

## Certain Principles of Biomorphic Robots

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*Abstract-The field of biomorphic robotics can advance as quickly as clear principles of biological systems can be identified, implemented, and tested in robotic devices. Here, we describe the implementation of three principles: (1) The prediction of the sensory consequences of movement and its role in the extraction of novelty and awareness; (2) Learning affordances and the direct perception of what an agent can do at a particular instant and how it can do it; (3) Exploitation of the physical dynamics of a system to simplify robot control.*

### 1. Introduction

In this article we outline three general principles of biomorphic robots which may be particularly useful in the design of future autonomous robot explorers. We will illustrate these principles by recent work at Iguana Robotics and in conjunction with collaborators.

The principles are: (1) Prediction of the sensory consequences of movement; (2) Learning affordances using neural methods; (3) Exploitation of the natural system dynamics to simplify computation and robot control.

### 2. Prediction of the sensory consequences of movement and extraction of novelty

An animal's sensory system is presented with volumes of sensory data. Some of that data results from changes in the surrounding environment. Yet significant sensory stimuli results from voluntary movement of the animal. Examples include: optic flow, tactile, and proprioceptive information from joints and muscles. The animal must disambiguate self-generated stimuli from environment generated stimuli. This ability is ubiquitous in animals, from electrosense in fish (Bastian 1998) to the prediction of tactile self-stimulation in humans (Blakemore et al. 1999).

We briefly describe a robot mechanism that detects fine environmentally significant data embedded in significant self-movement generated sensory stimuli.

A 14-cm tall tethered biped is used in the following experiments (See Fig. 1). The tether allows forward/backward and up/down translation of the body. The hip's rotation is held fixed. Two miniature cameras give the robot a view from its feet to the horizon. Images from the cameras are processed to create estimates of disparity at each point in the image. Pixel-wise disparity data is summed over large, non-overlapping, receptive fields. Two vectors ('left' and 'right') of these cells encode surface information in front of each foot in 'disparity vectors.'

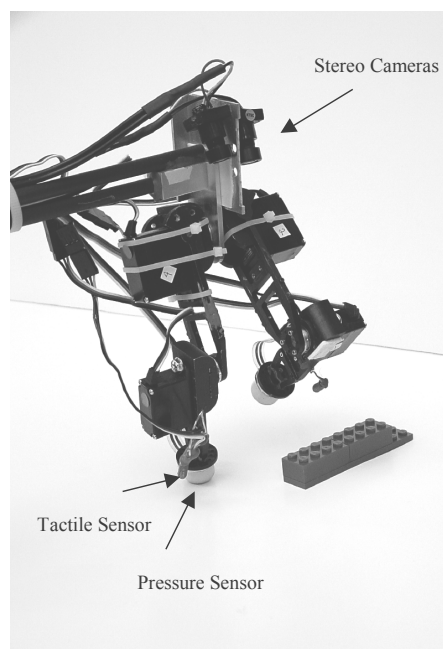


Figure 1. Biped used in the visual control of gait experiments.

