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Perception Driven Robot Locomotion

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Abstract- *The problem of robot locomotion has historically been considered as a problem in control. Despite years of research by many labs, the best robots cannot match the general performance of a human child.*

Here we suggest that we re-examine the focus on control and consider locomotion from a new perspective, that of perception.

This new perspective is suggested by recent results in the incorporation of visual information with walking and in the incorporation of reflexes during walking.

It is suggested that a key role of the central pattern generator is to coordinate the fusion of the influence of perception on the step cycle.

1. Introduction

Walking machine research spans about 40 years. The Phoney Pony, built in the 1960's at the University of Southern California [2], is considered the first computer controlled walking machine. Since then, the Leg Lab at MIT has given rise to machines that hop [3], perform gymnastics [4] and that walk using simplified control laws [5].

Dynamical systems techniques have been exploited in real robots. Case Western Reserve University has produced a number of highly capable hexapod robots based on inspiration from insects [6]. Recently developed quadrupeds using dynamical coupling of the environment, the robot's mechanics and its control system have been demonstrated [7, 8].

We have investigated how to use adaptive techniques in the context of the dynamical systems approach including robots that learn how to walk [9, 10].

Advances in the construction of robots and actuators has made significant progress recently. Researchers at Stanford have been highly innovative in fundamentally changing the way robots are constructed [11] and in the realization of a hexapod with extremely high running frequency [12]. Exceptionally highly crafted commercial robots from Honda and Sony have been recently introduced. The MIT leg lab has developed an innovative series of elastic actuator which is perhaps the first self-contained electric actuator suitable for systems that couple environment and robot dynamics [13].

Finally, the problem of addressing coupling of the environment to the robot using long-range sensors (as opposed to joint sensors and contact sensors) has recently been addressed. The ambler at CMU was one of the first walking machines to effectively incorporate distal sensor information in the selection of gait [14]. Very recently, work has been done developing methods for smoothly modulating gait based on visual perception [15, 16] in the context of dynamical systems techniques.

However, given so much research effort, robot locomotion has not reached its potential. Humans, in contrast to walking robots, are capable of much more than slow, stable gaits (or even dynamic hopping). In normal situations, the human may change direction, avoid bumping into other people, step onto a moving platform, descend down a ladder, play a game of soccer, skip rope or stand on the deck of a rocking boat.

Common to all of these tasks is swift, smooth coupling interaction with the environment.

A common lament among researchers is that walking machines are difficult to *control.* There is often an assumption that the key difficulty in walking machines is the control problem. This belief may be a key unexamined assumption of walking machine research.

It is evident that the gateway from the environment to the robot is via *perception.* If the robot cannot perceive what the environment is 'suggesting', then the robot would have a perceptual blindness that cannot be compensated by the most sophisticated control. Perhaps less emphasis should be placed on control and more on the problem of perception.

Here we examine the walking machine problem from the point of view of *perception*, and propose that 'control problems' may be rooted in choosing the correct perceptual elements to extract from the world.

The organization of this paper is as follows.

(1) We will argue that the control of walking is intimately linked to perception.

(2) We will recast the central pattern generator (CPG) system, found in the spinal cord of animals, as a structure for integration of perception.

(3) We will discuss the problem of perceptual overload. We will outline a general strategy for sorting meaningful information from an enormous flow of perceptual information generated during walking.

(4) We will discuss how to associate potentially meaningful percepts with motor actions.

(5) We will discuss future challenges in walking machines and perception.

2. The Locomotion/Perception link

Walking machines feature an array of sensors: touch, force, vision, and vestibular. However, the control system of a walking machine requires more than sensory information. Walking machines require *perception*.

For our purposes, let us define perception as the process of computing a percept, or an element of knowledge about the robot-environment relationship. Percepts derive ultimately from sensor information. This perceptual computation extracts fundamental qualities from the sensory array that do not depend on the specifics of the data, but rather on the relationship between sensor elements.

Once percepts are formed, the original sensor information is lost and cannot be recovered by an inverse computation. The construction of percepts is fundamental to the control of walking machines. Many of the problems unique to walking machines are tied to the need to discover an appropriate set of percepts needed for control.

