Advanced Robotics, Vol. 21, No. 10, pp. 1115–1129 (2007)

Full paper

Integrating robotics and neuroscience: brains for robots, bodies for brains

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Received 7 November 2006; accepted 30 January 2007

Abstract—Researchers in robotics and artificial intelligence have often looked at biology as a source of inspiration for solving their problems. From the opposite perspective, neuroscientists have recently turned their attention to the use of robotic systems as a way to quantitatively test and analyze theories that would otherwise remain at a speculative stage. Computational models of neurons and networks of neurons are often activated with simplified artificial patterns that bear little resemblance to natural stimuli. The use of robotic systems has the advantage of introducing phenotypic and environmental constraints similar to those that brains of animals have to face during development and in everyday life. Consideration of these constraints is particularly important in light of modern brain theories, which emphasize the importance of closing the perception/action loop between the agent and the environment. To provide concrete examples of the use of robotic systems in neuroscience, this paper reviews our work in the areas of sensory perception and motor learning. The interdisciplinary approach followed by this research establishes a direct link between natural sciences and engineering. This research can lead to the understanding of basic biological problems while producing robust and flexible systems that operate in the real world.

Keywords: Humanoid; neural modeling; active vision; learning.

1. INTRODUCTION

Modern robotics faces extraordinary challenges. Robots working in unconstrained environments need to operate and plan their actions on the basis of noisy signals and ambiguous sensory information. Furthermore, in order to remain efficient for long periods of times, these systems need to be able to cope with unpredictable changes in the environment and the functional characteristics of their own sensors and motors. Not surprisingly, researchers in robotics and artificial intelligence have often taken inspiration from the biological world to find strategies for solving their problems. Indeed, nature has faced these very same challenges. During the course

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of evolution, highly robust and flexible organisms have developed, which adapt well to the major phenotypic and environmental changes experienced during their lifetime.

Until recently, the transfer of information from biology to engineering was the primary liaison between neuroscience and robotics. The last decade, however, has witnessed the development of a new link between these two disciplines. Interest in the use of robotic systems has emerged within the neuroscience community, as neuroscientists have recognized that robots offer a means to quantitatively test and analyze brain theories [1–8].

An important contribution to the emergence of this new link between robotics and neuroscience has come from the growing field of computational neuroscience. Computational modeling is a standard tool of brain science as it is in many scientific disciplines. Computational models of neurons and networks of neurons enable levels of analysis which cannot be achieved by means of more traditional *in vivo* or *in vitro* experimental techniques. For example, large-scale simulations of neuronal ensembles allow monitoring of the activity of arbitrarily large numbers of neurons for indefinitely long periods of time, a feat that cannot be accomplished with current neurophysiological techniques. Models also enable the execution of virtual experiments, which the Institutional Review Boards would not permit with animal species. Furthermore, models allow the isolation and selective manipulation of individual elements and mechanisms at a level that cannot be achieved in living cells and organisms. The synergy of these and other features has contributed to the establishment of computational modeling as a highly effective tool to test the self-consistency of theories, refine hypotheses and formulate experimental predictions aimed at validating theoretical proposals.

While models are instrumental in solidifying theories which would otherwise remain at a speculative stage, they do present a significant limitation. In any model, the validity and implications of results critically rely on the accuracy with which biological processes are replicated. Unfortunately, in many computational studies of sensory perception and motor control, this problem is exacerbated by the fact that neural models do not operate in isolation. Instead, these models typically work in conjunction with other models—also limited in accuracy—which replicate the interactions between the phenotype and the surrounding environment. This coupling of different kinds of models often results in a paradoxical situation, in which sophisticated neuronal models are activated by artificial patterns that bear little resemblance to natural stimuli and are exposed to simplified simulated environments, which poorly replicate the environmental changes resulting from motor actions. This problem has fundamental importance, as even the results produced by extremely accurate neural models are questionable if they are obtained in the presence of unrealistic sensory signals. For example, the utility of a developmental model is limited if the constraints resulting from the interaction between the phenotype and the environment are not carefully considered. An extensive body of evidence documents the major influence of sensorimotor experience on neural development. The coupling of neuronal models with robotic systems enables the circumvention of this problem by the introduction of phenotypic and environmental constraints similar to those that the brains of animals have to face during development.

