INTRODUCTION
Classical symbolic systems in psychology have proven to be powerful in explaining human cognition and behavior, especially in contrast to the preceding behaviorist approach. The engineering aspect of this approach, symbolic artificial intelligence, has similarly shown itself to be capable of mimicking and often exceeding average human cognitive abilities. However, both the cognitive science and AI communities have experienced an increasing dissatisfaction with these approaches within the last decade or so. The problems manifest in both fields are similar. The things humans do with the most ease (e.g., recognizing patterns, moving around in the world, learning to speak) are the most difficult to explain and mimic with a symbolic approach. In both domains, this dissatisfaction has led to the acceptance of different viewpoints. In cognitive science, connectionism and ecological psychology are having major influences, and in AI, specifically the fields of robotics and computer vision, distributed or non-representational architectures are having a strong impact.

BEHAVIOR-BASED ROBOTICS
In the case of robotics, an essentially new field has developed in the past decade or so and been termed behavior-based robotics (Brooks, 1991a). Although earlier work in robotics has had a few isolated successes in mobile robots, e.g., SRI’s Shakey (Nilsson, 1983) and Moravec’s (1981) CART, these older robots were generally of the “sense-model-plan-act” variety, engaging in quarter-hours of computation between moves (Brooks, 1991b). By contrast, the new approach (Brooks, 1991b) is concerned with creating robots, or more generally, agents, that are 1) situated in the sense of needing to respond now to the environment; 2) embodied, meaning that the agents have bodies and are in a constant, dynamic relationship with the world; and 3) autonomous, in that they are preferably unethered, but in any case, functioning without further input from the designer, in a word, surviving, and surviving in the real-world and in real-time.

Perhaps the most crucial aspect of behavior-based robotics is that of mobility—the ability to move around in the world, avoid obstacles and seek goals. Since most mobile robots have used sonars or laser-light stripers to sense the world, traditionally most of the work in mobile robots has used this information to create metric maps for planning paths through the environment. Robots using visual input have typically been programmed in a similar way, using two cameras to create a three-dimensional model of the environment, or using one camera at two time frames to do the same. However, the new approach in robotics is slowly creeping into this domain, as evidenced by recent papers (Aloimonos, 1992; Ballard & Brown, 1992; Aloimonos & Rosenfeld, 1991; Nelson & Aloimonos, 1989). These researchers are beginning to ask whether the robot need model the visual world at all before acting upon it.

ECOLOGICAL PSYCHOLOGY
In general, the flavor of behavior-based robotics is very palatable to the field of ecological psychology, first developed by J. J. Gibson. The Gibsonian approach (e.g., Gibson, 1966, 1979) views animals and their environments as “inseparable pairs.” As such, the environment should not be described in terms of physics (e.g., atoms and coordinates) but at an ecological scale with a medium, substances and surfaces existing in a place. Animals perceive the latter not the former, and in the case of vision, they detect the layout of surfaces, not the coordinates and sizes of objects. These surfaces, when illuminated, give structure to the ambient light—that light which comes to any point from all directions. A main tenet of the ecological approach is that the ambient light provides adequate information for the detection of the layout of surfaces without further cognitive processing (e.g., inferences). This view is called direct perception: the animal has direct knowledge of, and a relationship to, its environment through ecological laws. In fact, Gibsonians limit perception “to relations governed by such laws” (Turvey et al., 1981, p. 244).

At any point of observation, an “optic array” is formed of all the rays converging on this point. Since the optic array is different at each point in the environment, as the point moves, the array changes continuously, creating an “optic flow field” (Lee, 1980; Gibson, 1958). This optic flow field specifies a great deal of information, both about the layout of surfaces and about the motion of the point of observation; specifically, the locus of expansion (FOE), that point from which the radial flow emerges, will specify the observer’s heading. Also, if the observer is moving at a constant velocity, then a surface facet, reflecting a ray of light onto the retina at retinal distance $r(t)$ from the FOE, and moving radially from the FOE at a rate $v(t)$, will have a time to contact specified by