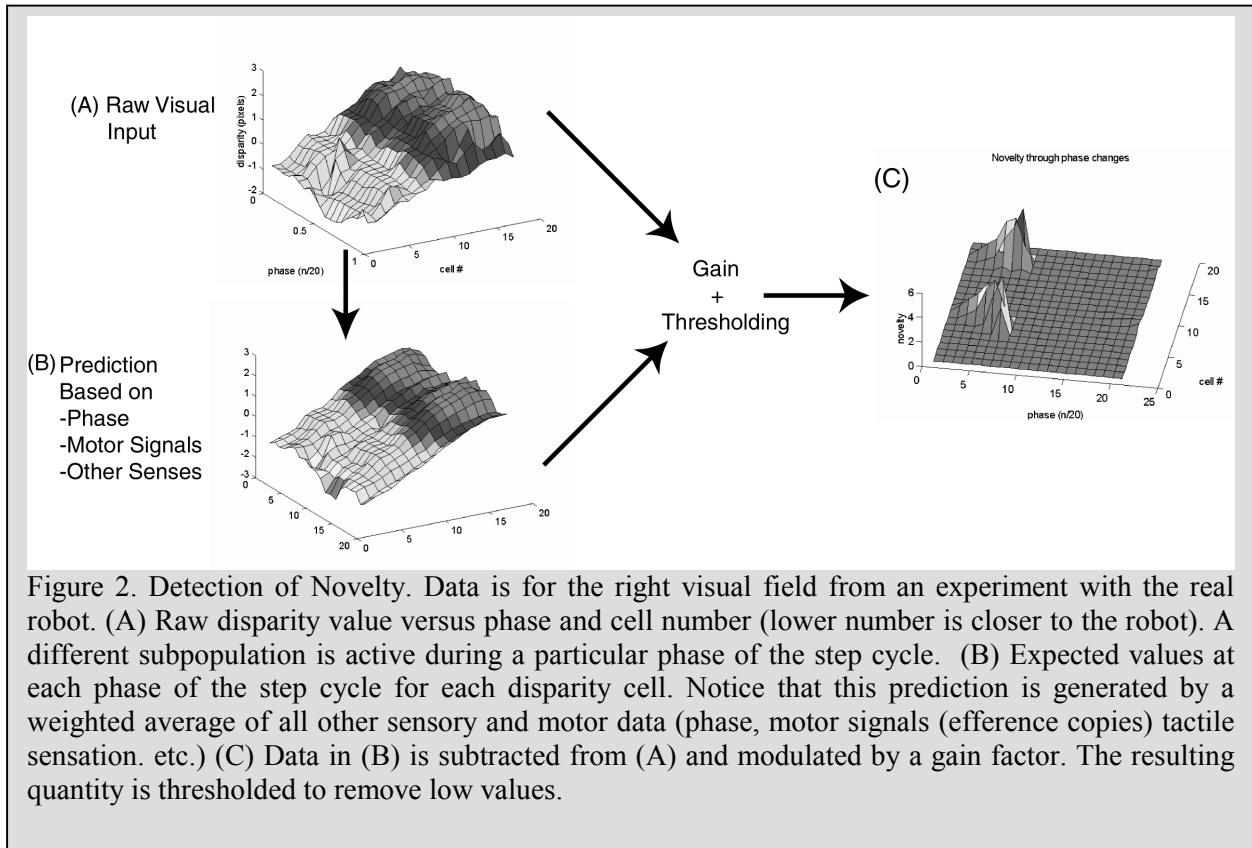


Figure 2. Detection of Novelty. Data is for the right visual field from an experiment with the real robot. (A) Raw disparity value versus phase and cell number (lower number is closer to the robot). A different subpopulation is active during a particular phase of the step cycle. (B) Expected values at each phase of the step cycle for each disparity cell. Notice that this prediction is generated by a weighted average of all other sensory and motor data (phase, motor signals (efference copies) tactile sensation, etc.) (C) Data in (B) is subtracted from (A) and modulated by a gain factor. The resulting quantity is thresholded to remove low values.

A dynamic attention mechanism (see Fig. 2) detects unexpected visual stimuli based on the state of all perceptual information and the locomotor controller (i.e. Joint commands, tactile, disparity, and phase of gait information.) The three key layers are: (1) Raw data input, (2) Prediction, and (3) Novelty detection.