There are two important ways in which neuronal modeling benefits from the use of robotic systems. A first advantage is a more realistic assessment of the degree of robustness of the modeled system. For example, a theoretical mechanism of synaptic plasticity which guarantees adaptability with simulated sensory signals might fail in the presence of realistic noisy inputs. Use of a robotic platform not only eliminates the need to model sensory signals, it also allows examination of the capability of the system for recovering from realistic manipulations of its own sensory and motor characteristics. The functional changes resulting from these manipulations are often difficult to model. A second important advantage resulting from the use of robotic systems is that these systems also give exposure to the sensory signals that occur during behavior. It is known that changes in the sensory inputs produced by planned motor actions provide useful information regarding the structure of the environment [9, 10]. This information, which has also been shown to greatly simplify sensory processes in machine perception [11–13], is extensively exploited by biological organisms. Again, accurate modeling of these sensory inputs is not an easy task and can be completely avoided through the coupling of neuronal models with robots.

In this paper, we summarize results from two research projects to provide concrete examples of these two important advantages resulting from the use of robots in neuroscience. In Section 2, we describe the development and calibration of orienting behavior toward auditory and visual stimuli in the brain of the barn owl. In this study, a detailed model of some of the neural structures dedicated to spatial localization was interfaced to a robotic system emulating the head of the barn owl [3, 14]. Use of a robot provided realistic sensory stimulation and enabled rigorous evaluation of the robustness of a learning paradigm, that we proposed in order to account for the flexibility of orienting behavior in the barn owl. Similar to the barn owl, this system was able to acquire accurate localization of targets in different sensory modalities and maintain efficient behavior even in the face of drastic manipulations of the sensory and/or motor conditions.

In Section 3, we focus on the extraction of depth information that emerges during eye movements. In the eye of many species, including primates, the optical nodal points do not coincide with the center of rotation. As a consequence of this misalignment, a rotation of the eye produces information regarding distance in the form of a parallax. That is, a redirection of gaze shifts the projection of an object on the retina by an amount that depends not only on the amplitude of the rotation, but also on the distance of the object with respect to the observer. We have replicated this parallax in the pan/tilt unit of a humanoid robot. By means of this system, we were able to quantify the depth information present in the human eye during oculomotor activity. Control of this system by means of recorded traces of human eye movements produced accurate estimation of distance. We show that use of this cue greatly simplifies challenging visual tasks such as image segmentation and figure/ground segregation.

A brief discussion in Section 4 concludes the paper.

2. STUDYING ADAPTIVE SPATIAL LOCALIZATION IN THE BARN OWL

Accurate spatial localization is crucial in many animal species. Success in capturing prey or escaping from predators very often relies on the ability to quickly and reliably determine the position of targets. However, redirecting the line of gaze toward a perceived target is not a trivial operation. Different sensory inputs are represented in different manners and spatial cues are not always explicitly available, as in the case of vision. Complex coordinate transformations are required in order to convert sensory stimuli into corresponding motor outputs. Since these transformations depend on the structure and characteristics of sensors and muscles, animals need to learn them during development and continuously tune them during their lifetimes in order to maintain good performance.

It is known that spatial localization relies on neural maps of extra-personal space, which have been found in brains of many vertebrate species [15–17]. These maps exhibit a close multimodal alignment. Nearby neurons are typically activated by stimuli in different modalities originating from the same spatial locations. Furthermore, these sensory maps are often aligned with motor maps of space in which the activation of neurons elicits movements of the eyes and/or head toward different locations. Such a registration among sensory and motor maps implements an economical scheme in which different modalities access a common motor output. However, the mechanisms underlying the development and maintenance of such alignment are unclear.

The barn owl is one of the preferred experimental species by neuroscientists studying spatial localization. The barn owl is a nocturnal predator that relies on accurate visual and auditory localization for hunting. The accuracy of auditory localization exhibited by this species is phenomenal: it is capable of identifying the position of potential prey within a few degrees even in complete darkness. There is little doubt that the barn owl learns to orient toward targets on the basis of sensorimotor experience. Even though the basic features of sensory signals are shared by all owls, the actual values of sensory parameters depend on the morphology of the body. For example, auditory signals depend on the size of the head and the shape of the facial ruff of feathers. During growth, when the body changes significantly in size and shape over a relatively short period of time, the brain of the barn owl must constantly tune the sensorimotor transformations in order to ensure accurate spatial localization. Experimental manipulations of sensory signals have emphasized the flexibility of the owl's spatial localization [18]. Young barn owls recover accurate orienting behavior even in the presence of drastic alterations of their sensory inputs.

