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Elegant Stepping: A Model of Visually Triggered Gait Adaptation

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Abstract

Existing visually guided walking machines have difficulty traversing terrain cluttered with obstacles. These walking machines use computationally intense approaches that require construction of a geometrically correct model of both the environment and the robot. However, most terrestrial vertebrates accomplish this task easily suggesting that better strategies exist.

We present a model inspired by recent research in cats and humans. In our model, perception and action are tightly coupled. The mapping is adaptive and based on experience. The goal of the adaptation is to use distance measurements to smoothly modulate a Central Pattern Generator (CPG) controlling gait. A key element in our model is the use of a temporal gating hypothesis. This hypothesis simplifies the learning problem and is consistent with biological observations.

Our approach does not require that a geometric representation of the environment be created or updated based on new observations. This is in strong contrast to current practice in machine vision and robotics of surface reconstruction as a prerequisite to planning.

Our simulation results indicate that the desired mapping can be learned quickly with few mistakes before perfect performance is achieved. The resulting gait modulation is smooth and coordinated with the phase of the CPG controlling the robot.

1.0 Introduction

When a wheeled vehicle goes over an obstacle, weight and energy is transferred to the obstacle. In contrast, when a walking machine goes over an obstacle, it can clear the obstacle without touching it. Because of this walking machines may inflict minimal damage on the environment while making stable progress over rough terrain. This gives walking machines a large advantage over wheeled vehicles.

To exploit this advantage, it is necessary to anticipate obstacle collisions and to make corrective gait modifications. A vision-based sensor can provide the fast, high-resolution depth information needed for a walking machine to anticipate a collision.

Visually triggered gait modification should be an essential part of a walking machine’s control system. This is particularly true for those robots that are inspired by vertebrate forms i.e. bipeds and quadrupeds. Yet remarkably little research has been done in the control of gait of walking machines using visual input.

One strategy that has been explored is to treat locomotion and perception as separate problems. Under this paradigm, one first solves the “vision problem” of recovering the 3-d geometry of a scene. This information is then passed to a planning system that has access to an explicit model of the robot. A good trajectory is found for each individual leg to move over the obstacle. This paradigm is illustrated in the work of Krotkov and colleagues (1994, 1996) in the control of the Ambler walking machine. The Achilles’ heel of this approach is the need to construct a geometrically correct model of the environment, and to have identified a kinematically (and perhaps dynamically) correct model of the robot. This solution is computationally intense and, as demonstrated in their work, too slow for real-time control using moderate power CPUs.

The explicit planning approach does not exploit the fact that the walking machine will be presented with a similar situation again and again. If the robot were to operate for long periods of time, it may experience substantially identical situations thousands of times. An adaptive system that incorporates past history to make quick decisions may be more efficient.

The approach considered here is to eliminate the intermediate explicit model and consider creating a direct coupling of perception to action with the mapping being adaptive and based on experience.

A model for the desired capability is illustrated by the locomotion ability of the cat. As the animal walks, it flexes its legs to clear low-lying obstacles and minimize the possibility of stumbling or tripping. The act of stepping over obstacles is based on a smooth modification of this basic gait pattern and occurs over several step cycles. The limb movement anticipates contact with the object based on previous experience. This gait modification is graceful, smooth and coordinated. We call it *elegant stepping*. In robots, *elegant stepping* emulates the movement of the robots' elegant, agile biological counterpart.

2.0 Biological Background

The inspiration for a solution comes from recent neurophysiological and behavioral studies in cats and humans. We give a brief synopsis of this current work below.

2.1 Physiological and Behavioral Studies in Cats

The vertebrate spinal cord contains the Central Pattern Generator (CPG), a distributed system of neural oscillators capable of producing the basic periodic signal needed for walking movements (Grillner, 1981). Interneurons, in the spinal cord are phasically modulated, in synchrony with the step cycle via pyramidal tract neurons whose signal originates in the motor cortex. This modulation can regulate gait so that the animal can step over obstacles (Armstrong, 1986; Drew, 1991, 1993; Rossignol, 1996). However the motor cortex itself does not receive the gait phase information needed for phasic modulation directly from the spinal cord. Another brain center very important in visuomotor coordination and motor learning, the cerebellum, receives both visual input and gait phase information and in turn could send this information to the motor cortex (Arshavsky et al., 1983; Glickstein et al., 1994). Step related phasic modulation has been recorded in the cerebellum itself (Armstrong and Marple-Horvat, 1996) and very recently in relation to visually guided step modifications (Marple-Horvat et al., 1998). Finally, additional vergence information, implicitly coding depth, could be available through the cerebellum (Zhang et al., 1991, 1992; May et al., 1992). This information might be used to gauge depth to an object.

Where can a training signal originate in the nervous system? We choose the occurrence of a paw extension or paw placement reflex as a natural training signal. If the leg is extending when the foot strikes the obstacle, tactile stimuli on the paw of an animal will cause the limb to extend to support the weight of the animal. If the leg is flexing when the foot strikes the obstacle, the same kind of stimuli will cause the paw to lift higher (Forssberg, 1979).