Let us consider certain examples. The Center of Pressure, CoP, (coincident with the Zero Moment Point) is where normal contact forces are balanced so as to produce no net tangential torque on the foot. It can be imaged that at the CoP, the robot could balance momentarily on the tip of pencil. The relationship between CoP and the center of gravity determines a moment acting on the robot's body.

From CoP, it is impossible to reconstruct the unique foot forces that gave rise to it. Therefore, we consider the knowledge of the CoP point as a percept. In a similar way, FRI or Foot Rotator Index can be considered a percept. The reader is referred to Goswami's work for a comparison between the CoP, ZMP and FRI concepts [17].

An open question in human perception is whether CoP or FRI or neither are perceived and used in the control of human locomotion.

Now, even if FRI or CoP is a kind of perception, it may not be a particularly useful perception. A useful perception might be one that indicated an impending fall which requires a certain kind of correction. Or, a perception that indicated that given the current state, new motions are now possible (such as a quick turn, or a jump or a braking motion). CoP/ZMP or FRI, in themselves, would probably not be useful percepts. Rather, perception of the CoP/ZMP entering certain zones, at certain points of the step cycle, might form the basis of percepts which trigger stabilizing force application.

Another example of perception, which explicitly connects to action, is the idea of an *affordance*. The environment both assists and inhibits movement. J.J. Gibson made the hypothesis that animals can directly perceive this quality of the environment and called this percept an affordance [18]. Recent neurophysiological evidence has pointed to the idea that areas of the brain dealing with spatial perception may compute movement affordances [19].

Reflexes in animals are a third example. In CPG based systems researchers have found the stumble correction reflex [20] important [8, 16].

In the animal world, if the top (dorsum) of a cat's paw is touched while the limb is in swing phase, the animal will retract its limb in a stereotypical fashion. This behavior prevents the animal/robot from stumbling when contacting a low level obstacle. If the limb is in stance, the limb has a decrease in extension, followed by a large impulse which causes an extended flexion in the next swing phase [20].

What is important here is that clearly the animal is forming the percept of 'something that may cause it to trip.'

As before, information is thrown away. It is apparently not important which sensor elements are triggered, as the response is similar even if parts of the leg closer to the body are stimulated.

This stumble correction is a very low level example. However, it is important because it also illustrates how the Central Pattern Generator integrates perceptual information into the step cycle. The response to the percept is clearly dependent on the phase of the step cycle.

A fascinating percept, which is related to the stumble correction reflex, is a visual-tactile response reported by Graziano [21, 22]. Graziano describes neurons in the brain related to spatial awareness that respond not only to touch on the surface of the skin, but *impending* touch. That is, the cell responds to visual information, yet the frame of reference of the visual information is the surface of the skin.

This kind of perception would be remarkably useful in controlling limb movement in cluttered environments.

A final property of perception is that it appears to be used discontinuously. It can be experience sporadically [23]. A perception driven robot needs some autonomous center to generate a stream of commands, unlike a feedback control system.

In summary, walking robots should be thought of as perception driven devices.

3. The role of CPGs in Perceptual Integration

If percepts are computed sporadically, another structure is needed which can generate smooth pattern movement in the moments between the arrival of new percepts. In addition, this structure must be capable of fusing and arbitrating between many perceptual inputs. Further modulations suggested by percepts should be smoothly integrated into this system.

In biological systems, the Central Pattern Generator circuits in the spinal cord and associated structures fill this role.

CPGs have been well studied and applied to the control of simulated and real robots [8, 9, 24-33].

A central feature of the CPG is that in the absence of sensory of higher level input, these circuits will produced a pattern of rhythmic activity sufficient to generator locomotor like motion of limbs.

In the example of the stumble correction reflex, we clearly see the so-called phase dependence of the response.

Finally, due to the overall organization of the spinal cord, all higher level commands must be integrated in this region before proceeding to the muscles. Direct control of the limb and digits is an exceptional case seen in few species.