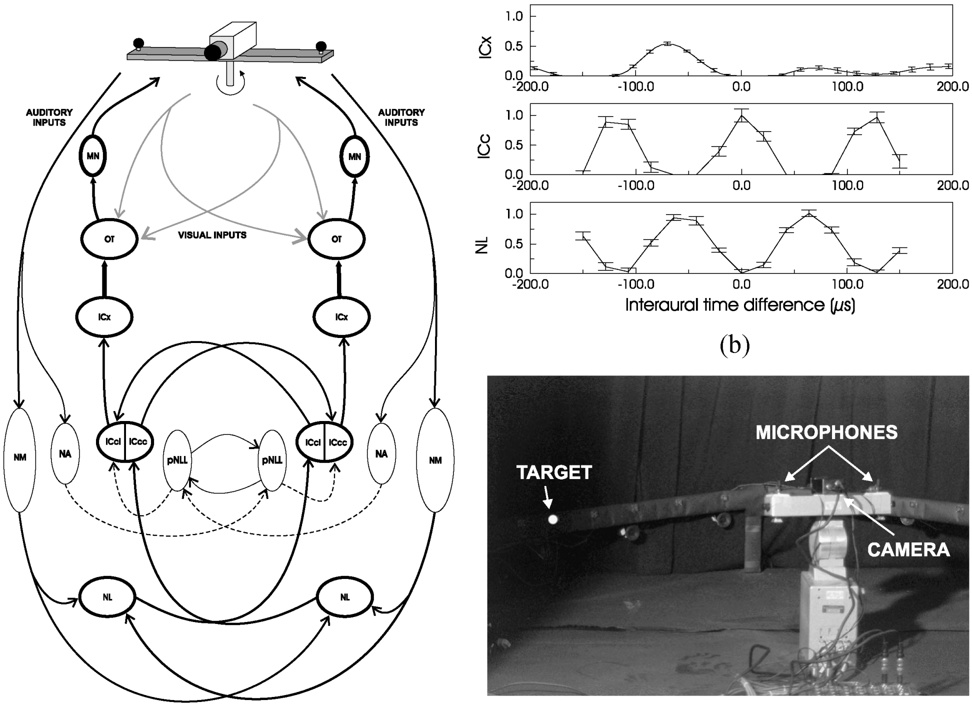
Most studies on the barn owl have focused on the neural pathways converging on, and departing from, the optic tectum. This subcortical multimodal center—the equivalent of the superior colliculus in mammals—is well known to play a critical role in the production of orienting behavior. Detailed anatomical and physiological characterizations of many neural structures present in these pathways are now available. These investigations have revealed that the barn owl relies on the processing of two separate auditory cues for localization in terms of the azimuth and elevation of a sound source. Differences in the time of arrival of the sounds at the two ears (interaural time differences (ITDs)) are used for localizing the azimuth and differences in amplitudes (interaural level differences (ILDs)) are used for estimating the elevation. Physiological investigations have shown the existence of two separate parallel neural pathways specialized for the independent analysis of ITDs and ILDs (see Ref. [19] for a review). A schematic overview of some of the barn owl's sensory pathways to the optic tectum is illustrated in Fig. 1.

2.1. Proposed learning paradigm

To study the neural mechanisms underlying the adaptive orienting behavior of young barn owls, we developed a model of the some of the neural pathways mediating the localization of auditory and visual targets. The neural structures included in the model are marked by bold boxes in Fig. 1a. The main concern in building this model was to incorporate as much physiological and anatomical data as possible in order to accurately replicate the characteristics of cells in different brain areas. As illustrated in Fig. 1b, the responses of simulated neurons in different model areas closely replicated neurophysiological data with a wide variety of stimuli. The model is briefly described in Fig. 1. Expanded descriptions of modeled areas can be found in previous publications that have dealt with specific aspects of this work [3, 14, 20].

The basic element of the model was a firing-rate neuron modeled as a noisy leaky integrator. Each structure in the model was composed of a collection of units. The output of a unit can be viewed as representing the average firing rate of a collection of cells in the barn owl and its response properties can be considered as representative of a typical cell within such a group. In the barn owl, each area is duplicated on each side of the brain, where it processes the contralateral part of space. In the model the two parts were collapsed together so that each modeled area was dedicated to the analysis of signals from the whole surrounding space.