2.2 Behavioral Studies in Humans

There is clear evidence that *continuous* visual input is not necessary for walking. Humans can walk with brief flashes of light or with intermittent visual sampling (Patla et al., 1996). Even in a difficult task such as flagstone stepping, uninterrupted visual input is not necessary for accurate stepping (Hollands and Marple-Horvat, 1996). In addition, during flagstone stepping, the eyes move in tight synchrony with foot movement (Hollands et al., 1995; Hollands and Marple-Horvat, 1996).

All visual samples do not have the same potential for control of limb movements. Samples taken when the foot to be controlled is in stance phase (or shortly before) are far more effective in modulating gait. Samples taken in swing phase are largely ineffective. Thus, it has been suggested that during stepping and obstacle avoidance visual information is used during the stance phase in a feed-forward manner to plan and initiate changes in the swing limb trajectory (Holland and Marple-Horvat, 1996; Patla et al., 1996).

As one would suspect, regulation of gait also depends on distance to the obstacle. Data from athletes in the long jump have demonstrated that just prior to lift-off the athlete modulates his stride length over the last three steps (Lee et al., 1982). Also, the standard deviation of the footsteps *decreases* over the last three steps.

Taken together this may indicate that gait is modulated at discrete intervals. This modulation may be a highly stereotyped program that depends on a brief sampling of the visual environment to instantiate it (cf Patla et al., 1991). This hypothesis is intriguing for roboticists because it implies that after a brief sample, it is not necessary to store an internal representation of the world that needs to be shifted and updated during movement.

3.0 Model of Elegant Stepping

3.1 Problem Statement

The adaptation problem can be described abstractly as follows. We wish to make associations between a distance to the obstacle and a change in stride length. We wish to adjust this mapping adaptively based on experience. If a reflex is triggered while the leg is extending, then the paw had almost cleared the obstacle. In this case we adjust previous associations between distance and stride length to make longer strides in the future. If a paw placement reflex is triggered when the leg is flexing, we adjust the previous associations between distance and stride length to make shorter strides in the future.

One key difficulty in learning is how to propagate the error back in time. We note that changes in the step cycle are most effective during narrow time windows, as noted in section 2.2. Therefore, we hypothesize that sensory information from visual areas (e.g. distance) is gated periodically and in synchrony with the step cycle. This is our temporal gating hypothesis. This information is then held constant and used to modulate the gate over the following step cycle. Thus, as the robot approaches an obstacle, it makes at most three discrete decisions prior to going over the obstacle. These decisions occur at the three footsteps prior to going over the obstacle. This discretization simplifies the credit assignment problem.

We now turn to a detailed description of the simulation. The simulation has four main parts: (1) Range Encoder, (2) Locomotory Generator, (3) Model of Environment/Leg interaction, and (4) Learning System. The relationship of the components is given in Fig. 1. The values of critical constants are given in the Appendix.

Insert Figure 1 about here

3.2 Range Encoder

An interval-coded vector $x^{spatial}$ encodes distance to the obstacle. Each element represents a narrow range of distances (in our case the range is 0.1 stride lengths for all elements). These units are nonoverlapping and no spatial ordering of units is assumed. At any time, only a small percentage of these cells are active. These elements are gating into Short Term Memory (see Section 3.5.1).

3.3 Locomotory Generator

The CPG is modeled as a clock oscillator. This oscillator drives two output functions given diagrammatically in Fig. 2. The output signal *Lift,* used to drive the leg, is given in Fig 2A. It is characterized by its amplitude, softness, period, and burst length. The *burst length neuron* directly controls the burst length of this function. This in turn controls how long the leg is in the air and hence the stride length. Details of the CPG model can be found in Lewis (1996).

The second output function, *Phase,* is a brief pulse of activity that occurs at the beginning of each step cycle. This is used in perceptual gating.

In addition, a visually mediated *lift reflex* increases the input to the limb if we are within one stride of the obstacle (not shown in Fig.1). This reflex increases the amplitude of the CPG output.

Insert Figure 2 about here

3.4 Mechanical System

The parameter *Lift* drives a muscle that we simulate as a low pass filter:

$$t^{Flex} \frac{dFlex}{dt} = -Flex + Lift \qquad (1)$$

where $Flex$ is used to drive the flexion of a 1-DOF leg. The leg has two links of length $A/2$. The height H of the foot is: $H = (1 - \cos(Flex)) \cdot A$.

When the foot is off the ground, it moves forward and at constant speed (with respect to the ground). When it is on the ground, it has zero speed with respect to the ground. We express this as: $x = 4.0 \cdot F$ where $F = \begin{Bmatrix} 1 & if & H > 0 \\ 0 & if & H = 0 \end{Bmatrix}$.

Each obstacle is simulated as being a rectangle with dimensions $0.2 \cdot scale$ (width) and $1.0 \cdot scale$ (height) where $scale$ varies from $[0.2 \ldots 1.5]$. Here a height of 1.0 unit is the maximum step height without the addition the *lift reflex* when the system is within one stride of the obstacle.

3.5 Learning System

3.5.1 Temporal Gating

The activity of the $x^{spatial}$ vector is one-to-one gated into short-term memory cells x_i^{STM} in synchrony with the step cycle. The gate used to accomplish this is a shunting inhibition signal originating in the CPG of the robot. By our convention, g is 1.0 when the foot is on the ground. Thus

$$t^{STM} \frac{dx_i^{STM}}{dt} = -x_i^{STM} + g \cdot x^{spatial} \qquad (2)$$

where t^{STM} is a time constant on the order of the length of one step cycle.

