ADAPTIVE DYNAMIC BALANCE OF A BIPED ROBOT USING NEURAL NETWORKS

Andrew L. Kun
(ak@hopper.unh.edu)

W. Thomas Miller, III
(wtm@hopper.unh.edu)

Robotics Laboratory, ECE Dept., University of New Hampshire, Durham, NH 03824

An adaptive dynamic balance scheme was implemented and tested on an experimental biped. The control scheme used pre-planned but adaptive motion sequences. CMAC neural networks were responsible for the adaptive control of side-to-side and front-to-back balance, as well as for maintaining good foot contact. Qualitative and quantitative test results show that the biped performance improved with neural network training. The biped is able to start and stop on demand, and to walk with continuous motion on flat surfaces at a rate of up to 100 steps per minute, with up to 6 cm long step.

1. Introduction

The first successful walking controllers for experimental bipeds emphasized walking with static balance, passing through a succession of states of static equilibrium. When walking with dynamic balance, the projected center of mass is allowed outside of the area inscribed by the feet, and the walker may be falling during parts of the gait cycle. A foot must be moved so as to catch the biped at the proper instant, breaking the fall and achieving a desired net translational acceleration or deceleration. The control problems for dynamic walking are more complicated than for walking with static balance, but dynamic walking promises to provide higher walking speeds and greater efficiency with more versatile walking structures.

The control of the dynamic balance of two-legged walking machines is difficult for several reasons:

- The control goals (translating without falling) are not easily decomposed in terms of the actions of individual actuators.
- The system is unstable, or only marginally stable (depending on foot design).
- Time delays in the control loop amplify stability problems.
- The system nonlinear dynamics and kinematics are difficult to model accurately, and simplified models are generally not adequate.
- Other significant properties are difficult to model accurately (gear stiction, gear play, foot flex, etc.).
- Since the robot has no direct connection to an inertial frame of reference, the controller must rely on often noisy sensors (foot-force sensors and accelerometers, for example) to represent the relationship between the robot and the external environment.

Largely as the result of these difficulties, practical biped robots have not yet been developed in research or industrial settings. In research at the University of New Hampshire, the following general strategies were proposed to deal with these problems:

- Use simplified frontal and lateral plane kinematics to translate logical “posture” commands (e.g. body angles relative to floor, foot motion relative to body) to joint commands.
- Depend primarily on pre-planned, but adaptive, smooth posture motion sequences with sensory triggers, rather than reactive closed-loop control.
- Utilize the concept of phase-locked central pattern generators to conform to and make use of the natural dynamics.
- Depend on on-line adaptation of the posture motion sequences during sequentially more-difficult tasks, rather than on accurate dynamic models.

The UNH biped was designed and implemented using these strategies, in order to test their validity.

2. Background

As a result of walking with static balance early bipeds had serious constraints on both the biped structure and walking efficiency. Generally, static bipedal walkers had large feet and moved slowly. When using reasonably small feet, even walking slowly with static balance is difficult, since it requires a very accurate model of the robot kinematics and of the distribution of mass within the robot. Summary discussions of the early history of biped walking machines have been presented by Raibert [1] and others.

Numerous investigators have discussed specific theoretical results relevant to the dynamic modeling and control of biped robots. Extensive considerations of the major issues in walking with dynamic balance have been presented by Raibert [1], among others. Several investigators have studied walking with dynamic balance using experimental bipeds. Miura and Shimoyama [2] used inverted pendulum dynamics and linearized equations of motion to control the three degree-of-freedom BIPER-3 and seven degree-of-freedom BIPER-4 robots. Furusho and Masubuchi [3] used a reduced order nonlinear dynamic model of an experimental biped structure to determine reference signals for steady walking. Raibert [1] extended his work with monoped hopping machines to consider biped running. They used a dynamic model of the multi-link structure to perform foot placement planning, and developed decoupled control systems for body attitude, body height, and foot placement. Zheng et al.[4,5] studied dynamic walking using an eight degree-of-freedom biped (the SD-2). He developed an explicit model for the multi-link biped dynamics, and designed a feedback controller which optimized the trajectory of the center of mass using stability margin criteria. Furusho and Sano [6] used independent control models for sagittal and lateral plane motions of an experimental biped robot (the BLR-G2). Their work focused on the role of force/torque control of the sole and ankle during dynamic walking. Kajita et al. [7] developed simple linear differential equations for an ideal biped with massless legs, assuming that the body mass was restricted to horizontal motions. This simple model was used to control a four degree-of-freedom biped with low-mass legs. Recently, Grishin et al. [8] presented results of walking experiments using a simple two degree-of-freedom biped constrained to motion in a single plane. Their approach emphasized the use of nominal actuator trajectories computed off-line using a dynamic model of the biped, augmented by linear adaptive terms in the on-line controller. These systems all exhibited some success on horizontal surfaces. In addition, the SD-2 robot was able to walk on modest slopes [5]. However, none of these systems represented a general purpose solution to the problems of walking with dynamic balance, in the sense of being able to achieve a variety of stepping rates and lengths, starting and stopping at arbitrary times, walking on various grades, and so forth.

