Foot Placement Selection using Non-Geometric Visual Properties

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SYNOPSIS

Geometric information alone is not sufficient to guide foot placement in a robotic device. A travel path may be firm or soft, slippery or sticky and will thus affect locomotion. In humans, associations are made between various travel surfaces and gait modification. If a preferred foot position is unavailable, an alternate is selected. This selection is biased, and not random. Here we present a model of alternate foot placement. We demonstrate some novel properties of the model, thus showing its predictive value. We give results in a small bipedal walking mechanism. The power of our approach is that it captures key features of human performance and can be easily implemented in most walking machines.

1 INTRODUCTION

1.1 Affordances and Locomotion

At each instant, the environment presents many potentials for action. Gibson terms these potentials *affordances* [1]. Consider a walking machine traversing a mountain trail. It is confronted with uneven surfaces, obstacles across its path, and sparse footholds. At each moment, the walking machine must select from a variety of actions, that is, where to step, and how to modulate its gait. The identification of each afffordance requires both a detection of the geometric properties of the substrate as well as recognition of surface properties not evident by geometric analysis alone. For example: "Is that surface icy or muddy?"; "Is that the surface of a river that will not support locomotion?"; "Is that obstacle strong enough to support the weight of the robot should it need to step on top of it?" Therefore, while the geometry of the surface is *necessary* for selecting a step, it is not *sufficient* for selecting a step: additional information, determined by learned associations between colour, texture and pattern cues and environmental properties are needed to inhibit potentially dangerous or otherwise undesirable actions.

Clearly, affordances are dependent upon the observer: a patch of ice that is impassable for child may merely require a quick hop for an adult. Thus learning must shape perception and likely continues through the lifetime of a human.

1.2 Human Foot Placement Selection

Previously, Patla reported the choice of alternate foot placements when the preferred foot placement was not permitted [2]. In general, when the most desirable foot placement is not available, humans will choose a longer foot placement more frequently than a shorter foot placement. Human subjects will also choose a medial (closer to the mid-line) versus a lateral foot placement more frequently. These choices can be understood in terms of stability. Choosing longer versus shorter and medial versus lateral foot placement is thought to be more stable for humans. Longer foot place can assist in braking. Medial versus lateral places the centre of pressure under the centre of mass thus reducing lateral acceleration.

From this we can hypothesize that for each spot in front of a human, there can be assigned a preference for foot placement. When the most preferential foot placement is not available, then the next best spot will be chosen.

If stability is the most important factor in foot placement, then the quality of the surface will be important as well as factors related to the momentum of the subject. If a surface has very low friction (e.g. mud or ice), then the preferred step may be shorter. If the subject is moving at high speed over a high friction surface, the preferred step length will be longer.

People undoubtedly learn through experience to assign such values to varying surface conditions and internal states (i.e. the subject's momentum).

1.3 Model Focus

Our focus is on creating a model of foot placement that (1) Uses an explicit representation of foot placement preference; (2) Identifies differing surface textures and maps them to a variety of foot placement preferences; (3) Fuses together multiple foot placement functions and automatically selects the best foot placement given a mixed surface, that is, a surface that may be composed of multiple surface qualities; (4) Is capable of quickly re-planning if the surface appearance changes.

We develop the framework needed to solve this problem. In future work we will address the on-line determination of parameters needed to instantiate this framework.

2. MODEL OF FOOT PLACEMENT SELECTION

2.1 Robot System

The robot setup is shown in Figure 1. The robot is a small bipedal mechanism powered by 4 hobby type servo motors. A single downward looking camera monitors the surface in front of the robot. All visual processing is done off board on a PC workstation. Small coloured paper cut-outs of various colour and texture were used to simulate various walking surfaces.