Although some of the neural changes that mediate the adaptation of orienting behavior have been measured, the mechanisms regulating such changes are not known. In a series of studies, we have used this model to examine whether the development and maintenance of accurate spatial localization can be explained in the context of a neurobiologically plausible paradigm of reinforcement learning [14]. According to this proposal, diffuse-projecting neuromodulatory systems broadcast signals related to the saliency of sensorimotor events to different parts of the brain, where they modulate synaptic changes. This learning paradigm is



(a)

(b)

(c)

Figure 1. (a) Some of the neural pathways to and from the optic tectum (OT) involved in spatial localization and the production of orienting behavior in the barn owl. In the auditory pathway, separate structures process interaural time and amplitude differences (ITDs and ILDs). The nuclei magnocellularis (NM) and laminaris (NL) are dedicated to ITDs, the nucleus angularis (NA) and the pNLL process ILDs. The two pathways converge at the level of the central nucleus of the inferior colliculus (ICc). The first site in the auditory pathway which contains a neural map of space is the external nucleus of the inferior colliculus (ICx). In the OT this auditory map is aligned with a visual map of space created through topographic projections from the retina. The OT projects to motor areas (MN) that control head movements. The areas marked in bold were included in a neuronal model to study the adaptation of orienting behavior [14]. With the exception of the NL and the ICc, in which units were arranged in two-dimensional arrays in the model, all modeled areas consisted of linear array of units. All modeled areas, apart from the input stages (NL and the retina), included a pattern of intrinsic connectivity based on a local range of excitatory connections and a longer range of inhibitory ones, i.e., nearby units tended to activate each other, whereas units farther apart were mutually inhibitory. Thick lines with filled arrowheads indicate sites of plasticity ICC → ICx and OT → MN. (b) Unit responses in three modeled areas. The periodicity in the response to ITD at the level of the NL and ICc is lost in the ICx, where each unit responds strongly to a single value of ITD, i.e., to a single spatial location. (c) A robotic phenotype of the barn owl. A pan/tilt head was equipped with a camera and two microphones. Microphones were located at the opposite sides of the camera, at a distance of approximately 30 cm apart. An array of lights and loudspeakers located in front of the robot provided sensory stimulation. Auditory stimuli consisted of white-noise bursts.

based on a large body of biological evidence. In the model, a simplified modulatory system activated by the occurrence of salient sensorimotor events functionally replicated the proposed role of neuromodulatory subcortical centers. This system consisted of a single unit, which received afferents from both the fovea and the motoneurons. The modulatory unit was highly active when a movement resulted in a stimulus on the fovea and moderately active when the two events (motor action and foveal stimulation) occurred separately.

Synaptic modifications were based on a modified Hebbian learning rule which included consideration of the modulatory term. A biphasic function weighted the contributions from the global signal provided by the modulatory unit and the local level of correlation between pre-synaptic and post-synaptic elements. These two terms have different functional implications. The first term is a global factor shared by all the plastic synapses. The second term reflects a local factor which was different for different connections. When the total level of these two contributions was lower than a first threshold the function had a value of zero, and no synaptic change occurred. In between the two thresholds it had a negative value, thus inducing depression of synaptic strengths. Above a second threshold, it assumed positive values, thereby potentiating the connections. In this way, potentiation occurred only for highly correlated units when the activation of the diffuse-projecting system was also high. This typically happened after a successful saccade, which brought the stimulus onto the fovea. By contrast, when the modulatory system was not strongly activated, such as when the system moved, but did not foveate the target, highly correlated units—the units mostly responsible for the production of the motor action—were mostly depressed. This decreased the probability of repeating a wrong movement.

2.2. Coupling the neural model with a robotic phenotype of the barn owl

This scheme of synaptic plasticity was first tested in a series of computer simulations [14]. The results of these simulations have shown that the model can account for the development of a spatial alignment between auditory and visual maps in the OT during exposure to simplified sensory stimuli. To provide realistic auditory and visual stimulation, we coupled the neural model with a robotic system which emulated the barn owl's phenotype. As illustrated in Fig. 1c, the robotic platform consisted of a mobile camera and two microphones. Similarly to the barn owl, the robot could aim in different directions, while maintaining the position of the microphones and the camera fixed with respect to each other.