3.5.2 Direct Mapping of Perception to CPG modulation

We model the computation of the adaptive burst length neuron (BLN) as follows:

$$s_i^{bl} = w_i \cdot x_i^{STM} \qquad (3)$$

where s_i is the activity in the ith synapse. In each synapse a memory is kept of activation:

$$t^{act} \frac{dx_i^{act}}{dt} = -x_i^{act} + s_i^{bl} \qquad (4)$$

Here x_i^{act} is a variable that is dependent on recent activation. This variable is used during learning. Finally, the output is given by:

$$\Delta bl = \sum_{i=1}^{N} s_i^{bl} \qquad (5)$$

$$t \frac{dbl}{dt} = -bl - \Delta b a^{bl} + T_{bl} \qquad (6)$$

where the bl variable modulates the Central Pattern Generator and controls flexion duration of the foot during a step cycle. Also, T_{bl} is a tonic burst length level. The variable a^{bl} is called 'authority' and controls how much the burst length can be modified based on the neural input. The variable bl is limited with a hard saturation at bl^{+} and bl^{-}.

3.5.3 Learning

At the beginning of a step cycle (corresponding roughly to when the foot is in contact with the ground), a gate is triggered that transfers the current disparity activity to a short-term memory unit. The short-term memory activates synapses in the BLN. Traces in these synapses maintain an activity trace or brief memory of having been activated.

If a reflex is triggered, then a heuristic is used to modify the BLN's weights. If a paw placement reflex has occurred, then all synapses contributing to this decision should be incrementally decreased. If a paw extension reflex occurs, they should be increased.

We let $d = \left\{ \begin{matrix} 1 & if & pp \\ -1 & if & pe \end{matrix} \right\}$ where pe stands for the triggering of the paw extension reflex and pp stands for the triggering of the paw placement reflex. We use the following learning rule:

$$\Delta w_i = d \cdot x_i^{act} \cdot (|w_i| + e) \cdot a^{act} \qquad (7)$$

We are multiplying the training signal, d , by a factor $x_i^{act} \cdot (|w_i| + e)$. This factor is meant to reflect how much a given weight contributed to limb trajectory. The weight that contributed the most to the current decision should be the one that is most changed. The constant e is a small value needed to start the learning algorithm. After each learning iteration we re-normalize w such that $\|w\| = 1$. Finally, note that x_i^{act} decays exponentially with time. Thus more recent decisions are weighted more heavily.

4.0 Simulation Experiments

Here we describe simulation results in learning using the model presented in the previous section.

4.1 Experiment 1: Quick Learning

In this experiment, an obstacle of $scale = 1.2$ is used. The foot is initialized at a random starting position in the range $[-6,-7]$ stride lengths from the obstacle.

A typical encounter with an obstacle by the simulated robot before and after training is illustrated in Fig. 3. As can be seen the gait adapts successfully to clear the obstacle (thick solid line). In this instance, the stride length is reduced before stepping over the obstacle. Also shown in the diagram is a gait generated by a simulated robot prior to learning (thin solid line). In this case the robot's foot goes through the obstacle (no attempt was made to simulate the physics of the foot's collision with the obstacle).

Insert Figure 3 about here

In Fig. 4 we see the modulation of burst length with time. The absolute difference in burst length between the adapting robot and the non-adapting robot is shown. As the robot moves toward the obstacle, the burst length is gradually altered. After passing the obstacle, the burst length gradually relaxes back to its former value. Thus the gait is smoothly altered.

Insert Figure 4 about here

In Fig. 5 we see a graph of reflex triggers versus learning cycles. After about 100 trials, no more mistakes are made in the gait. As can be seen, remarkably few errors occur before the system's performance becomes perfect.

Insert Figure 5 about here

4.2 Experiment 2: Footstep Variance

In long jump athletes, the variance in footstep decreases just before the final footstep. We should see a similar phenomenon in this system as well. The robot should find a 'sweet' spot to land on just before going over an obstacle. This 'sweet' spot should be small if the object is larger. In addition, we would predict that this variation should decrease with time.

To measure standard deviation of the footsteps, we recorded the footsteps over a period of 200 trials after learning had converged. We measured the position of the foot to within 0.1 stride lengths. Next, for the intervals (0…1), (1…2),(2…3),(3…4) we grouped the footsteps together and computed the standard deviation of the position. In addition, we varied the obstacle height from 0.2 to 1.4 units of height.

A 3-d plot shows the standard deviation versus distance to obstacle and obstacle height (Fig. 6). We see clearly, that the standard deviation (given in units of stride length) decreases dramatically during the run-up to the obstacle. The effect of the application of the burst length modulation is to *reduce the uncertainty* of the foot position as the robot nears the obstacle. Secondly, the uncertainty reduces with increasing object size. This is reasonable as the 'sweet' spot should shrink as the object becomes larger.

Insert Figure 6 about here

4.3 Experiment 3: Weight Changes with Object Size

Next we looked at the resulting weight patterns after learning. The system was allowed to converge and then a snap shot of the learned weights was taken. The weight patterns for three different sized training obstacles (0.6, 1.1, and 1.4 height units) is shown in Fig. 7.