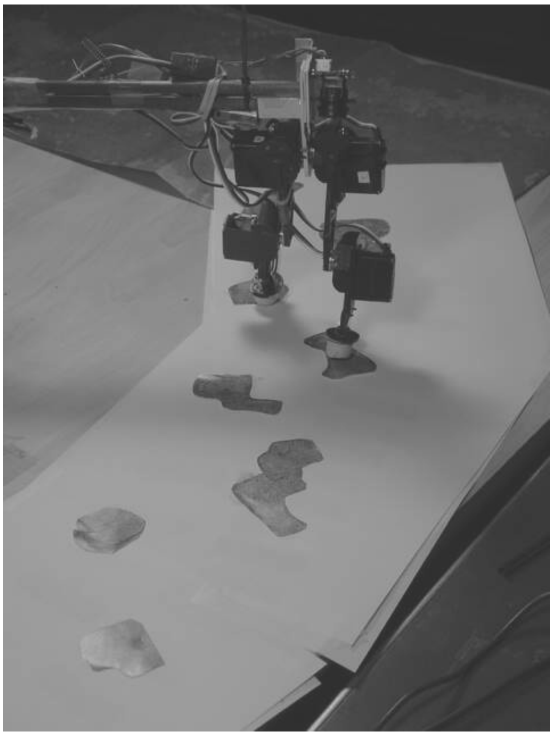

Figure 1. Experimental setup. A small (15cm) bipedal mechanism is shown. The textured regions represents areas of high walking utility, the white regions represent areas of low walking utility.

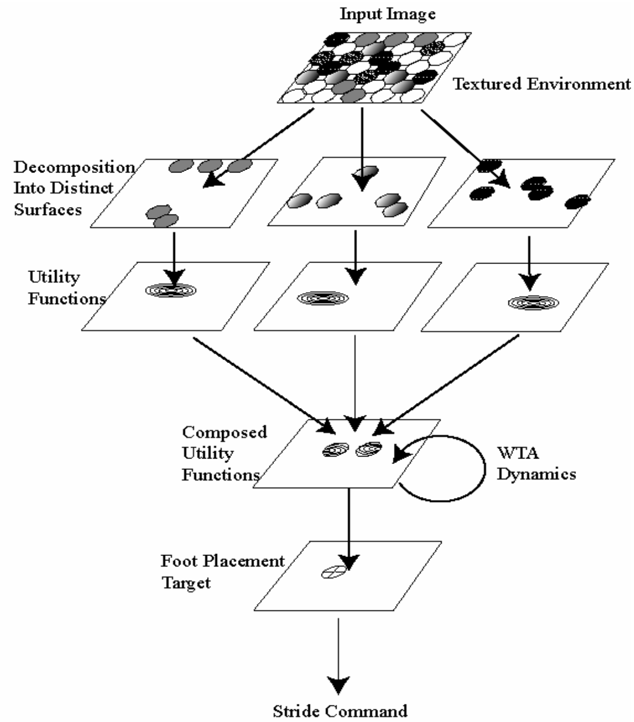

Figure 2. Processing architecture of robot. See text for details.

2.2 Dynamic Fusion Model

In Figure 2, we see the flow of information processing in the model. The input image consists of a combination of various surfaces. Each surface region is characterized by a distinct combination of texture and colour. The input region is divided into small patches. We assume that a resolution of approximately 0.5 foot widths will be sufficient for directing foot placement. The choice of this sampling resolution is arbitrary and may be driven by the foot placement requirements of the robot. The incoming image is divided into many subregions according to this criteria. Each of these regions may be classified into exactly one of several classes. In some instances in the environment, a certain region may belong to several classes. For example, a water surface covering ground is optically a mixture of two surfaces: the top surface of the water and the ground underneath. Further, a liquid may have suspended particle partially obscuring the ground beneath. In this work, multiple class membership problem is not addressed.

Because the camera of the robot is fixed, the retinal image is essentially identical to an egocentric map. In the case where the camera must pan and tilt, a system might be used to rotate the retinal image into egocentric coordinates. Pouget has proposed an elegant solution to this problem [3].

This retinal image is segregated into several maps. This segregation is done for the sake of clarity. It is not supposed that the brain spatially separates these maps. Instead, these maps could be intermingled in the same brain region.

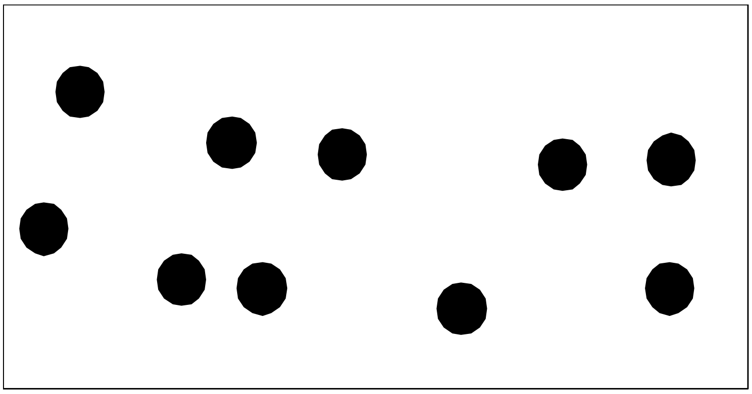

Figure 3. A typical test track used in the experiment. Alternate foot placement experiment. Illustration drawn from actual travel path used.

