Bee vision

Cognitive Science term project Sashank Pisupati Mentor: Prof. Amitabh Mukherjee

Introduction

Motivation: Motivation

•Bees rely heavily on visual cues to locate themselves, and combine these with

- scent cues to learn about good sources of nectar
- •The (single) neurons that do this learning must receive visual input that
- -Is low dimensional (Steveninck, Bialek& Ruyter, 2005)
- -Reliably represents feedback to the motor acts



Dimensionality reduction: theoretic considerations

What?

- The stream of visual input is very high dimensional
- Useful information however (for example which direction I am moving in) is much lower dimensional
- Most feature sensitive neurons are only sensitive to low dimensional subspaces of inputs.

How?

- Nonlinear dimensionality reduction of images using methods such as Dijkstra algorithm (Isomap)
- Can discover low dimensionality of the inputs **Claim**: This can be achieved linearly through hebbian learning, or nonlinearly through lateral inhibitory structures such as in the insect brain (Reichardt, 1976)

Why?

Claim: Images of/seen by a system with 'n' degrees of freedom will lie on an 'n' dimensional manifold (Amitabh, Ram et. Al)

- This low dimension is useful because it matches DoF, for visuomotor feedback
- Entire set of images must be preserved
 - o Memory intensive
 - \circ $\;$ But because of this, bee can adapt $\;$
 - Different situations will have entirely different image sets but low dimensional computation can remain same.



Experimental Setup

The eyes and environment of the virtual bee was simulated using Andy Giger's java simulation "B-EYE", that simulates an array of the bee's photoreceptors, taking into account the optical properties of its ommatidae. Images were collected at 10 fps while the virtual bee foraged in this environment, in either two(X,Y) or three (X,Y,Z) dimensions

Question: Can the foraging bee, by virtue of its visual stimulus alone, figure out where it is?







Results



As one can see, the images gathered by **2D** foraging (top rows, above and below) lie on a manifold best explained by 2 dimensions, similarly for **3D** foraging



Conclusions

•The dimensions of the low-dimensional visual input is representative of the degrees of freedom of the bee

•The bee can hence use this low dimensional description to infer where it is (i.e. its coordinates or configuration)

•This low dimensional data can now be used by higher order "feature sensitive" neurons, and is adaptive to context.

The next step: Closed loop bees

Since this low dimensional visual output is the same dimensional motor DoF, it can be used as **input** to a reinforcement learning neuron.

Such a neuron(similar to Montague and Sejnowski's model),, could then learn which locations are salient, i.e. nectar bearing

References



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