Active Vision and Neural Development in Animals and Robots

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Introduction

Brains are characterized by limited bandwidth and computational resources. At any point in time, we can focus our attention only to a limited set of features or objects. One of the most remarkable –and often neglected– differences between machine vision and biological vision is that computers are often asked to process an entire image in one shot and produce an immediate answer whereas animals are free to explore the image over time searching for features and dynamically integrating information over time.

Coevolution of Active Vision and Feature Selection

I will show that the co-evolution of active vision and feature selection can greatly simplified computational complexity of visual performance. Each of these processes has been investigated and adopted in machine vision. *Active vision* is the sequential and interactive process of selecting and analyzing parts of a visual scene (Aloimonos et al., 1987; Bajcsy, 1988; Ballard, 1991). *Feature selection* instead is the development of sensitivity to relevant features in the visual scene to which the system selectively responds (Hancock et al., 1992, e.g.). However, the combination of active vision and feature selection is still largely unexplored.

We carried out a series of experiments on co-evolution of active vision and feature selection for behavioral systems equipped with primitive retinal systems and deliberately simple neural architectures (Fig. 1). In a first set of experiments, we show that sensitivity to very simple features is co-evolved with, and exploited by, active vision to perform complex shape discrimination. We also show that such discrimination problem is very difficult for a similar vision system without active behavior. In a second set of experiments, we apply the same co-evolutionary method and architecture for driving a simulated car over roads in the Swiss alps and show that active vision is exploited to locate and fixate simple features while driving the car. In a third set of experiments, we apply once again the same co-evolutionary method and architecture to an autonomous robot equipped with a pan/tilt camera that is asked to navigate in an arena located in an office environment. Evolved robots exploit active vision and simple features to direct their gaze at invariant features of the environment and perform collision-free navigation. In a fourth set of experiments, we apply this methodology to an all-terrain robot with a static, but large, field of view that must navigate in a rugged terrain. Here again, the system becomes sensitive to a set of simple visual features that are maintained within the retina by the active vision mechanisms.

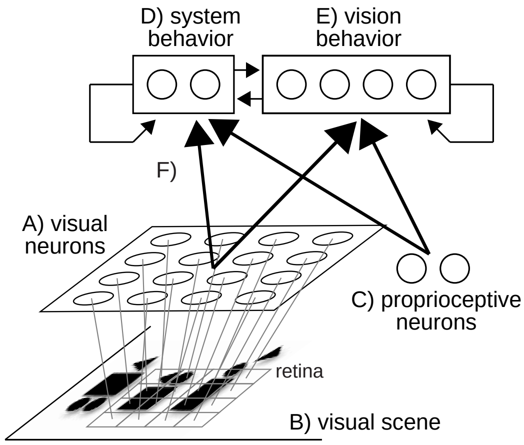

Figure 1: The architecture is composed of A) a grid of visual neurons with non-overlapping receptive fields whose activation is given by B) the grey level of the corresponding pixels in the image; C) a set of proprioceptive neurons that provide information about the movement of the vision system; D) a set of output neurons that determine the behavior of the system (pattern recognition, car driving, robot navigation); E) a set of output neurons that determine the behavior of the vision system; F) a set of evolvable synaptic connections. The number of neurons in each sub-system can vary according to the experimental settings.

Active Vision and Receptive Field Development

We go one step further and investigate the *ontogenetic development* of receptive fields in an evolutionary mobile robot with active vision. We use a Koala (K-Team S.A.) wheeled robot equipped with a pan/tilt camera (Fig. 2). In contrast to the previous work where synaptic weights for both receptive field and behavior were genetically encoded and evolved on the same time scale, here the synaptic weights for receptive fields develop during the life of the individual. The synaptic weights of the neural network (Fig. 3) are genetically encoded and evolved, but the synaptic weights from visual photoreceptors to internal neurons (receptive fields) can also be modified by Hebbian synaptic plasticity (Sanger, 1989) while the robot moves in the environment. The Hebbian mechanism and architecture is one of those used in the literature for modeling