Using this system, we have examined the degree of robustness of the model in producing and maintaining accurate orienting behavior in the real world. In a series of experiments we have examined the development of spatial localization during chronic exposure to various sensory conditions and after sudden changes in the system's sensorimotor characteristics [3, 4]. In each of these experiments, the task of the model was to discover the sensorimotor transformations leading to successful localization of visual and audio-visual targets, given the relative structural arrangements of the system components and their functional characteristics. Each experiment consisted of the same sequence of events. First, the system was positioned so as to aim in a randomly selected direction. A visual or an audio-visual target was then presented at one of 15 available locations and as a result the head moved according to the activity determined within the neural model (see Fig. 1c). After the execution of the movement, synaptic plasticity occurred. The stimuli were then removed and the cycle repeated.

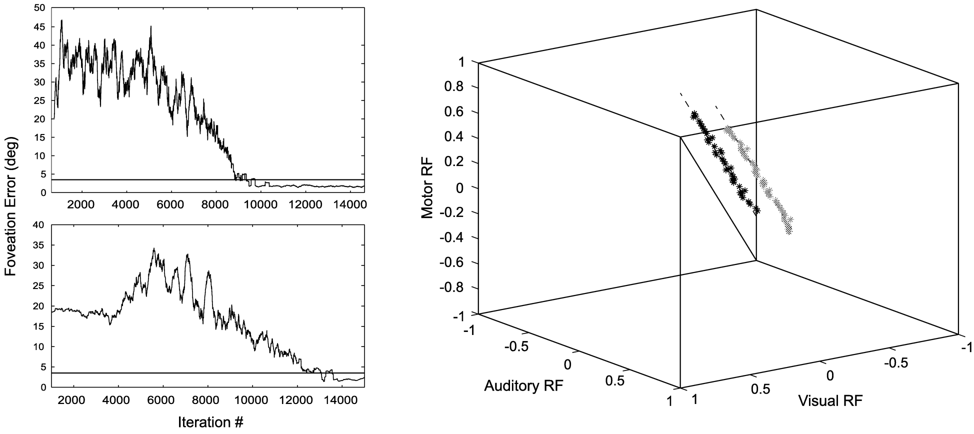
Before exposure to sensory experience, orienting behavior was determined by the random pattern of connectivity assumed at the sites of synaptic plasticity. Whenever a stimulus was presented, the system responded in a reflexive way by reorienting toward a random location. Sensory experience shaped the patterns of connections in the model by strengthening selected synapses. Due to the learning rule adopted, only those synapses that were active during successful saccades (those which brought the stimulus on the fovea) were strengthened; all others (weak pre- and/or post-synaptic activation or unsuccessful saccades) underwent depression. During saccades toward visual stimuli, learning occurred mainly at the level of the OT. Both OT and ICx were affected during movement in responses to audio-visual stimuli. As a result, each ICx unit connected strongly with all the ICc units that were sensitive to the particular ITD corresponding to the same location in space, independent of the frequency.

Examples of accurate development of orienting behavior and recovery after manipulation of sensory signals are shown in Fig. 2. These experiments have shown that the system was able to (i) discover the proper sensorimotor transformations for a wide range of initial conditions and (ii) quickly recover good foveation performance after sudden changes in both the sensory and motor characteristics. As illustrated in Fig. 2c, changes in behavior reflected variations in the response characteristics of simulated neurons, which closely replicated the changes observed in the brains of barn owls. These experiments provide an example of the way robotic systems might contribute to test theoretical proposals in neuroscience.

3. A HUMANOID ROBOTIC PLATFORM TO STUDY VISUAL NEUROSCIENCE

To provide an example of the use of robots to reproduce the sensory changes that occur during behavior, this section summarizes our ongoing research with a humanoid robot.

One of the most important operations performed by the visual systems of many species is the estimation of the distance of objects and surfaces. Accurate depth perception is not only necessary for properly interacting with the environment, it also provides critical information to the processes of image segmentation and figure/ground segregation. Visual distance estimation is a difficult task as depth information is lost in the projection of a three-dimensional scene onto the two-dimensional surface of the retina. However, many monocular and binocular cues exist, which provide information regarding distance. One of these cues is motion