$$t_g(t) = r(t)/v(t)$$  \hspace{1cm} (1)
where $\tau_D$ is the “optic variable” tau-global (Tresilian, 1991; Lee, 1976). Information of this type can be obtained because the optic flow is a function of the forces acting on the observer, forming a Law of Ecological Optics, i.e.,

$$\text{flow} = f(\text{Force})$$  \hspace{1cm} (2). \hspace{1cm}

**Laws of Control**

Gibson (1958) described how optic flow might be used by an animal to control its actions. For example, he writes that “to begin locomotion, therefore, is to contract the muscles as to make the forward optic array flow outward. To stop locomotion is make the flow cease…. To aim locomotion at an object is to keep the center of flow of the optic array as close as possible to the form which the object projects” (p. 187). Other rules can be formulated for approaching, steering among, and pursuing moving objects.

These types of rules have been noted by scientists studying the role of vision in the control of flight in flies. For example, ambient orientation, or hovering, is controlled by cancelling the global optic flow, e.g., purely vertical flow (say, upward) will induce increased thrust by the fly to cancel that flow (Srinivasan, 1977; Gotz, et al., 1979). Similarly, a fly placed in a rotating drum will produce a differential thrust with the two wings, tracking the rotating drum by rotating about its own vertical axis (Collett, 1980).

Warren (1988) formalized these behaviors in terms of laws of control. The Law of Ecological Optics shown in Equation 2 has an inverse, the Law of Specification,

$$\text{Force} = g(\text{flow})$$  \hspace{1cm} (3),

that is, the force acting on the observer is specified by the optic flow. Forces can be due to both internal ($F_{\text{int}}$) and external ($F_{\text{ext}}$) factors (e.g., movement of the medium, gravity). One solution to disambiguate the two sources of force is to make a copy of the intended force ($F_{\text{int}}$) and subtract the expected flow from that observed. To maintain an ambient orientation, say, the remaining force can then be compensated for. However, a consistent relationship between intentions and expectations requires supplemental assumptions. A more parsimonious approach is to act to achieve a desired type of flow. If the organism-environment relationship changes, the optic flow will also change. Thus, to maintain ambient orientation to the environment, a corresponding change in $F_{\text{int}}$ is required. This is a Law of Control:

$$\Delta F_{\text{int}} = g(\Delta \text{flow})$$  \hspace{1cm} (4).

Warren (1988) formalized Gibson’s verbal descriptions of how animals use flow by proposing laws of control which might regulate the flight of flies. For example, the laws of control for maintaining ambient orientation in the face of vertical and horizontal flow, respectively, could be

$$\Delta U = (k/c)\dot{y}$$  \hspace{1cm} (5)

and

$$\Delta (F_L - F_R) = (k/c)\Delta w$$  \hspace{1cm} (6),

where $U$ is the amount of upthrust given by the two wings, $(k/c)$ is the ratio of the drag constant to an optical coefficient, $\dot{y}$ is vertical optical flow, $F$ is the forward thrust given by a wing, and $W$ is the horizontal optical flow. Other laws of control are proposed for approach, pursuit, and landing. Which of these laws the fly follows at any one time depend upon the goals, or “global action modes”, of the fly: mating, foraging, etc. Within each of these global action modes, the objects in the environment “afford” various actions. For example, while foraging, a flower affords landing, other stationary objects afford avoidance, and an open medium affords cruising flight. However, if the fly is not hungry, a flower affords avoidance, and large stationary objects afford approach and landing for rest. Once an action mode is adopted, the laws of control noted above direct the actual output of the fly.

**Ecological Robotics**

To make use of this information, all one needs is a device to register the optic array and optic flow. Most animals have eyes and corresponding visual systems for this purpose, but a CCD camera and a computer can be just as effective for a robot. In fact, the laws of control concerning optic flow can be applied universally to any moving agent with the adjustment of some constants. Thus the study of optic flow for the control of action provides a unique domain in which experiments in two separate fields, ecological psychology and mobile robotics, can have direct relevance and benefit to each other.