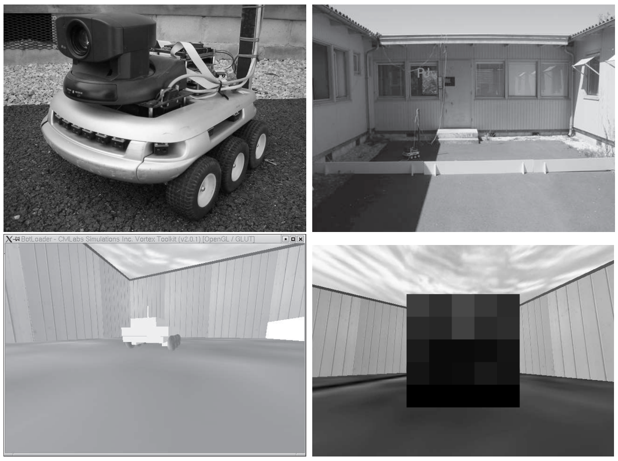

Figure 2: Top left: The Koala mobile robot by K-Team S.A. with a pan/tilt camera. Top right: The real environment. Bottom left: Simulation of the robot and the environment. Bottom right: View from the simulated camera. The robot is capable of visually accessing the five by five pixels in the center of the image.

receptive field formation (Hancock et al., 1992). In these experiments, behavioral abilities and receptive fields develop on two different temporal scales, phylogenetic and ontogenetic respectively. The evolutionary experiments are carried out in physics-based simulation and the evolved controllers are tested on the physical robot in an outdoor environment.

We show that robots evolved in simulation with Hebbian visual plasticity display more robust adaptive behavior when transferred to real outdoor environments as compared to robots evolved without visual plasticity. We also show that the development of visual receptive fields is significantly and consistently affected by active vision as compared to the development of receptive fields with grid sample images in the environment of the robot. Finally, we show that the interplay between active vision and receptive field formation amounts to the selection and exploitation of a small and constant subset of visual features available to the robot.

Contribution of Active Body Movement to Visual Development

Such a neural architecture with Hebbian visual plasticity for a freely moving behavioral system also allows us to consider an old question derived from (Held and Hein, 1963). Held and Hein devised an apparatus in which the gross movements of a kitten moving almost freely (*active kitten*) were transmitted to a second kitten that was carried in a gondola (*passive kitten*). Consequently, they received identical visual stimulation, but only one of them received that stimulation as a result of self-movement. Importantly, only the active kitten developed normal behavior in several visually guided tasks, such as paw extension on approaching horizontal surface from above and blinking at object put in front of its eyes, while the passive one failed. The authors concluded that visual stimulation correlated with self-actuated movement was necessary for the development of the visual control of behavior. However, it is still not clear how the active body movement of the kitten

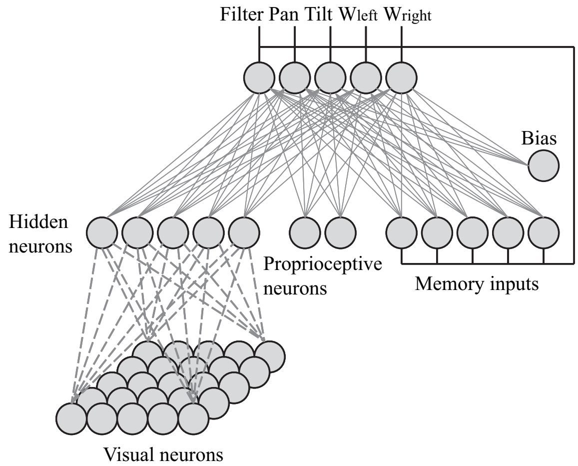

Figure 3: The architecture with Hebbian visual plasticity. The synaptic connections (receptive fields) from visual neurons to hidden neurons are randomly initialized at the beginning of the life of each individual and they can be modified by Hebbian plasticity while the robot moves in the environment. Other connections are evolved online by means of a genetic algorithm.

enabled it to develop such visually guided behaviors.

Here we explore the role of active body movement in the formation of the visual system by studying the development of visual receptive fields and behavior of robots under active and passive movement conditions. The receptive fields in the best evolved mobile robot are developed during active and passive movements with a Hebbian learning rule. We show that the receptive fields and behavior of robots developed under active condition significantly differ from those developed under passive condition. A set of analyses show that the coherence of receptive fields developed in active condition plays an important role in the performance of the robot.

Acknowledgment

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References

Aloimonos, J., Weiss, I., and Bandopadhay, A. (1987). Active vision. *International Journal of Computer Vision*, 1(4):333–356.

Bajcsy, R. (1988). Active perception. *Proceedings of the IEEE*, 76:996–1005.

Ballard, D. H. (1991). Animate vision. *Artificial Intelligence*, 48(1):57–86.

Hancock, P. J., Baddeley, R. J., and Smith, L. S. (1992). The principal components of natural images. *Network*, 3:61–70.

Held, R. and Hein, A. (1963). Movement-produced stimulation in the development of visually guided behavior. *Journal of Comparative and Physiological Psychology*, 56(5):872–876.

Sanger, T. D. (1989). Optimal unsupervised learning in a single-layer feedforward neural network. *Neural Networks*, 2:459–473.