As can be seen in Fig. 7A, there are fairly broad areas in which no correction takes place. For example, such areas are centered about weight indices 5, 15, and 25. Weight index 15 corresponds to visual units sensitive to an obstacle depth of 1.5 stride units. In Fig. 7B, these areas have decreased slightly. Finally, in Fig. 7C these areas have disappeared. When the object is 1.4 units in size we cannot find a solution with perfect performance.

Insert Figure 7 about here

5.0 Discussion

The key hypothesis introduced here is the use of the temporal gating of the visual signal i.e. distance estimation. This hypothesis enables the formulation of the problem as a direct mapping of perception to action The temporal gating hypothesis also simplifies the credit assignment problem. This results in quick learning. A side effect of this formulation is the fact that no geometric representation of the environment is needed. Although we use cells that respond to distances, these cells are not ordered to be able to produce a disparity map of the environment, for example. This non-geometric representation of the environment represents a radical departure from current machine vision literature where it is assumed that the first step in visual processing is to form a smooth depth map. The model provides at least one case where this is not necessary. This may also assist neuroscientists in interpreting certain observations. For example, one characteristic of the cerebellum is fractured somatotopy (Shambes et al., 1978). Indeed, retinotopic organization of the sensory space is not needed for our model.

A key benefit of the direct mapping of perception to action is that we do not need to generate and maintain an accurate geometric model of the environment, as in the case of the work of Krotkov and colleagues (Krotkov and Simmons, 1996; Krotkov and Hoffman, 1994).

6.0 Summary and Conclusions

Walking machines can walk over obstacles without touching them only if they can anticipate contact and make a suitable gait modification. This problem can be addressed by first creating a model of the environment, based on sensory data, and then applying planning techniques to determine foot placement. An alternative approach, suggested by recent research in cats and humans is presented here. We propose the use of a gated mapping of perception to action. At discrete moments during the step cycle, visual information is gated into a short-term memory location and then is used to provide a signal to smoothly modulate the burst length of a CPG. This in turn has the effect of lengthening or shortening the stride length. A training signal is very naturally derived from the occurrence of reflexes when the robot (or animal) strikes the obstacle.

We present a model of visually triggered gait modification that we term *elegant stepping.* It is demonstrated that this technique can quickly learn a good mapping from perception to action. Furthermore this mapping allows a smooth modulation of gait. Finally, this system qualitatively reproduces human data where the uncertainty in footstep decreases with approach to an object.

We conclude that an intermediate, geometrically correct representation of the environment is not necessary for elegant stepping. We conjecture that many visuomotor problems may not require reconstruction of the environment as a necessary first step.

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Appendix

The following are constants used in the simulation presented here. Euler integration was used throughout.

Constant	Description
$t^{STM} = 1.0$	Time constant of STM neurons
$t^{ELIG} = 1.0$	Time constant of BLN synapse
$t^{bl} = \frac{1}{3}$	Time constant of BLN
$a^{bl} = 0.5$	BLN 'authority' factor
$T^{bl} = 0.25$	Tonic Excitation of BLN
$bl^{+} = 0.3$	Max Saturation value of BLN output
$bl^{-} = 0.3$	Min Saturation value of BLN output
$\Delta t = 0.01$	Euler Integration Step size
$a^{act} = 0.0005$	Weight Learning Rate
$e = 0.1$	Small value to initiate learning.
$t^{FLEX} = 5.0$	Mechanical time constant of robot
$A = 6$	Distance from foot to hip

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Figure Captions

Figure 1. System diagram of *elegant stepping*. (A) An obstacle appears in the robot's path. It is detected using a range encoding system. Its distance is determined in uncalibrated units and activates a single cell. At the beginning of each step cycle, the current distance estimate is transferred to short term memory (STM). The STM units emit a phasic response with a slow decay. This phasic response is sent to the adaptive burst length neuron (BLN). Depending on the strength and sign of a weight vector, the BLN increases or decreases the burst length of the CPG controlling leg flexion. The stride is thereby adjusted. (B) Learning occurs when the robot strikes an obstacle. If the leg is flexing and the foot strikes the object, a paw placement reflex is initiated with a **+1** training signal. If the leg is extending and the foot hits the top of the obstacle a **-1** training signal is given.

Figure 2. Output signals of the CPG. (A) Parameters of the output function. Here we model the bursting of the CPG as an average firing rate. The rate at which the firing rate increase/decreases is the softness, the greater the softness, the slower the rate. The amplitude is the maximum firing rate. The burst duration is the percent of the period that the CPG is firing. In addition, the overall period can be controlled. Thus the output is characterized by a total of 4 parameters. (B) The phase signal indicates the beginning of a step cycle (CPG period).

Figure 3. Typical gait trajectories. Examples of gait trajectory before and after learning.

Figure 4. Burst Length modulation versus foot position. The x-axis is the distance to the obstacle. The y-axis is the ratio of the change in burst length to the nominal burst length.

Figure 5. Performance of algorithm versus time. The vertical impulse lines indicate errors. As can be seen, the algorithm performs well after about 40 training cycles.

Figure 6. Standard deviation for varying object sizes and distances to object. As the robot approaches the obstacle, its variance decreases. Variance also decreases with increasing object size.

