- Friday, December 17, 2010
  Prediction, extrapolation and scheduling time to gather information in object motion

  Prediction and extrapolation form key problems in many perceptual tasks, which are particularly salient in processing object motion. In the first part of the talk I will address the problem of scheduling time for perceptual information gathering. Is it best to act now with uncertainty, or postpone until more information can be gathered? For example, how long to observe a tennis ball's trajectory before executing an interceptive action? Longer observation times insure less uncertainty about the ball's trajectory but leave less time to make the movement, increasing motor error. Recent results from our lab show that people understand this trade-off and are able to schedule time for perception to minimize task errors. In general, scheduling time for perceptual information gathering is an instance of the exploration/exploitation problem, and I will discuss human and optimal behavior on this problem. Extrapolation with occlusion is a key exemplar of the need for predicition: an object moves along a variable path before disappearing and a prediction of where the object will reemerge at a specified distance beyond the point of occlusion is made. In general, predicting the trajectory of an object during occlusion requires an internal model of the object's motion to extrapolate future positions given the observed trajectory. In recent work (Fulvio, Maloney & Schrater, VSS2009), we showed that people naturally adopt one of two kinds of generic motion extrapolation models in the absence of feedback (i.e. no learning) - a constant acceleration model (producing quadratic extrapolation) or a constant velocity model (producing linear extrapolation). How such predictive models are learned is an open question. To address this question, we had subjects extrapolate the motion of a swarm of sample points generated by random walks from different families of dynamics. Simulation results from the ideal learner predict that learning motion models will depend on several factors, including differential predictions of the motion models, consistency of the motion type across trials and limited noise. To test these predictions, subjects performed a motion extrapolation task that involved positioning a "bucket" with a mouse to capture the object as it emerged from occlusion, and feedback was given at the end of each trial. While subject performance was less than ideal, we provide clear evidence that they adapt their internal motion models toward the generative process in a manner consistent with statistical learning.

Paul Schrater
University of Minnesota