Joint Development of Smooth Pursuit Behavior and Motion Perception

Project Code: SB5-13

Student: LI, Xiaoya
Supervisor: Professor Bertram SHI

Introduction
We implemented a robotic eye system that could learn to perform simple motion tracking by learning from the interaction with its environment. The learning process consists of two parts: the representation of visual information and the mapping from this representation to an action. A framework for this joint development based on reinforcement learning and sparse coding has been built in previous work and tested by computer simulation. Here we want to implant this framework to a robotic eye.

Project Overview

Overview
Our system is designed to perform the smooth pursuit behavior for motion tracking, which is simulated by instructing the robotic eye to follow a moving image. The visual perception part is implemented by a camera, whose visual signal is represented using sparse coding algorithm. The action part is implemented by a servo motor, which controls the motion of the camera and acts according to a policy obtained from reinforcement learning during the training process.

Block Diagram

Methodology

Environment

Robotic Eye System

Environment

Robotic Eye System

Environment

Robotic Eye System

Environment

Robotic Eye System

Environment

Robotic Eye System

Results

System Performance
In this experiment, we evaluated the performance of the system by computing the mean square error of target velocity and actual velocity. After training the system for around 90,000 iterations, we were able to obtain a satisfying performance in motion tracking.

Development in Visual Perception

In the visual perception unit, the basis functions in sparse coding algorithm are updated to minimize the reconstruction error in online signal representation. The basis functions were retrained at the beginning and after training, each function converged at a certain pattern.

Development in Behavior

In the action unit, the servo action is given by a policy implemented by a three-layer neural network that choose an action connected with large reward from a suggested set. We use Natural Actor-Critic reinforcement learning algorithm for policy learning.

The policy computes the probability of choosing an action connected with each state, which is represented by visual signal. The figures show the probability distribution of each connected (a) and corresponding to target speed difference (b) at the beginning and after training, respectively. The policy learned to choose an online framed to a velocity difference, which matches previous simulation result.