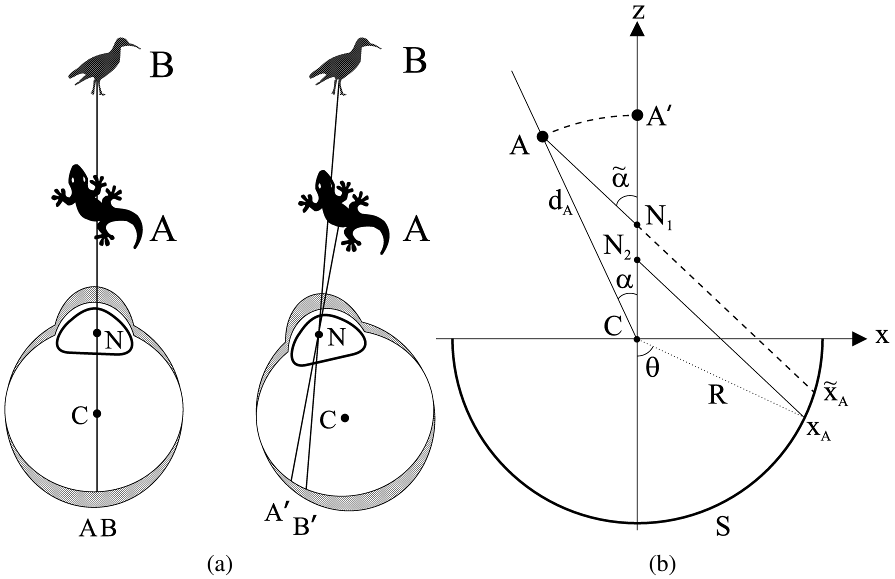
(a) (b)

Figure 2. (a) Improvement in the accuracy of orienting behavior toward auditory targets with learning. The two graphs refer to the initial development of orienting behavior (Top) and to the recovery of correct auditory localization following a chronic translation of the visual field by 20° to the left (Bottom). In this case, the system adapts by aiming to the side of the target by an amount equal to the visual displacement. (b) Development of the alignment of auditory, visual and motor maps in the OT. As in the barn owl, neuronal maps are in close spatial alignment after learning has occurred. Each unit responds to auditory and visual stimuli from the same spatial location and elicits a redirection toward the stimulus. Filled and gray circles represent measurements conducted before and after recovery from a 20° translation of the visual field, respectively.

parallax, i.e., the different apparent motions of stationary objects at different distances, which occurs in the eyes of a moving agent [9, 10].

In many species, a motion parallax is also generated by eye movements. This oculomotor parallax occurs because the optical nodal points are not coincident with the center of rotation in the eyes of these species. Therefore, as the eye rotates, the shift in the retinal projection of an object depends not only on the amplitude of the eye movement, but also on the distance of the object with respect to the observer (see Fig. 3). Several species, such as the chameleon and the sandlance, make extensive use of the depth information produced by this cue and perform small eye movements to estimate distance. In these species, the optics of the cornea and lens maximize the distance between nodal points and the center of rotation [21, 22]. A similar parallax is also present in the eyes of primates [23–25], although it is unclear whether humans actually use it to evaluate distance. In favor of this hypothesis is the empirical observation that the oculomotor parallax appears to produce retinal shifts that are well within the range of human visual acuity during the normal scanning of a visual scene.

To rigorously quantify the distance information resulting from oculomotor parallax, we have replicated sequences of eye movements in a robotic pan/tilt unit designed to mimic the human eye. We show that the oculomotor parallax that emerges



(a) (b)

Figure 3. (a) Distance information provided by the oculomotor parallax. In the human eye, the center of rotation C is not coincident with the position of the nodal point N. During a relocation of gaze, the projection of an object on the retina moves by an amount that depends on the distance of the object. For clarity, a single nodal point is shown here. (b) Oculomotor parallax in the human's eye. x_A identifies the projection on the sensor of a PLS at distance d_A and eccentricity α.

during the small saccades that characterize human oculomotor activity provides reliable depth information within a range of nearby distances.

3.1. The oculomotor parallax

Figure 3 illustrates the depth information produced by the oculomotor parallax. The geometry of the problem is shown in Fig. 3b for the case of a Point Light Source (PLS), that produces a projection of a single point on the retina. In this example, the PLS is located in front of the eye at position $A = (-d_A \sin\alpha,\ d_A \cos\alpha)$.