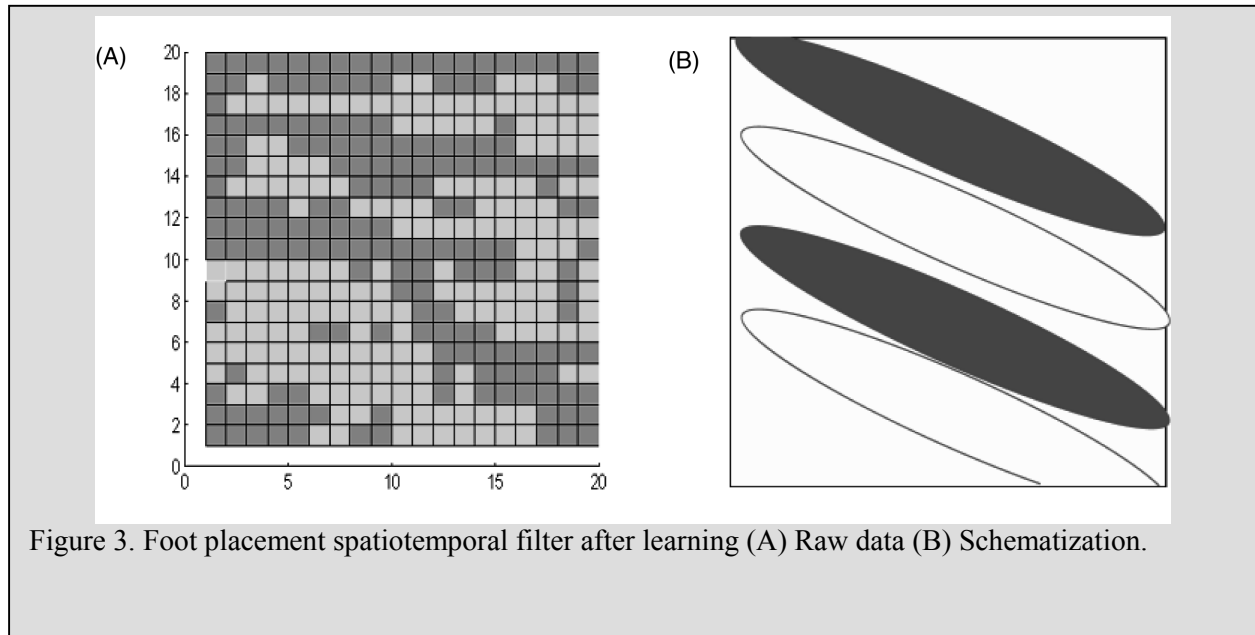
*Raw data layer*—Figure 2(a) shows the activation of the right disparity vector cells, with 18 elements, versus phase, which is divided into 20 discrete segments, for a total of 360 cells.

*Prediction layer*— Figure 2(b) shows the activation of the prediction layer, also organized by disparity and phase. Each cell receives input from all sensors (encoded in a sparse code). The weight for each signal is determined by a Woodrow-Hoff LMS associative learning rule, where the target is the activation of the corresponding cell in the raw data layer. The learning rule minimizes the weight from sensors with little predictive value and maximizes those with good predictive value. This adaptation is continuous through the ‘life’ of the robot. The

overall architecture is robust against loss of any sensor modality as all sensory information contributes to prediction of each other sensor.

*Novelty Layer*—The novelty layer receives the difference between the raw data layer and the prediction layer weighted by a variable *gain* factor. The gain factor for novelty detection varies due to a local feedback mechanism. The gain adjusts to maintain a low average firing rate at all times. If a certain cell has little predictive value, the cell's gain is reduced. If other cells predict the actual sensory input very accurately, that cell's gain is increased, allowing finer discrimination. The output function of the novelty layer is a hard-limit threshold.

In practice, during walking the robot detects fine environment features such as steps less than 6mm thick, corresponding to a fraction of a disparity value. Disparity values can easily vary +/- 1 disparity value for a particular cell during walking and 3-4 disparity values between cells. Learning converges rapidly: Good predictions are obtained within 120 seconds after initiation.



As a result of creating expectancy, the robot also learns to expect a smooth surface in front of it when trained on a smooth surface, and without being explicitly told about smooth surfaces. Hence the surface in Fig. 2(b) appears as a slanted plane. The valleys and ridges are due to the up-down motion of the robot versus phase of gait.