Thus, while this center has been modeled as a rather simple group of coupled oscillators, fully explaining the mechanism within the spinal cord of animal may shed light on how to fuse perceptually triggered commands.

4. Perceptual Overload

A robot/animal's sensory array is continuously stimulated during movement. Because locomotion is largely periodic, much of this sensory data is repetitive, predictable, and can therefore be separated and filtered out from the rest of the incoming data.

All animals have this ability to separate the perceptual consequence of self-generated movement from that of their environment. For example, certain fish hunt prey using an electrosense sense system. Movement of the body can activate this system. These fish are able to cancel out this self-generated stimuli by predicting the consequences of self-generated movement [34]. This ability involves a cerebellar-like structure.

Movement stimulates most sensor modalities and results in systematic changes in the perceptual stream. For example, optic flow, stereo perception, tactile stimuli all changes during locomotion. How can the robot (or animal) distinguish self-generated stimuli from that generated by the environment?

A simple structure for accomplishing that is given shown for the case of Optic flow in Fig 2. In this case, computation is applied to the visual stream to create perceptual elements indicating 'optic flow' (or more correctly normal flow) in the image.

At the same time, CPG phase information is presented to a Neural Network Predictor. The phase information uses interval coding. At each instant in time, a subpopulation of neurons within the neural network predictor are activated by this phase signal.

The activated subpopulation can then learn an association between OF events and joint position information.

As a result, a prediction can be made of what OF events should be experienced by the robot at a particular time. This expectancy reflects the flowfield generated by self-movement.

By comparing the expected versus the actual OF field, it is possible to tease out fine variations in the environment.

Using this approach, we could find a 1 cm high surface variation while walking [15], see Figure 2.

The identical structure is not dependent on the perceptual type. We can identify anomalies in tactile foot patterns and stereo information as well [16]. For example, as the robot is walking, a very tiny push on the robot's body is easily

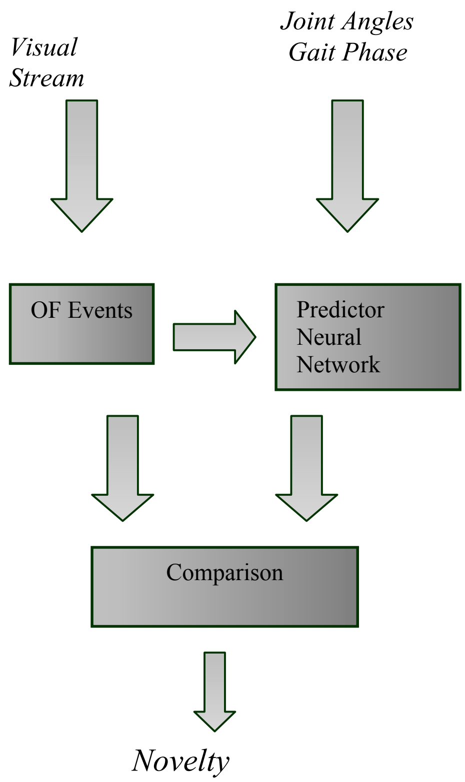

Figure 1. Prediction of Optic Flow Processing. Based on Gait phase and joint angle, a Neural network predicts possible OF events in the image. Simultaneously, a visual stream is processed and optic flow events are generated from real data. The Neural Predictor updates its estimates. A comparison module computes the difference between the actual and expected optic flow events. The comparator adjusts its sensitivity based on statistical assumption about the frequency of 'novel stimuli' in the environment. If the rate of novel stimuli reaches a predefined threshold. The robot stops, having detected an environmental anomaly. In future implementation, this anomaly detection may be used to adjust foot placement and trigger the robot to step over the obstacles. See a description of how this was done using another visual cue, stereopsis, in.

extracted in the sensory pattern of tactile foot falls.

5. Associating Novel Precepts with Action

Using the prediction system described above, we can tease out anomalies in the perceptual stream. What remains is to produce some action based on these anomalies. This forms an association between an perceptual anomaly and action.