In the next level of processing, each surface region is classified into one of several possible classes, e.g. "slippery surface" or "solid surface." In this case many types of surfaces, for example, wet tile, wet linoleum, an icy sidewalk, and mud might be under the same class and will ultimately be considered as equivalent surfaces to walk on. Over time, these surfaces might be distinguished in a finer manner, i.e. mud may constitute its own class separate from "icy sidewalk." This fine-tuning can lead to finer movement control.

Each class has a utility function associated with it. This utility function tells us which are "better" foot placements according to some criteria. We have argued that stability is likely the key criteria used by humans. The separate maps are then integrated in a dynamic fusion layer where a Winner-Take-All type neural network selects foot placement.

3.0 EXPERIMENTS IN A REAL ROBOT

3.1 Real Robot Experiment

To test our model, we performed three experiments with the real robot. Throughout the experiments, the camera provides a scene of 640x480 pixels and we divided it into 21x16 blocks using a unit block size of 30x30 pixels. We assigned index number 15 to blocks in the row nearest the robot and index number 0 blocks in the row farthest from the robot. Block index numbers are used to control the robot's stride length and to set the centre of the utility functions.

Targeting, or causing the foot to land on a specific point in the image was achieved by training a 2 layer radial basis function network. The input to the network was the step length of the previous step and the block index number. The robot's step length control command is set to be an integer value in the range [0,50]. This function is somewhat nonlinear but could be learned easily by our network. After training, the commanded step length ranged [6,43] for the left foot and [10,50] for the right foot for visible targets.

3.2 Alternate foot placement experiment

The first experiment is about the selection of alternate foot placement. The focus is to observe whether the robot's foot placement changes when the *affordance* from the visual scene changes. In a real-world situation, this experiment is analogous to stepping on stones in a pool of water. In terms of utility, it is a normal-utility object against a zero-utility background.

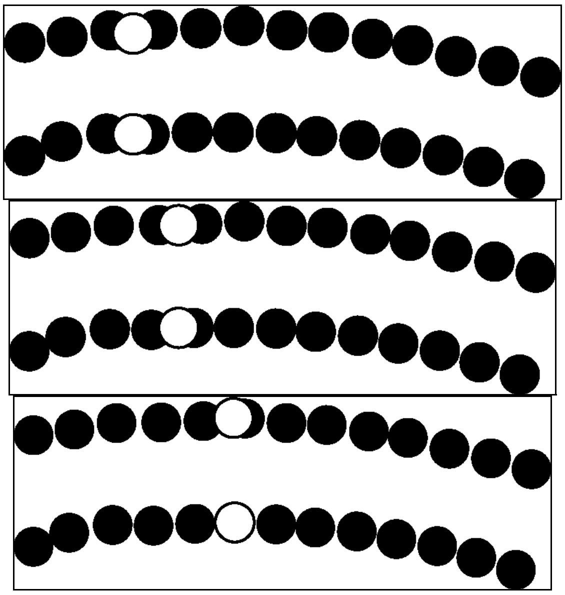

Figure 4. Lengthening dangerous region experiment setup. The filled circles are regions of low utility. The unfilled circles, of high utility. Illustration drawn from actual travel paths used.

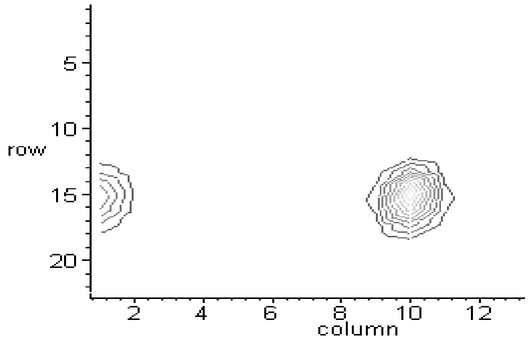

Figure 5. Contour map of utility function for lengthening dangerous region experiment. The peak on the left corresponds to low utility, and the peak on the right corresponds to high utility functions.