Figure 7. Weight distribution versus object size. (A) Obstacle size is 0.6 (B) Obstacle size is 1.1 (D) Obstacle size is 1.4

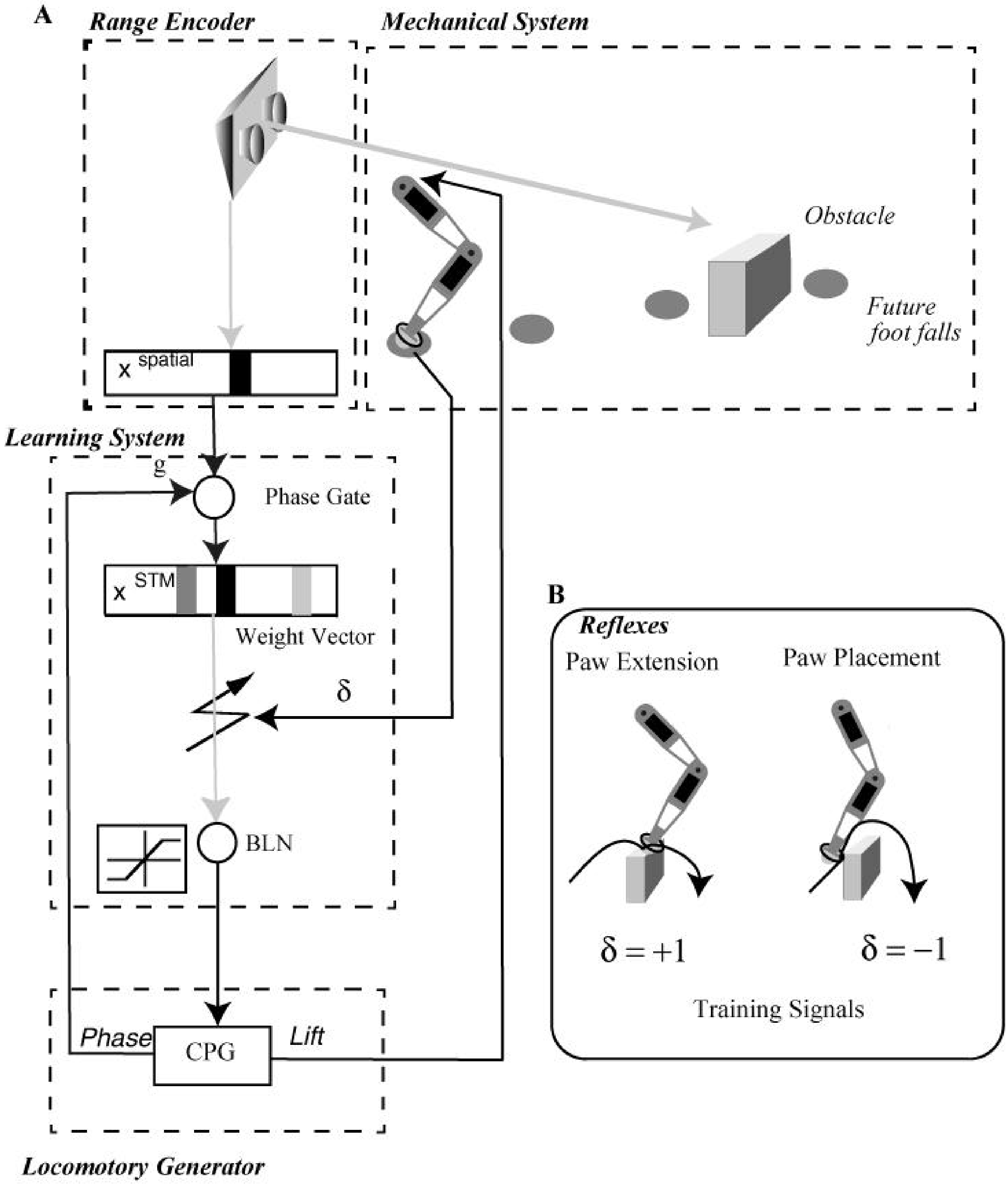

A
Range Encoder
Mechanical System
Obstacle
Future foot falls
x spatial
Learning System
g
Phase Gate
x STM
Weight Vector
δ
BLN
Phase
CPG
Lift
Locomotory Generator
B
Reflexes
Paw Extension
Paw Placement
δ = +1
δ = −1
Training Signals