The problems in achieving good performance under varying conditions have led several investigators to the study of on-line gait adaptation. Wagner et al. [9] reported a rule-based strategy for switching on-line between predefined gait controllers. The same group also investigated the use of a linear adaptive model for step length control as a function of body attitude and velocity, using on-line least squares adaptation [10]. Igarashi and Nogai [11] reported a technique for adaptively combining members of a set of predefined gaits in order to handle variations in walking command parameters (such as step length) and walking environments. The above studies involved at least partial control system evaluation using experimental bipeds. Other investigators have studied the use of neural network learning for on-line gait modification. This approach makes possible the learning of new gaits which are not weighted combinations of predefined gaits. Kitamura et al. [12] proposed a walking controller based on a Hopfield neural network in combination with an inverted pendulum dynamic model. The optimization function for the Hopfield network was derived using a detailed model of the biped kinematics. Salatian and Zheng [13] studied both off-line and on-line reinforcement learning techniques for adapting a gait designed for horizontal surfaces, in order to walk on sloping surfaces. All of the above neural network algorithms were evaluated using dynamic simulations.

In our initial research concerning two-legged walking, we combined standard supervised learning and temporal difference learning [14] in order to achieve gait adaptation for a simulated two-dimensional biped with massless legs [15]. This work focused on learning appropriate gait adaptations for achieving sudden body translational accelerations and decelerations, and for recovering from unexpected disturbance forces, starting from a model of steady walking. Similar issues were subsequently studied in our laboratory by Latham [16], using a more realistic two-dimensional biped simulation which accounted for leg masses and foot/floor impact forces. His approach emphasized adapting gaits derived from an inverted pendulum model, in order to accommodate the unmodeled (in the controller) aspects of the biped dynamics. The adaptive walking control strategies developed initially in simulation were then tested and extended in a series of studies using two generations of experimental bipeds [17,18,19].

3. The UNH Biped Robot System Description

The biped hardware developed in this research is shown in Figure 1. The biped is approximately *61 cm* tall from foot to hip, and *43 cm* tall from hip to the top of the body. The separation between the legs is *20 cm*. Each foot (a flat metal plate) is *7 cm* wide and *12 cm* long, with the ankle attached near the center-rear corner of the foot. The biped weighs approximately *11 kg*. Each hip and ankle is actuated by two gearmotors, one for rotation of the leg towards the front of the biped and one for rotation towards the side. Each knee is actuated by a single gearmotor. The ten gearmotors are driven by *12 V* pulsewidth-modulated (PWM) motor drivers. The positions of the ten joints are sensed by optical position encoders on the gearmotors. Polymer thick film force sensing resistors are mounted on the underside of each foot, near each corner (four *1"* diameter sensors per foot). Each sensor is sandwiched between the upper metal foot plate and a thin disc of rubber, which in turn is bonded to a semi-rigid Plexiglas and rubber bottom plate. Two piezoresistive accelerometers oriented along orthogonal horizontal axes are mounted near the top of the body in order to provide two-dimensional body acceleration sensing (it is assumed that the vertical body acceleration is dominated by the constant gravitational term). All PWM and sensor circuits are interfaced to a single Siemens *20 MHz* 80C166 *16-bit* microcontroller. This microcontroller performs sensor and actuator management, low level PD actuator control, and communicates with the host processor over a *57.6 Kbaud* serial communications line.

High level control computations are carried out on a single *66 MHz* 486 personal computer running the MS Windows NT real-time multi-threaded operating system. This processor is responsible for communications with the biped microcontroller, for gait and balance control computations, for neural network computations, and for the user command and status interface.