That ecological psychology and the new trend in mobile robotics are very closely tied, especially in their relation to the traditional views in their respective fields, can be seen in the following argument. Gibsonians contend that because information about the environment is available and specific, perception can give a non-inferential source of knowledge about an animal’s environment. For example, an animal need not infer that the ground gives way to a cliff in front of it, this it can see and it will avoid moving in that direction. How far into cognition perception plays a role is an open question, but minimally the information contained in both the perception and the action could be used as evidence for other, non-perceptual inferences an animal might need to make. Overall, natural law is pushed as far as possible into cognition, thus putting more restraints on the cognitive system.

On the other hand, psychologists have traditionally believed that the stimuli reaching the animal are im-
poverished and the animal must make a guess as to what the object is (and its relationship to the object) that could have produced the stimuli it perceived. Thus animals perceive only stimuli and base their actions only upon the conclusions of inferences. Animals must have a substantial internal model of the world then to make veridical inferences and survive.

The revolutionary approach of the Gibsonians in contrast to traditional views of perception and psychology (see Reed, 1988) can be summarized in the idea that it is more desirable to put the animal in its environment, than to put the environment in the animal. It is unlikely that animals can contain all the information required; however, they are good at using it when they need it. This is the "fundamental hypothesis" of the ecological approach to vision:

Optical structure specifies its environmental source and ... therefore, mobile organisms with active visual systems that can pick up this information will see their environments and suitably adjust their activity, if and when they detect that information, and only then (Turvey et al., 1981, p. 243, emphases added).

If we replace "mobile organisms" with "mobile robots", this hypothesis is just as applicable. Also, if we substitute "robot" for "animal" in this paragraph, the argument still holds relating behavior-based robotics with traditional robotics. That is, the construction of appropriate perception-action pairs in the robot leads to a non-inferential source of information upon which other aspects of computation (planning, mapping, reasoning, etc.) can be based and by which they can be limited.

EXPERIMENTS
The utility of optic flow for robot navigation has long been known (e.g., Waxman, 1984), but even the most recent work has had a traditional flavor. Although metric models are no longer reconstructed, other types of intermediate representations are still used. For example, Aloimonos (1992) and Nelson & Aloimonos (1989) produce "hazard maps" based on flow-field divergence from which a least hazardous path is planned. Franceschini et al. (1992) developed analog "elementary motion detectors" based on the housefly's compound eye and hard-wired an obstacle avoidance algorithm which produced a "snap-map" of obstacles in polar coordinates. Though not stated explicitly, Horswill (1993) took a more ecological approach. He constructed a robot which looked at the ground and could distinguish the untextured carpet from other textured objects on the floor and thus could relate height in the image to open area. Despite its success, this kind of control law does not have the universality we would like. Using a higher-order optic variable such as motion allows the robot to function in more diverse environments. We propose and show implementation here of two simple laws of control that do not make use of distance, mapping, or raw pictorial information for obstacle avoidance. No goals were introduced as in the previous two references, but we plan to pursue this aspect in the future from a Gibsonian viewpoint as well.

A major problem in using optic flow is the difficulty of extracting robust information from image sequences in real time. Fortunately, Camus (1994) has recently developed an algorithm to do this. This algorithm makes a time-space tradeoff when matching pixel intensities across frames. Instead of searching through all pixels for a best match between frames, the algorithm only searches one pixel distance, but searches for a best match over a number of frames. Thus, the maximum speed detectable is 1 pixel / frame (one pixel is equal to about 0.5' of visual angle in our set-up), and the next fastest speed is 1 pixel / 2 frames, and so on. The algorithm outputs a dense motion field (we use a 32 V × 128 H array of pixels to include peripheral information) and can be run reliably on a SPARC 10 with the control programs at 4-5 frames / second.