The same algorithm has been applied to tactile foot sensor prediction. By using the same techniques for novelty detection as in the case of visual input, the robot can easily detect an experimenter's light touch on the robot, or other subtle disturbances during locomotion.

Through these mechanisms, the robot is 'aware' of unexpected features in the environment as well as the sensory consequences of its own movement.

### 3. Learning Affordances: Automatically Linking Perception and Action

The environment both enables and impedes locomotion, to varying degrees, depending on the animal or robot. For example, a smooth, flat, level, hard surface allows locomotion for most bipeds. In Gibson's terminology, a floor is a locomotor *affordance*. Gibson postulates the direct perception of affordances (Gibson 1986).

Affordance encompasses *how to perform an*

*action*. A person, seeing a mug, immediately perceives the way(s) to grasp it. Affordance perception includes the motor capabilities of the observer. Arbib (Arbib 1997) has linked affordances to neural substrates in the brain.

How might a neural system learn an affordance? We study this question in the biped. Our paradigm is the problem of visually triggered gait adjustments prior to and during stepping over a small obstacle.

There are two key desirable behaviors in a robot when surmounting an obstacle: (1) Foot placement adjustment and (2) stepping over the obstacle at the correct time. Prior to the last steps before going over an obstacle, the robot must adjust its foot placement to step smoothly over the obstacle. Without these adjustments, the robot may need to break its stride. The robot must recognize *when* to lift its foot. It must accurately predict a collision with the obstacle and step at the correct time, and integrate the corresponding adjustment with the step cycle to prevent collision or loss of stable posture. This is called the step-over capability. Here we focus on the foot placement.

The robot faces a demanding perceptual problem: "*How does it know what constitutes an obstacle without being told?*" Both terrain with

and without obstacles produce complex patterns of visual stimuli. If the robot collides with the environment, how does it refer back to what it saw previously and use that information to adjust its control system to not make the same mistake again? Here, an obstacle becomes implicitly defined as any potentially destabilizing element of the environment.

The solution involves the integration of a Central Pattern Generator (CPG) based locomotor center, learning modules, visual perceptual modules, and tactile reflexes. Lewis and Simó (1999) described a method of adjusting stride length during locomotion. The purpose of that algorithm was to determine a mapping between visual input and modulation of the CPG so that the robot will gradually adjust its stride length prior to encountering an obstacle. This study was done in simulation.

Recently that algorithm was extended to the case of a real-robot biped (Fig 1.) Briefly, the learning computation is as follows: (1) Novel events are detected following the computation in section 2.0; (2) An activated novelty cell triggers an ‘eligibility trace’ (Sutton and Barto 1998). This is a short-term memory delay signal which allows association between future and current events; (3) If the robot’s foot collides with the environment, a training signal is sent to a mapping from the novelty cells to a variable that adjusts stride length in the CPG. The training signal can be positive  $\delta^+$  (increase stride length) or negative  $\delta^-$  (decrease stride length). The actual amount of weight adjustment is a function of the training signal and the eligibility trace.

After learning, we see a pattern of weights that map the novelty cells to modulation of the locomotor CPG. They appear as interleaving bands of positive and negative weights. Figure 3 (A) shows the actual weights and (B) shows a schematic drawing of these bands.

The pattern of the weights is reminiscent of spatiotemporal filters for velocity estimation in a 1-d array. However, while the cells are responsive to moving objects, speed is *not* measured as distance per unit time, but rather

*distance per unit phase. Perception is thus scaled to the size of the robot.* The interested reader should compare this to the concept of PI units (Warren 1984).