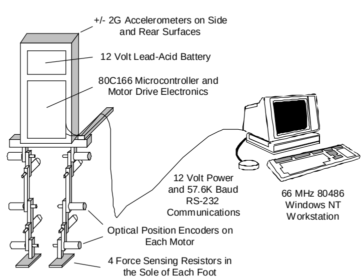

Figure 1. *The biped hardware*

4. Adaptive Control of Dynamic Balance Walking

Figure 2 shows the basic walking gait of the biped robot. As a result of the distribution of mass within the structure, the biped cannot simply lift a foot without falling. In order to move a foot, it is necessary to first generate a lateral momentum toward the opposite side. The foot can then be lifted and moved to a new location. The resulting gravitational force when the foot is lifted breaks the momentum and allows the biped to fall back on to the lifted foot.

Figure 3 gives the outline of the control architecture. Variables in angle brackets are sampled physical measurements. Variables depicted in capital letters are parameters set by the user. Variables in lower case letters represent results of control calculations. The side-to-side and foot movement motions in the walking process are initiated by the gait generator, based on simple heuristics and an approximate model of the biped kinematics. CMAC neural networks [20,21,22] are used to modulate the gait generator as a function of desired step parameters (step length and step rate) and immediate sensor feedback. These CMAC neural networks are responsible for the control of front-to-back and side-to-side balance, as well as for maintaining good foot contact. The control strategy uses pre-planned (but adaptive) smooth motion sequences with sensory triggers, rather than reactive closed-loop control. In the case of biped walking, the sensory triggers are the instances of each foot contacting or breaking contact with the ground, as detected via the foot force sensors. The closed loop system forms a phase-locked-loop which synchronizes the gait generator and the biped dynamics. This way the central pattern generator conforms to, and makes use of, the natural dynamics. The phase error is derived from the sensory triggers, and the period of the natural dynamics is regulated by modifying the magnitude and velocity of the commanded side-to-side lean.

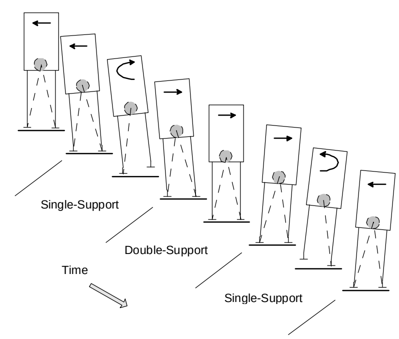

Figure 2. *The basic walking gait. The arrows indicate the direction of motion of the body.*

In Figure 3 CMAC 1 is used to control the instantaneous front/back position of the hips relative to the feet. Let us define a variable called the *Front-Back Center of Force (FBCF)*. Let FR_1, FR_2, FL_1, and FL_2, be the readings from the pressure sensors in the front of the two feet (the "toes"), and FR_3, FR_4, FL_3, and FL_4 the readings from the pressure sensors in the back of the two feet (the "heels"). The *FBCF* is then calculated as:

$$FBCF = \frac{\sum_{i=1}^{2} FR_i + \sum_{i=1}^{2} FL_i - \sum_{i=3}^{4} FR_i - \sum_{i=3}^{4} FL_i}{\sum_{i=1}^{4} FR_i + \sum_{i=1}^{4} FL_i} \cdot 40$$

The *FBCF* is in the [-40, 40] range. It reaches its maximum when all the force on the biped feet is on the “toes” of the feet, and it reaches its minimum when all the force is on the “heels”. CMAC 1 provides adjustments to the relative body position in order to achieve a value of *FBCF* close to zero. In other words the output of CMAC 1 is used to achieve an equal overall distribution of force between the toes and the heels of the feet during the stepping motions. This has the effect of preventing the biped from falling forward or backward. The neural net is trained using the *FBCF* as the training error signal. A state of imbalance at a given time during walking generally results from incorrect postures at earlier times, rather than from an incorrect current posture. Thus, the general technique of temporal difference learning [15] is used to distribute the information from the delayed supervised learning over sequential time steps.

CMAC 2 is used to predict the correct amplitude and velocity of side-to-side lean during each step. An insufficient lean causes the foot to lift for too short a duration (or not at all), while too much lean causes the foot to lift for too long a duration (or for the robot to fall over laterally). The proper amplitude of lean is dependent on the state of the robot at the beginning of the step, and varies somewhat from step to step. It varies significantly for different desired step lengths and rates. CMAC 2 is trained after each step, based on the difference between the desired and observed foot lift durations for that step.

