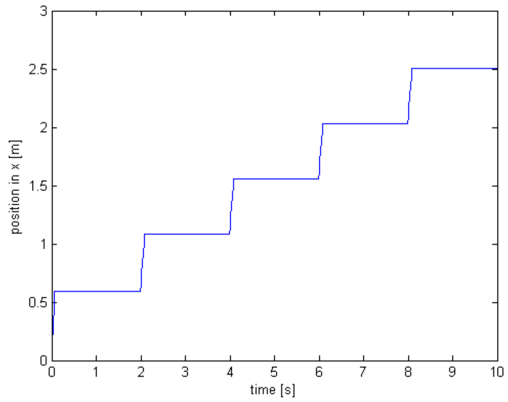

Fig. 9. Displacement of Robot Body

Following gait is obtained using the cost function J_2 with angle constraints.

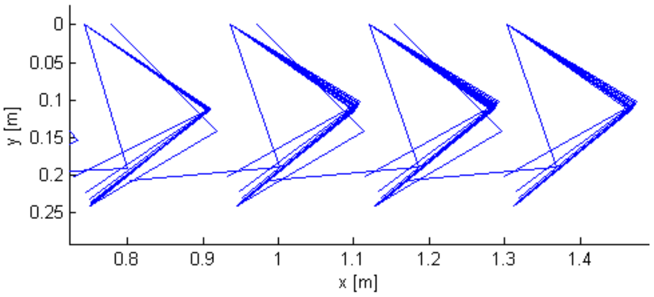

Fig. 10 Simulation of Walking Gait with Constraints and J_2

Displacement of the body with time is given below.

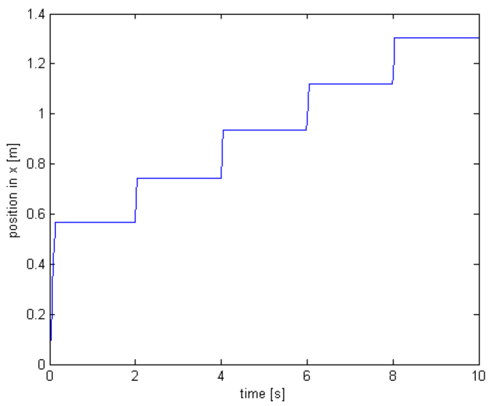

Fig. 11 Displacement of Robot Body with J_2

It is seen that energy terms in the cost function produces the gaits that reduce the displacement in the same time duration of 10 s. This is an expected result.

Small time intervals are preferred in optimizations to reduce computational time expense. In addition, in the next step of our study, we would like to implement this evolutionary gait generation procedure on the physical legged body with sensors and actuators. Iterations with small time durations are practical to our test bench and gaits are produced in a shorter distance along x-axis.

6. DISCUSSION

In this study our test bench for bioinspired control systems on robot locomotion is presented. Evolutionary gait generation is also discussed. Central pattern generators based on Rowat-Selverston neuron model are implemented. Parameters are determined by genetic algorithm to minimize defined cost functions. Shaping the cost function different gaits are reached. Individuals with 20, 30 and 50 members are employed. Increasing the number of individuals increases the computational cost and time. Distributed computing will be utilized for the genetic optimization to decrease the computation time. Using a high computational power, hundreds of individuals can be used to minimize the complex cost functions with a dynamic model and various kinds of central pattern generators. This system will provide an opportunity to investigate the optimal designs and features in nature.

Instead of the kinematic model, a kinetic model will be utilized for the gait generation in the following steps. Generated gaits will be applied to the physical leg system of the test bench. Sensor measurements will also be used within the central pattern generators and learning algorithms on physical system. Mathematical model will be replaced with the real system and acquired data from the sensors of the physical system will be processed to find optimal rhythmic motions.

Higher levels of biological control will be studied on the test bench also. Next step is to implement cerebellar control architectures. State estimation in the control loop to maintain the stability or to overcome some obstacles is one of the possible scenarios to ignite the higher levels.

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