Figure 1

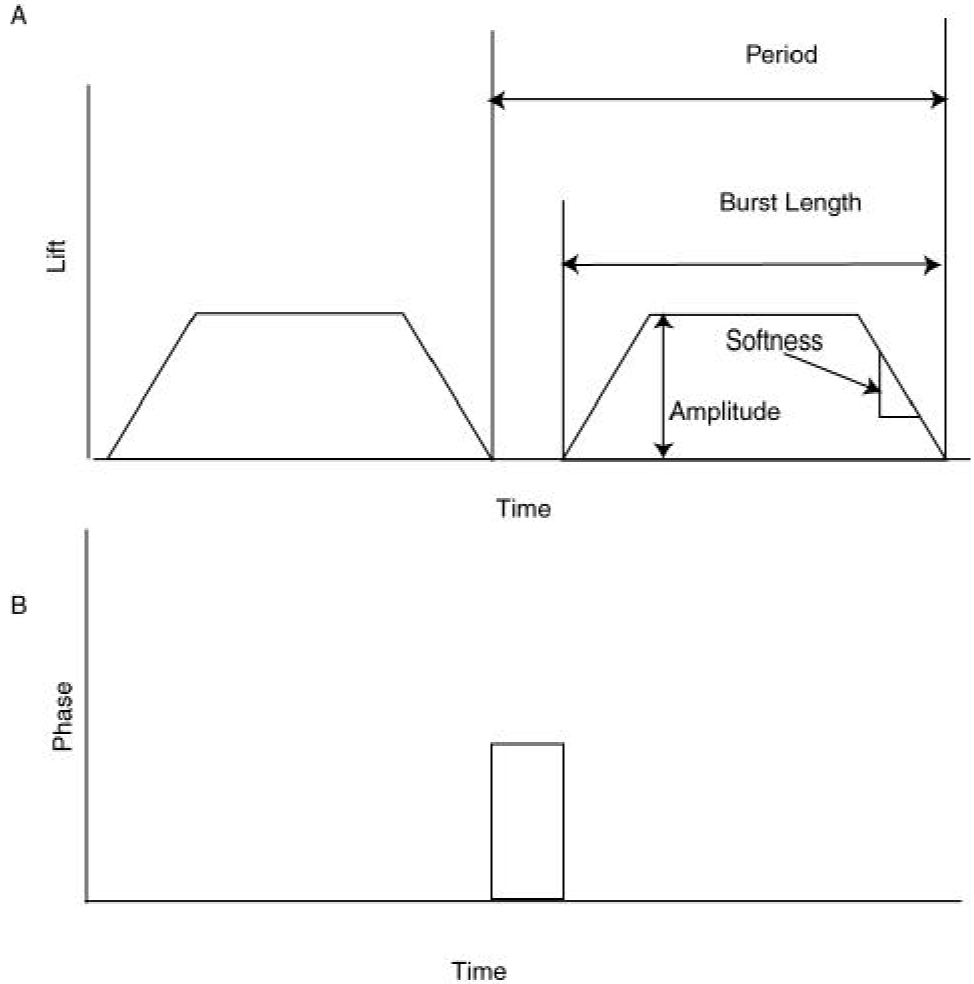
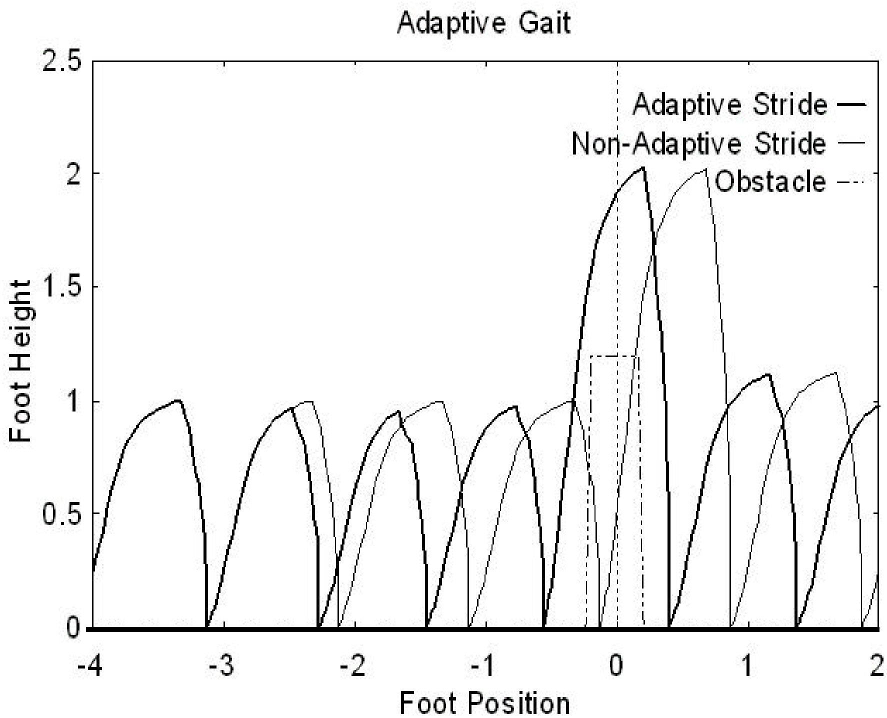

A
Period
Burst Length
Lift
Softness
Amplitude
Time
B
Phase
Time

Figure 2



Adaptive Gait
Adaptive Stride
Non-Adaptive Stride
Obstacle
Foot Height
Foot Position
2.5
2
1.5
1
0.5
0
-4
-3
-2
-1
0
1
2