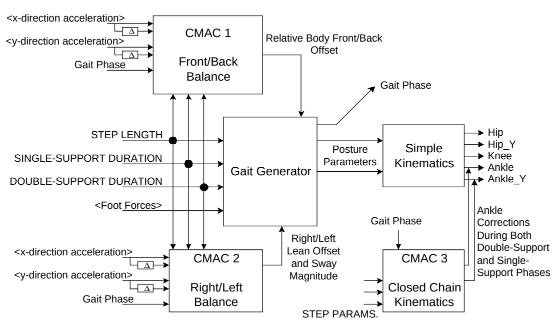

Figure 3. *Biped learning control architecture*

CMAC 3 is used to learn kinematically consistent robot postures. Whenever it is desired that both feet be in solid contact with the floor (double-support phases), the closed-chain kinematics of the structure have to be addressed. Target positions for all ten motors cannot be specified independently. In our current controller, hip and knee angles are produced directly by the gait controller. CMAC 3 then predicts ankle position corrections in order to keep the biped feet parallel to the floor with the force balanced in the middle of each foot.

5. Neural Network Training and Qualitative Results

Training of the biped typically proceeds as follows. The three CMAC neural networks are first trained during repetitive foot lift motions similar to marching in place (i.e. no attempt is made to translate the lifted foot). This is typically carried out for five minutes, with different settings for desired foot lift height (in the range *0.5* to *2.5 cm*). Frequent human support is required to keep the biped from falling during the first half of this training, and occasional support is required during the second half. Then, training of the three CMAC neural networks is carried out during attempts at walking (translating the lifted foot forward), for increasing step lengths, and/or for various step rates. Again, frequent human support is required during early training for each new parameter setting, while less frequent support is required after *2* or *3 minutes* of training at a given setting. After about *60 minutes* of total training time, the biped is able to shift body weight from side-to-side while maintaining good foot contact, and to lift a foot off of the floor for a desired length of time, during which the foot can be moved to a new location relative to the body. Using these skills, the biped is able to start and stop on demand, and to walk with continuous motion on flat surfaces at a rate of up to *100* steps per minute, with step lengths of up to *6 cm* per step (corresponding to *12 cm* stride lengths). Mpeg movies of the biped walking can be seen on the UNH Robotics Lab home page at *http://www.ece.unh.edu /robots/rbt_home.htm*.

6. Quantitative Results

All data about the state of the biped was taken using a function of the high level control program. Data was logged after every execution of the high level control thread, that is every *28 ms*. Desired values logged this way represent the complete set of values created by the high level digital controller during the logging period. The recorded measured values represent the sampled feedback about biped states received by the high level controller, since the low level software performs measurements every *2.8 ms*.

Two important parameters used in the high level controller are the desired distance of the feet from the ground (foot lift), and the *right-left center of force (RLCF)*. The *RLCF* holds information about the relative magnitude of forces between the feet and ground, as measured by the foot pressure sensors. If FR_i $(i=1,...,4)$ are the forces measured by the four force sensors on the right foot, and FL_i $(i=1,...,4)$ are the forces measured by the four force sensors on the left foot then the *RLCF* is:

$$RLCF = \frac{\sum_{i=1}^{4} FR_i - \sum_{i=1}^{4} FL_i}{\sum_{i=1}^{4} FR_i + \sum_{i=1}^{4} FL_i} \cdot 40$$

The *RLCF* is in the [-40, 40] range. It reaches its maximum when the weight of the biped is on the right foot, and its minimum the weight is on the left foot.

Figure 4 shows the relationship between the desired lift of the feet and *RLCF* at the beginning of training, and Figure 5 shows these variables after sixty minutes of training. The desired lifts of the two feet are combined into a single variable (desired right-left variable) by subtracting the desired lift of the left foot from the desired lift of the right foot. This way the desired right-left lift is positive when the right lift is greater than zero, and it is negative when the desired left lift is greater than zero. Note that the two desired lift values can never be greater than zero at the same time, since that would mean that the biped is in the air.