Two strategies an agent could use to avoid objects are the Balance Strategy and the Avoid-Closest Strategy. The Balance Strategy acts to equate the rate of optic flow in the left and right halves of the visual field, as observed in some insects (Srinivisan, 1992). The law of control for this strategy is

\[ \Delta R = k(|\hat{w}_L| - |\hat{w}_R|) \]  

(7),

where \( \Delta R \) is the amount of relative rotation from the current heading in degrees, \( k \) is a constant, and \(|\hat{w}|\) is the magnitude of optic flow on one side of the visual field (in our case, the camera and wheels are yoked so the heading is always in the middle of the visual field). A similar method was proposed by Sandini et al. (1993) for two cameras pointing left and right of translation for "divergent stereo". Here we show that one camera pointing forward can also use this strategy to avoid objects and can do so reliably with large agent rotations (up to 12' /frame).

The Balance Strategy would work best when moving down a hallway. As the agent moved closer to one side, the flow would increase on that side and the difference between the flows on the left and right side would dictate the amount the agent should turn. This has the benefit of pushing the agent towards the center of the hall. In addition, during a rotation, the amount of flow should be equal on the two sides, specifying \( \Delta R = 0 \), thus optic flow due to the agent's own rotation is cancelled.

Another strategy is the Avoid-Closest strategy in which the agent turns from the place in the visual field with the lowest time to contact. The control law for this strategy is

\[ \Delta R = \frac{1}{\tau_{\text{min}}} \times \frac{1}{\text{pos}(\tau_{\text{min}})} \]  

(8),

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where \( t_{\text{min}} \) is the minimum \( t_{\text{au}} \)-global value, specifying the lowest time to contact, and \( \text{pos}() \) gives the visual angle relative to the heading. An average \( t_{\text{au}} \)-global value is determined for each column in the array. The shorter the time to contact and the closer the column is to the heading direction, the more the agent will turn away. If \( k \) is taken as the maximum amount of rotation allowed per frame, then this amount of rotation will occur when the agent is one frame away from something that is directly in front of it. A complementary strategy of Seeking-Farthest is also possible, but this could have unfortunate consequences if visually the farthest point in the scene is next to the closest. Because this strategy does not take rotation of the agent into account, the flow information was filtered to give only radial flow.

In practice, if \( \Delta R \) is not above a certain threshold, it is set to zero. A maximum rotation is also set. For these experiments, the robot’s speed was set at a constant 4 cm/s. Because these strategies have been tested in a fairly unmodified computer lab lit only by track lighting, darkness is often a problem. Therefore, we added an emergency reflex of stopping and turning 90° when the average illumination was below a certain threshold. This darkness reflex acts as a fail-safe mechanism as well, i.e., if the robot does run into something, the camera lens will most likely be covered and the average intensity will be below threshold.

The last practical matter is that the Balance Strategy does not help much in avoiding a wall when the approach is head-on. Although noise in the system is helpful in breaking this kind of symmetry, at the frame and translation rates we used, the Balance Strategy itself is not successful in these situations. Consequently, we added an emergency \( t_{\text{au}} \)-reflex based on the average time to contact of a 20 pixel wide patch centered on the FOE (similar to Camus [1994]). If the time to contact is below a critical value (e.g., 4 frames), the robot will stop and turn 90°. This reflex is also present in the implementations of the Avoid-Closest Strategy.

**Apparatus.**

The robot used for the experiment was a three-wheeled, synchro-drive Real World Interface (New Hampshire) 12-inch platform. A Cohu 4910 CCD camera was mounted on top of a metal structure on the base at approximately 2.5 feet above the floor. One computer (Sun SPARCstation 1+) with a frame buffer (Irix 150/151) subsampled the NTSC standard video information down to a 128 × 32 pixel array and passed it by socket to another computer (Sun SPARCstation 10) running Camus’ optic-flow algorithm. The video image and the optic flow were then passed by socket to another computer (Sun SPARCstation 10) which ran the strategies and controlled the robot base.