Since the robot can move only in forward direction, this experiment is performed by placing highly-recognizable targets that have a good utility function only in front of the robot. The object recognition is based-on colour. In this experiment various brightly coloured targets were used, i.e. blue, red, green, and yellow sticker labels. These were assigned good utility values. All labels are 1.9cm in diameter, approximately equal to the robot's foot width of 1.6cm.

The 10 sticker labels (five labels on each foot path) are freely placed a letter sized graph paper (see Figure 3). Four test tracks containing 10 dots are presented to the robot on each trial. Each test track is presented 5 times resulting in 20 trials with different starting location on the graph paper.

3.3 Lengthening dangerous region

The second experiment is combining two objects that have different peak utility values. If a region ***A*** lies directly on the peak of a high utility region, the algorithm should choose this peak. However, as the region ***A*** moves *off* the peak, the region ***A*** becomes less and less desirable. Finally, another region may suddenly be selected. This corresponds to a bifurcation in the choice of foot placement. That is, the foot placement suddenly changes dramatically. This qualitative effect should be easily verified in human subjects. Figure 4 shows the experimental set up.

For each trial, we changed the placement of one high utility dot (a green dot) for each footpath on the line 5, 10, 15, 20, 25, 30, 35, 40, 45 and 50 on the graph paper. On the other hand, the low utility (red dots) are placed all over the footpaths. See Figure 4. Figure 5 shows plots of both the low and high utility functions.

3.4 Best foot placement selection among multiple objects

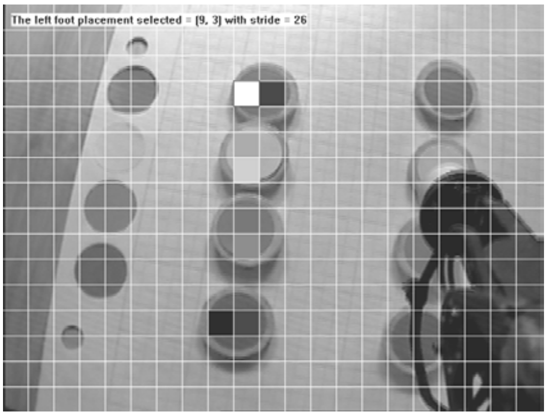

Figure 6: Best foot placement experimental setup.
The utility values are visualized by the grey gradient colour of the matched block.

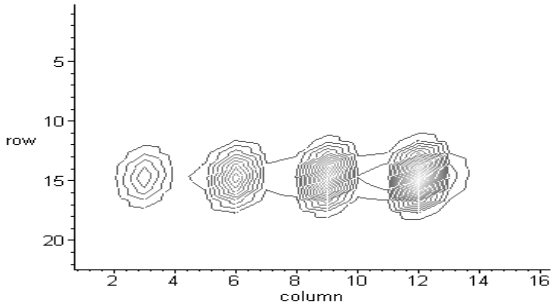

Figure 7. Contour map of utility functions for multiple objects experiment. Column number indicates the distance from the robot. Each peak is the centre of red, blue, yellow and green object (from left to right).

The final experiment is to consider the multiple objects scenario. By assigning different utility function parameters, the robot could find the best foot placement from the mixture of surfaces. We created 8 wooden circular blocks and placed the two green, yellow, blue and red stickers on them so that we can move and mix them freely on the robot's visual field (see Figure 6).
The centre of the utility function is set to 3 for green, 6 for yellow, 9 for blue and 12 for the red dot and the value of the utility function is set to be in the order of green, yellow, red, and blue (the highest for green and lowest for red). This function is illustrated in Figure 7.

4 REAL ROBOT EXPERIMENT RESULTS

4. 1 Alternate foot placement result

We counted the number of foot steps made and the number of correct foot placements.
The correct placement means that the robot's foot touches any portion of the coloured label after each movement. This was scored by a human observer and the overall accuracy was 91.5%. The result is shown in Table 1.

Table 1: Alternate foot placement accuracy

	Steps Made	Correct	Accuracy
Left Foot	59	53	89.8%
Right Foot	59	55	93.2%

Slipping and misalignment account for all errors. Our robot sometimes slips on the right foot when it tries to move the left leg. If the neural network between visual input and stride length command isn't aligned properly due to the lack of training, it generates the wrong stride command even if the selection in the visual field is correct.