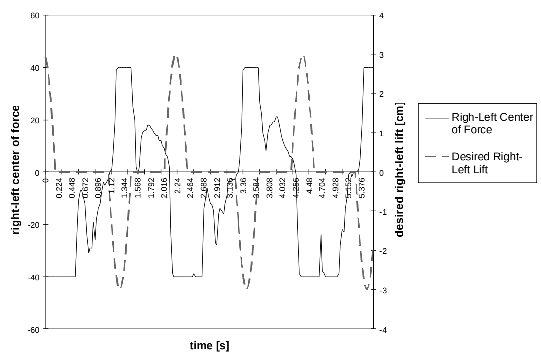

Figure 4. *Desired Right-Left Lift and Measured Right-Left Center of Force at the Beginning of Training*

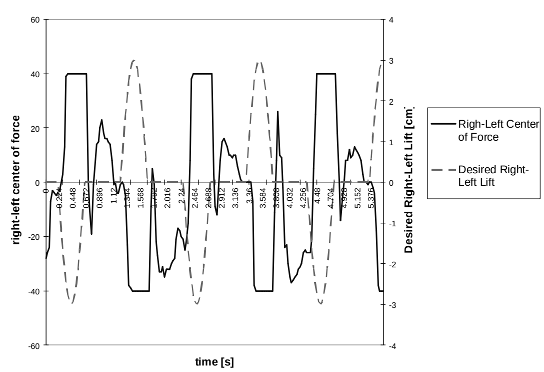

Figure 5. *Desired Right-Left Lift and Measured Right-Left Center of Force After Sixty Minutes of Training*

The high level controller uses another variable called the *Front-Back Center of Force (FBCF)*, introduced in Section 4. Figure 6 shows the relationship between the *FBCF* and the *RLCF* at the beginning of training, and Figure 7 shows this relationship after sixty minutes of training.

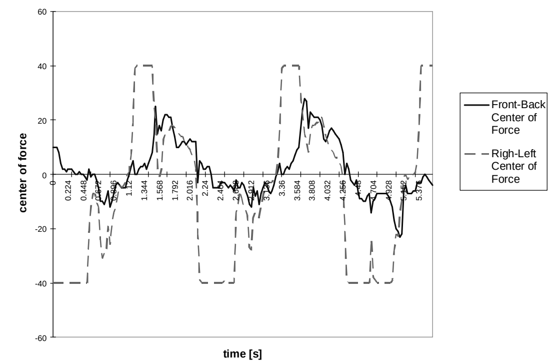

Figure 6. *Right-Left and Front-Back Center of Force at the Beginning of Training*

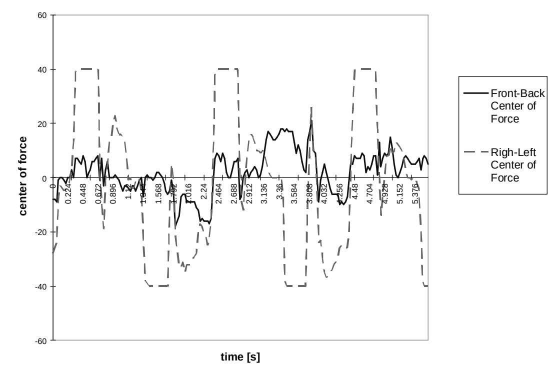

Figure 7. *Right-Left and Front-Back Center of Force After Sixty Minutes of Training*

7. Discussion

Figure 4 shows the desired lift of the feet, and the measured *RLCF*, at the beginning of training. From the desired right-left lift in Figure 4 we can see that the feet are commanded to be in the air for the same amount of time. However at the beginning of training they spend unequal time in the air. Figure 5 shows the *RLCF* and the desired right-left lift after sixty minutes of training. We can see that the feet are roughly spending equal time in the air, as desired. This shows that the neural nets were trained to augment the pre-planned motion control.

Figure 6 shows the relationship between *RLCF* and *FBCF* at the beginning of training. Ideally we would like the front-back center of force to be close to zero, however the value of *FBCF* oscillates and makes excursions as far as *-25* and *+30*. Figure 7 shows the right-left and the front-back centers of force after sixty minutes of training. Notice that the excursions of the front-back center of force around zero are smaller than they were at the beginning of training, which means that the biped front-back balance has improved with training.

8. Conclusion

The above results demonstrate that the general strategies listed in Section 1 can be used in creating a controller for dynamic bipedal walking. However the biped required human supervision, as failures occurred every few minutes, and the biped would fall without support. The lowest attainable walking speed was determined by the system dynamics: the biped could not walk at speeds that required sideways swinging at frequencies below the natural frequency. The top speed was limited by the highest possible swinging frequency, which in turn was limited by the available motor torques, and the bandwidth of the serial communication link between the high and low level controllers. Step length was limited by the masses of the motors at the knee and ankle joints. Reaction forces resulting from the acceleration and deceleration of these masses during steps increased the coupling between the frontal and sagittal plane balancing problems, causing the controller to fail.

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