**Results.**

As mentioned above, the Brown AI Lab where the robot was allowed to roam is typically poorly lit and the area beneath the tables was relatively dark. In addition, the camera was placed on the robot at a height just under the table tops which had black metal rims from which no motion could be registered. However, with these reflexes running and with both strategies, the robot often survived for up to five minutes, the run usually ending because of cable lengths or other understandable reasons, e.g., objects on the floor, thin objects at camera height (chair arms), and textureless objects (chair backs and walls). Another reason it failed at times was because the camera’s visual field was only 60° wide, but the base is twelve inches in diameter. The robot had no concept of its body-width; thus even when the camera safely passed an object, occasionally the robot base would not.

Figures 1 and 2 show maps of the room and the course the robot took using the Balance Strategy and the Avoid-Closest Strategy, respectively. Both strategies are susceptible to dark regions which register no flow (e.g., the table in the middle of the room), in one case because flow is only registered on one side, and in the other case because it is the relatively closest point which is avoided and this will always be on one side. When conditions were close to ideal (good lighting and reasonable distances from textured objects), both strategies worked well. Evidence for this can be seen in Figures 1B and 2B especially, where the robot avoided an object (a hand) which suddenly appeared in its path, and did so reliably.

As the goal here was simply to have the robot wander and avoid obstacles, these strategies were sufficient, considering the resolution of the visual system and the circumstances of the environment. More purposive action could be integrated into these control laws in various ways. For example, a simple way to produce a slightly more sophisticated behavior would be to place constants in the control law for the Balance Strategy (Eq. 7), allowing for a certain amount of flow on one side or the other and resulting in wall-following. Through similar additions to these control laws we hope to expand the robot’s repertoire such that it can play a game of tag. Pursuit, approach, docking, and escape can all be controlled with optic flow alone, as the descriptions by Gibson quoted previously would indicate.

**CONCLUSIONS**

Gibson’s insights into how optic flow can be used by animals to guide their actions have been formalized to some extent in Warren’s laws of control. We noted that these laws are applicable to any moving agent, thus this approach could be very successful in the domain of behavior-based robotics. To demonstrate this we devised control laws for the obstacle avoidance problem in mobile robotics. Two laws of control relevant to the problem were proposed and tested on an actual robot in an unmodified office environment. The success and occasional, yet understandable, failures of these two laws show that the Gibsonian approach to visually guided navigation is very promising.
Overall, the theoretical framework of ecological psychology could help guide the creation of even more complex agent behaviors, a task we intend to pursue in the future. For the moment though, it appears that investigating possible universal laws based on optic flow, such as those we implemented in a robot, can lead to insights into how animals, including humans, might control their own behavior. The Avoid-Closest Strategy, for instance, has not been proposed before. The Balance Strategy, however, is based on work in insects. Thus this avenue of research is a broad, twoway street and the study of control laws based on optic flow provides a unique opportunity for cognitive scientists, computer scientists, and engineers to work together, solving the exact same problems.

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Figure 1. Balance Strategy. A: Trial stopped due to tangled cables; 1250 frames. After rounding the small chair the robot heads for the darkness under the table in the middle. After a few tries it finds a lighter area, which happens to be the textureless back of a chair, which it runs into. It just misses a chair arm, then heads for the other end of the room, swinging into another chair back. It avoids the person's legs and heads down the middle of the room until it rolls over the cables which falsely induce a \( \tau \) value below threshold. B: Trial stopped due to floor debris; 499 frames.

Figure 2. Avoid-Closest Strategy. A: Trial stopped due to running into the back of a chair; 1173 frames. The \( \tau \) reflex helps the robot avoid the chair placed directly in front of it. After circling around in the dark, and avoiding the chair more easily when given time, it heads for the lighter part of the room, missing a person and a hand, before running into the textureless back of a chair. B: Trial stopped due to cable lengths; 1001 frames. Again the robot is positioned just in front of a chair and the \( \tau \) reflex works again. It avoids the hands placed in its path and just misses a chair arm before running into a dark area. It again has problems with the tables in the middle before heading down the middle of the room towards the farthest corner.