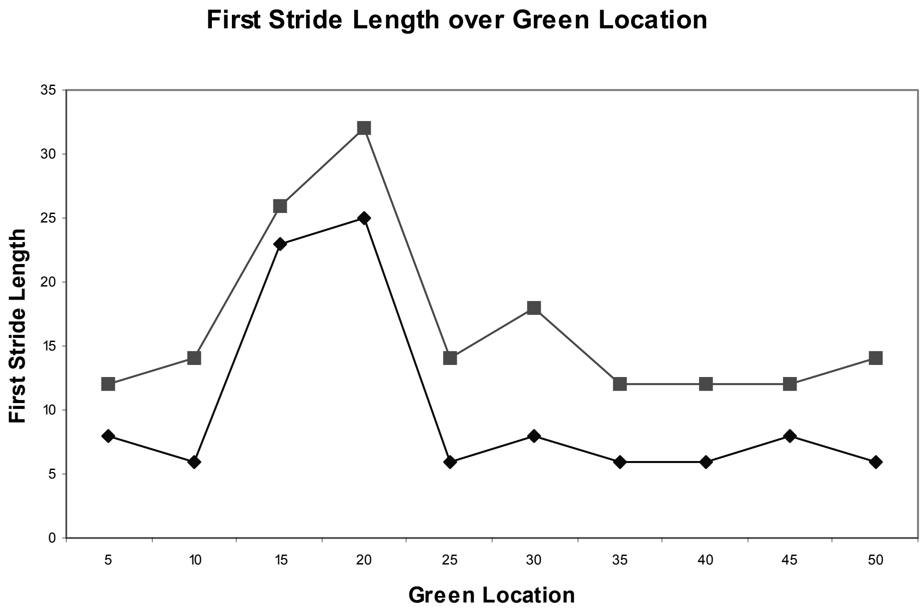

Figure 8. First stride length change against the green dot location. Location 5 is nearest from the robot and location 50 is the farthest. Upper line, left foot, lower line, right foot.

4.2 Lengthening dangerous region result

We measured the each foot's stride length on each movement and, as expected, the stride length abruptly increases when the green dot lies in the near 5th row block. The result in Figure 8 shows that when the robot's maximum stride length cannot afford the safe green region any more, the stride length drops suddenly again. This illustrated a strong bifurcation.

4.3 Best foot placement selection result

Table 2 shows the result of the controlled placement of each wooden piece exactly on row 3, 6, 9 and 12. We enumerated all possible orderings of colours and recorded the foot selection. The result indicates that the robot could pick up the highest utility region if it is within the sweet spot for the foot.

Table 2: The *P* means the best foot placement selection. The left-to-right order means farthest (row 3) from the robot and the nearest (row 12) from the robot.

Order	*P*	Order	*P*	Order	*P*	Order	*P*
G-Y-B-R	G	Y-G-B-R	B	B-G-Y-R	R	Y-G-B-R	G
G-Y-R-B	G	Y-G-R-B	Y	B-G-R-Y	G	Y-G-R-B	B
G-R-Y-B	G	Y-R-G-B	Y	B-Y-G-R	Y	Y-R-G-B	Y
G-R-B-Y	G	Y-R-B-G	B	B-Y-R-G	Y	Y-R-B-G	Y
G-B-R-Y	G	Y-B-G-R	Y	B-R-G-Y	B	Y-B-G-R	B
G-B-Y-R	G	Y-B-G-R	Y	B-R-Y-G	Y	Y-B-G-R	B

5.0 SUMMARY

We examine the problem of selecting alternate foot placement based on *non-geometric* constraints. We have argued that surface characteristics are extremely important in selecting good footholds for both robots and humans. To date, the focus in the robotics literature has been on the geometric properties of the surface.

The main contribution of this paper is a dynamical neural network model that can select good foot placements for arbitrarily complex surfaces. Such a system is essential for any real-world application involving walking robots.

We demonstrated that (1) The robot could select a good footholds on stepping stones placed freely in its path. (2) A sudden bifurcation effect illustrated a sudden switch in foot placement selection. This effect forms a prediction for human studies. (3) The correct foot placement selection in a complex field of objects was selected consistently.

A shortcoming of this current model is that it selects foot placement in a highly deterministic fashion. Human selection is biased but variable. The source of this variability remains a open question.

ACKNOWLEDGEMENTS

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