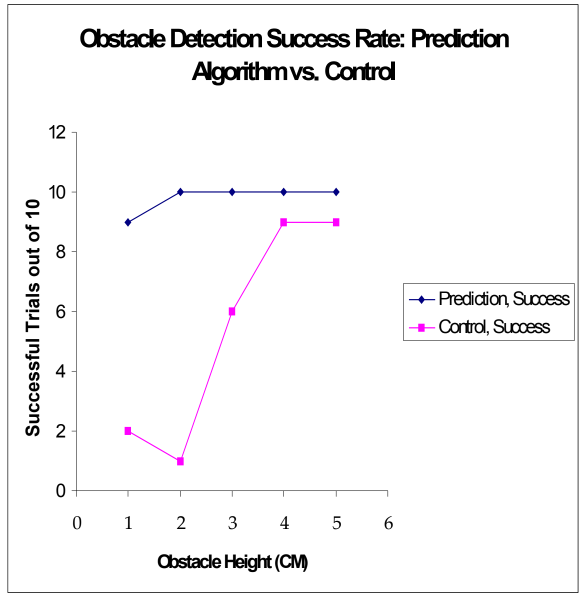

Figure 2. Obstacle detection success rate. The light gray line indicates success rate when no phase dependent prediction is used. As can be seen, objects must be about 4 cm or taller to be reliably detected. In contrast, the dark line shows the success rate with prediction. The results are much better, particularly for small feature size. See [1] for a full description of the experimental setup.

In order to form an association, we must determine which events are meaningful. To do this, we must identify events which have motor consequences.

In [16]we used the occurrence of a stumble reflex as an indication that something is wrong. Kimura and colleques [35] have illustrated nicely how various reflexes can be used to quickly correct gait before the robot falls over by use of a reflex interacting with the pattern generator circuits.

We used a similar reflex as an indication that a destabilizing event occurred.

Then, by the use of reinforcement learning techniques, we formed an association between novel stimuli and the reflex in question.

Once this association was learned, the next time the robot encountered the same anomalous stimuli pattern, the appropriate reflex was triggered before the robot reached the obstacle. As a result the robot stepped smoothly over obstacles. See Figure 3.

6. Future Challenges

The initial work has yielded very encouraging results. Under the paradigm that we have

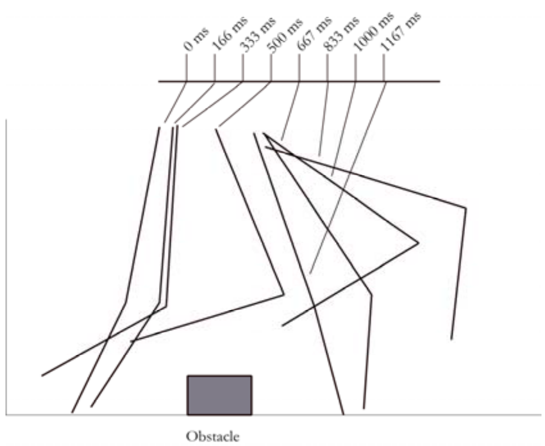

Figure 3. From video data of the real robot while stepping over an obstacle. Kinematic diagram of the right leg of the robot stepping over an obstacle under automatic control of the learning algorithm here.

outlined, the following questions must be answered:

What is the appropriate set of percept necessary to guide locomotion? These will include visual, vestibular, and contact pressure cues etc.

Second, how do we form perceptual expectancy caused by self generated movement under every possible configuration a robot may get into. Humans take a very long time to learn complex locomotive tasks. Perhaps this time is being used to learn new perceptual structures. We speculat that once a robot does evolve this capability, it may experience some of the same maladies of humans including motion sickness, nausea, and possibly dizziness.

Third, a problem not mentioned here is that in order for a system to learn what is expected, it must be able to generate a nominal gait on its own, and within the context of CPGs. Recent work [10] illustrates how a CPG can be tuned automatically to generate walking in a quadruped over a range of initial condition. A similar strategy should be developed for bipeds if possible.

Fourth, we must consider the problem of voluntary changes in movement. Certainly, a robot one day be able to 'dance' with the environment and interact smoothly with it. Yet it must also be able to choose between alternatives in order to truly duplicate human locomotor capability.

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