The oculomotor parallax present in the human eye can be studied by means of Gullstrand's schematic eye model [26]. In a two-nodal-point system as in Gullstrand's eye model, a ray of light going through the first nodal point, N_1, with an angle $\tilde{\alpha}$ exits the lens by the second nodal point, N_2, with the same angle. The intersection between this line and the sensor surface enables calculation of the projection θ of the PLS on the sensor as a function of its distance d_A and eccentricity α:

$$\theta = f(d_A, \alpha) = \arcsin\left(\frac{|-d_A C N_2 \sin\alpha|}{R\sqrt{CN_1^2 + d_A^2 - 2CN_1 d_A \cos\alpha}}\right) + \arctan\left(\frac{d_A \sin\alpha}{d_A \cos\alpha - CN_1}\right). \qquad (1)$$

Equation (1) shows that the projection θ depends on the PLS distance d_A from the center of rotation C. The origin of the oculomotor parallax lies in this dependence.

Direct recovery of the distance of an object from (1) is not possible. Given a retinal projection θ, there are an infinite number of possible PLS locations—any point on the line AN_1—that satisfy (1). However, the spatial position of an object in space can be disambiguated by rotating the eye. Consider the two projections, θ and θ' of a PLS on the retina before and after a rotation $\Delta\alpha$. For each of these two measurements, (1) establishes a relationship between possible values of the PLS eccentricity α and distance d_A. Although this curve cannot be expressed analytically, it can be shown to be continuous and monotonic. Since a rotation around C does not change the distance between the camera and the PLS, the two curves measured before and after the rotation intersect at a single point D. This point identifies the spatial coordinates of the PLS.

3.2. Replicating eye movements in a robot

To measure quantitatively the oculomotor parallax, we have equipped our APLab humanoid robot with a head/eye system which we have designed to mimic the human eye. As shown in Fig. 4a, this system consisted of two pan/tilt units (Directed Perception) mounted so that their respective rotation axes intersected at a specific spatial location (the center of rotation). Specifically designed aluminum wings ensured that the center of rotation was between the sensor plane and the nodal points, at the same exact distance from the receptor surface as occurs in the human eye (10.5 mm in our system *versus* 11 mm in the eye). Proper selection of the focal length of the lens mounted on the camera also enabled replication of the distance between the second nodal point and the center of rotation (around 6 mm in our system *versus* 6.05 mm in the eye). Thus, this system generated an oculomotor parallax very similar to that present in the human eye.

Using this system, we have measured the oculomotor parallax that occurs in humans during the normal viewing of a three-dimensional scene. Subjects were presented with several scenes and their eye movements were recorded by means of a Dual Purkinje Image eye-tracker (Fourward Technologies), a device with high spatial and temporal resolution. The same scenes were later presented to the robot while one of its cameras moved following the recorded eye traces. The images acquired by the robot's camera during the sequences of eye movements were recorded and later processed to extract the information of distance produced by the oculomotor parallax.

Figure 4c shows an example of recovery of distance information using the oculomotor parallax. This scene was composed of five objects located at various distances. Visual occlusions, together with similarities in the colors and textures of the objects, made segmentation of the scene difficult. Following a relocation of gaze, the correspondences between locations in the two images acquired before and after the saccade were evaluated by means of local cross-correlation. This procedure enabled estimation of distance at a number of equispaced locations