Figure 3

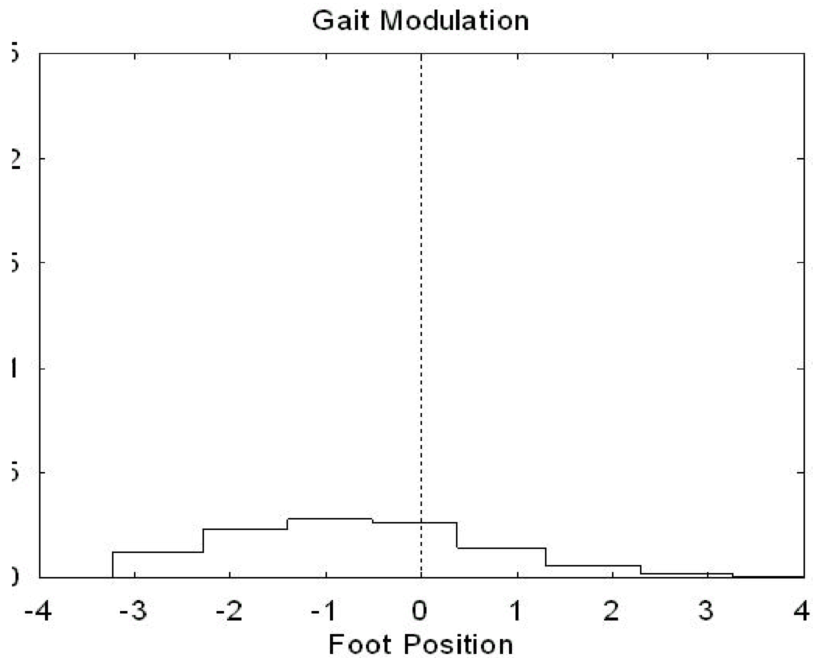
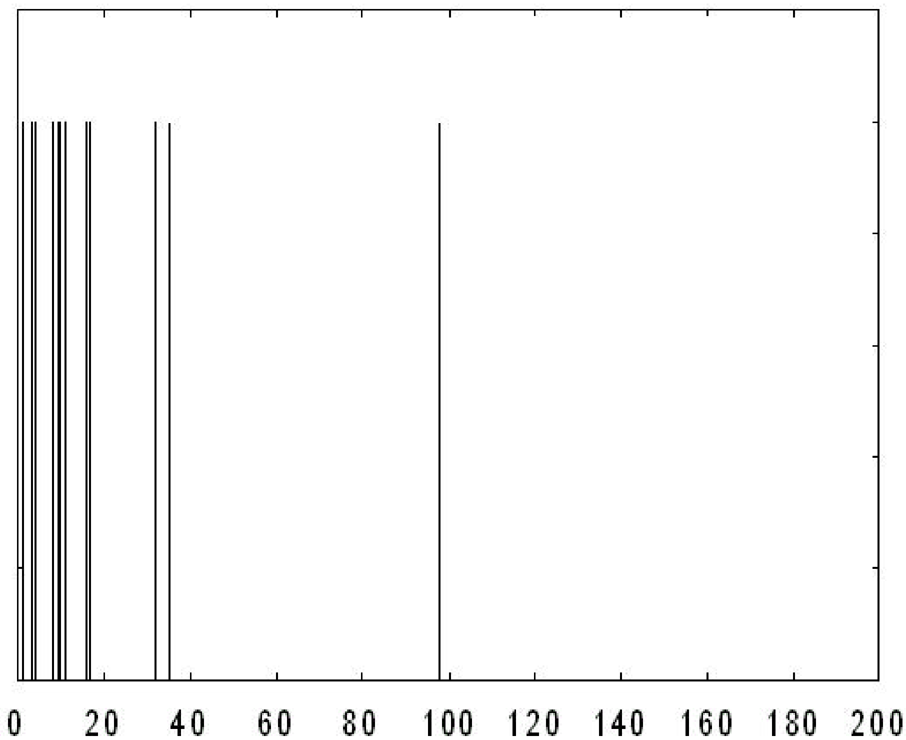