#### 4. Complementary Physical and Neural Dynamics

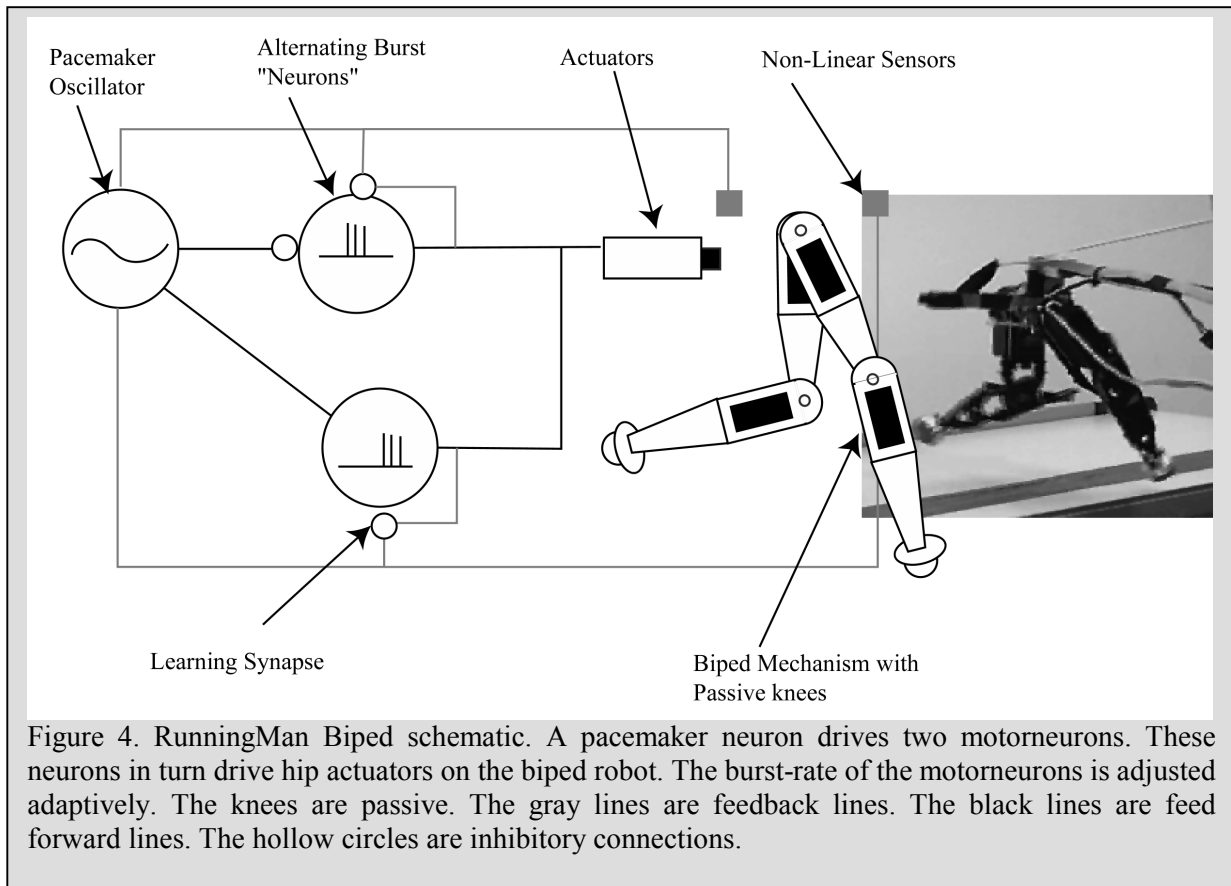
Not all of the wonderful properties of biological systems can be attributed to the nervous system. The biomechanics including muscles, tendons, and the complex anatomy of muscle insertions play a major role in producing smooth, efficient and robust movement seen in biological system.

Researchers have demonstrated and analyzed passive walker dynamics (Collins et al. 2001; McGeer 1990) and exploited the natural dynamics of walkers to simplify control (Pratt and Pratt 1999). The interplay between the neural and physical dynamics has been explored in real robots (Kimura et al. 1999) (and was also pointed out in animals by Russian physiologist Bernstein.)