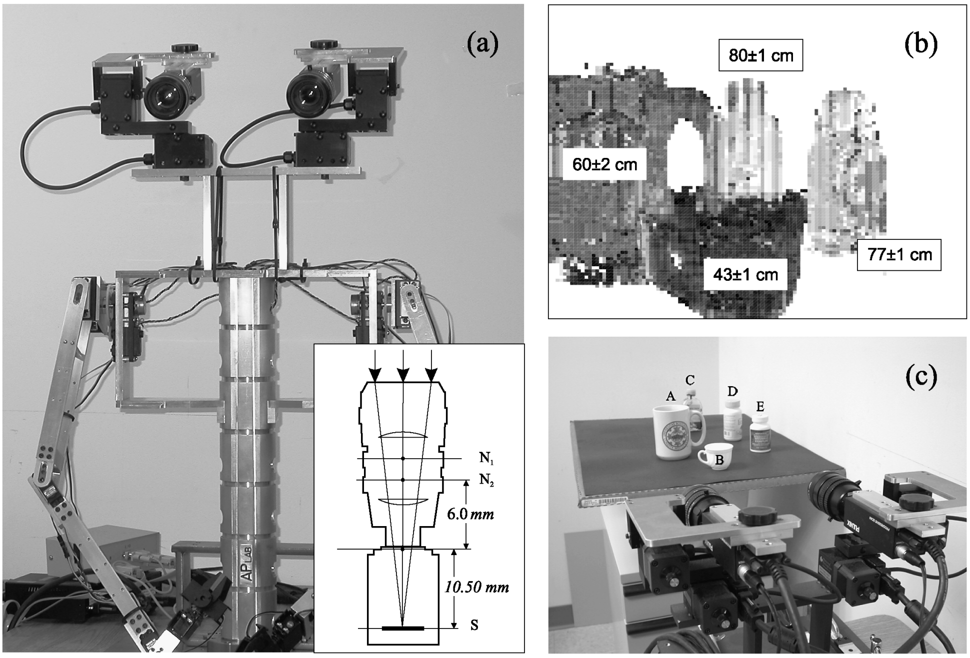


Figure 4. (a) The APLab anthropomorphic robot used in these experiments. The pan/tilt unit of this robot was designed to replicate the oculomotor parallax present in the human eye. The relative positions of nodal points, center of rotation and sensor surface precisely followed the arrangement of the eye. (b) Distance estimation during a recorded sequence of eye movements. This sequence of eye movements relocated the direction of gaze within the left region of the scene and did not allow recovery of the distance of E, which was outside of the camera's field of view. (c) A 3D scene used in the experiments. Object distances were: $A = 59$ cm; $B = 43$ cm; $C = 88$ cm; $D = 74$ cm; $E = 64$ cm.

within the image. The intensity of a pixel in Fig. 4c represents the mean distance estimated at the pixel's location over nine saccades. The white areas correspond to the uniform surfaces of the table and the background, which did not produce measurable parallax. These data show that the eye movements performed by human subjects produce reliable depth information. As emphasized by Fig. 4c, use of this information facilitates the visual segregation of individual objects.

4. CONCLUSION

We have focused on two important benefits resulting from the use of robotic systems to investigate fundamental questions in neuroscience.

The first advantage that we have addressed is a realistic assessment of the degree of robustness of a neuronal model. An example of such assessment is given by our research on modeling spatial localization in the barn owl. The barn owl's orienting behavior is one of the few cases described in the literature in which the adaptation of a motor action has been linked in detail to plasticity of neural maps.

The vast amount of anatomical and physiological data available on the barn owl allows the development of detailed models of key neural areas involved in the production of orienting behavior. Use of a robotic phenotype allows exposure of these models to sensory signals and motor outputs similar to those faced by the owl's nervous system. Study of the adaptation of spatial localization under these conditions resulted in a fair and rigorous evaluation of our proposed learning paradigm. Comparisons between behavioral and physiological data from the barn owl and equivalent data obtained from the robot strongly supported this learning scheme. Furthermore, accurate analysis of neural activity during stimulation with real auditory signals also contributed to clarify some of the mechanisms underlying robust localization in the model [20].

The second benefit in using robotic systems addressed in this paper is a precise replication of the sensory inputs occurring during behavior. The close interaction between motor and sensory processes is one of the most striking features of the perceptual systems of organisms. These systems have evolved in moving agents, and motor activity appears to be a necessary ingredient for their proper functioning. Motor contributions to perceptual computations have been shown in many species, ranging from insects [27] to birds [28] and humans [29]. By replicating eye movements in a robot, we have shown that the scanning strategy followed by humans produces oculomotor parallaxes that reliably predict the distances of objects and surfaces [8].

The two studies summarized in this paper are examples of an interdisciplinary approach to the study of perception, which establishes a direct link between the natural and engineering sciences. While in this paper we have focused on the implications of these studies with regards to the use of robotic systems in neuroscience, it is clear that this approach carries the potential not only for fostering our understanding of the way sensory information is processed in the brain, but also for innovative engineering applications. Like animals, autonomous robots must possess a high degree of flexibility and be able to create coherent representations of the world. In the past, neuroscience and robotics stood as two independent disciplines with only sporadic interactions (see, e.g., Refs [2, 30–33]). It appears that the times are now mature for systematic and fruitful collaborations between these two fields.

Acknowledgements

This work was supported by the National Science Foundation grant CCF-0432104.

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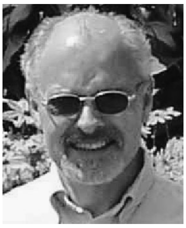

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