Figure 4

Error VS Learning Cycle



Learning Cycle

Figure 5

Standard Deviation of Robot Footfalls, Distance and Obstacle Size

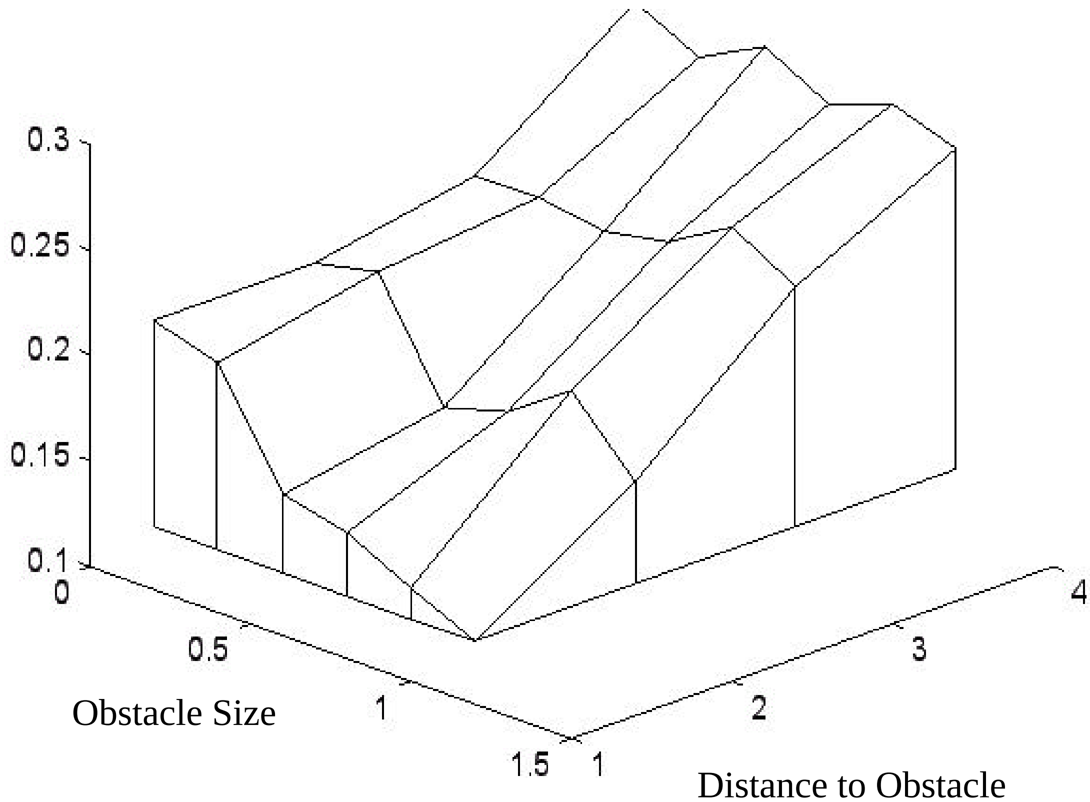


Figure 6

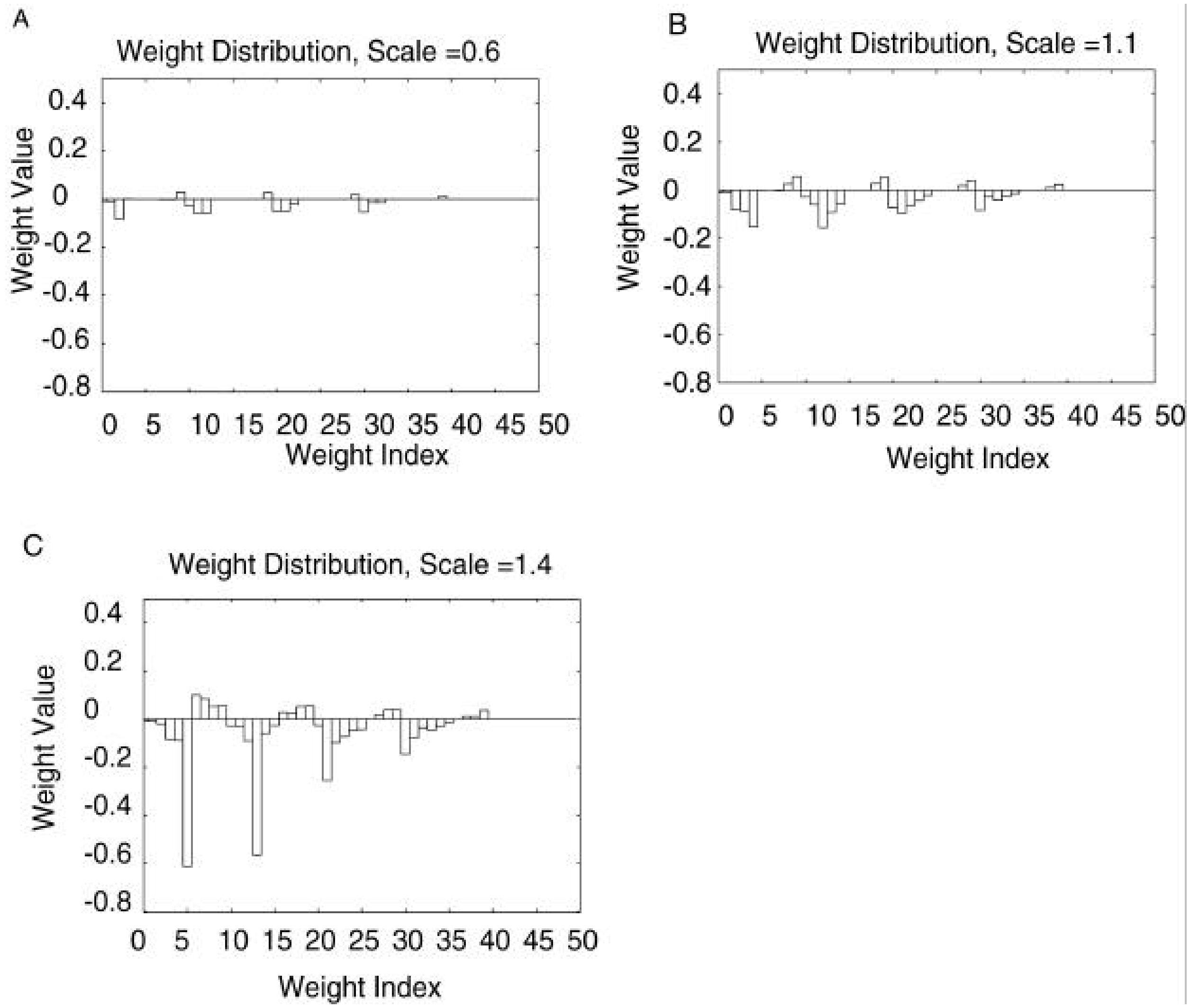

A
Weight Distribution, Scale =0.6
Weight Value
Weight Index
B
Weight Distribution, Scale =1.1
Weight Value
Weight Index
C
Weight Distribution, Scale =1.4
Weight Value
Weight Index
0.4
0.2
0
-0.2
-0.4
-0.6
-0.8
0 5 10 15 20 25 30 35 40 45 50

Figure 7