We consider "What is the minimal system that can illustrate the interplay between neural dynamics and mechanical dynamics?" We briefly describe a running biped driven by an oscillator and motoneurons, and implemented in a custom VLSI chip. On this chip, neurons are simulated using just a handful of transistors and capacitors. Some of the details of this work have been published in (Lewis et al. 2000). Here, we review and extend these results.

Figure 4 shows a schematic of the mechanism’s control system. A pacemaker oscillator sends signals to two motoneurons, one with an excitatory, and the other and inhibitory synapse. The motoneuron outputs are summed and drive the two hip actuators. Non-linear feedback (in this case, a step function) is provided to the pacemaker oscillator (for entrainment) as well as the motoneurons (to adapt their firing rate to achieve a proper stride length). The dynamics of the lower leg segment (shank) is given by the following equation:  

$$\ddot{q} = (-\sin(q) \cdot \ddot{y} - \cos(q) \cdot \ddot{x} - \sin(q) \cdot g) / l - \lambda \cdot \dot{q}$$
,  $q < \alpha$  where,  $\ddot{x}, \ddot{y}$  are knee accelerations,  $q$  is the shank angle,  $\lambda$  is velocity dampening,  $l$  is the shank center of mass relative to the knee,



$g$  is the gravitational constant, and  $\alpha$  the hip angle.

There are two key observations. First, in the absence of acceleration, the system is an inverted pendulum (with a joint limit). Thus, the system has a natural frequency related to  $\sqrt{g/l}$ . Our system ran at about 2 HZ, close to the predicted frequency of the system (about 3 Hz). Other effects, beyond the scope of this article, account for the discrepancy. Second, translational accelerations and joint accelerations of the knee are coupled. In the biped, the knee acceleration comes at the beginning and ending of the stride. Upon stance to swing transition the knee positive knee acceleration ( $\ddot{x} > 0$ ) causes a negative acceleration of the shank, and knee folding. When the knee decelerates  $\ddot{x} < 0$ , the shank is accelerated toward the joint limit. Video clips of the running robot can be found at <http://www.iguana-robotics.com>.

It is encouraging to note that: (1) A closed loop system using a simple pacemaker, active hip and passive knee can be made to run on a flat surface, (2) The dynamics of the leg and the dynamics oscillator contributed significantly to the overall trajectory, and (3) The computation has been implemented using a handful of transistors and capacitors. This is compelling evidence that the use of the physical dynamics may help simplify computation.

## 5. Summary and Conclusions

Biomorphic robots can give significant insights into how to build more efficient and more robust robots. In this article three principles from biology were explained and examples of robot implementations were given.

The prediction of the sensory consequences of movement is critical for the robot. Implementation of this strategy for all sensor modalities could result in a powerful learning machine that would compensate for sensor failures, identify novel stimuli and give the robot

a general sense of self-awareness and awareness of its surroundings.

Affordance theory suggests that systems should learn to directly perceive how to interact with the environment, and may do so using learning strategies.

Finally, exploitation of the physical dynamics may allow the construction of complex behaviors in rather simple machines with simple computational architectures.

These principles may be beneficial to future NASA exploratory missions. Prediction of the sensory consequences of self-motion will be important in supporting tasks in learning, failure diagnosis, and reconstruction of loss sensor modalities. Learning affordances allows the robot to *learn* direct mapping of sensation to action while respecting (possibly changing) capabilities of the vehicle. Exploitation of dynamics reduces computation and power requirements.

The key block in biomorphic robots has been the slow pace of transferring interesting and important principles to robots. Undoubtedly this is due in part to the multidisciplinary nature of the task, crossing the fields of physiology, psychology, mechanics and machine learning. The studies we have presented, along with the work of numerous others will accelerate this transfer.

#### **Acknowledgements**

The authors gratefully acknowledge support of ONR Grant No. N00014-99-0984 and influential discussions with M. Hartmann and A. Cohen, R. Etienne-Cummings C. Assad.

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