Probabilistic Tracking of Multiple Rodent Whiskers In Monocular Video Sequences

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Background

The Problem

The interest in studying rodent whiskers has recently seen a significant increase, particularly in the field of neurophysiology. As a result, there is a need for automatic tracking of whisker movements. Currently available commercial solutions either are extremely expensive, restrict the experiment setup, or fail when whiskers cross or overlap. A cheap, reliable solution to the tracking problem is needed.

A Probabilistic Approach

We propose solving the problem with a probabilistic approach. We use a technique known as the *Particle Filter* to propagate a whisker model between frames of high speed video. In each frame, the next state of the model is predicted by searching a pre-trained database, and filtering the results through the Particle Filter. The main difference between this and existing solutions is that it maintains a model of the whiskers. This makes it easier to keep track of them even when they cross or overlap.

The Probabilistic Framework

Our solution is based on the concept of discrete *Markov processes*, which are a type of stochastic processes. A stochastic process uses probability functions to describe how a system may pass between states. In the discrete case, the system makes discrete "jumps" through a discrete space of states, as opposed to the continuous case where both state transitions and state space may be continuous. A Markov process is a stochastic process that satisfies the *Markov property*, which states that the system's future depends only on the current state and is independent of past states. An example of a discrete Markov process is that of throwing dice and summing the results: the throws are discrete, the sum increases by a discrete amount for each throw, and the possible sums after the next throw depends only on the current sum.
In mathematical terms, the Markov property is formulated as follows (for a discrete stochastic process):

$$p\left(Z_{n+1}|Z_n, Z_{n-1}, Z_{n-2}, \ldots, Z_0\right) = p\left(Z_{n+1}|Z_n\right), \tag{1}$$

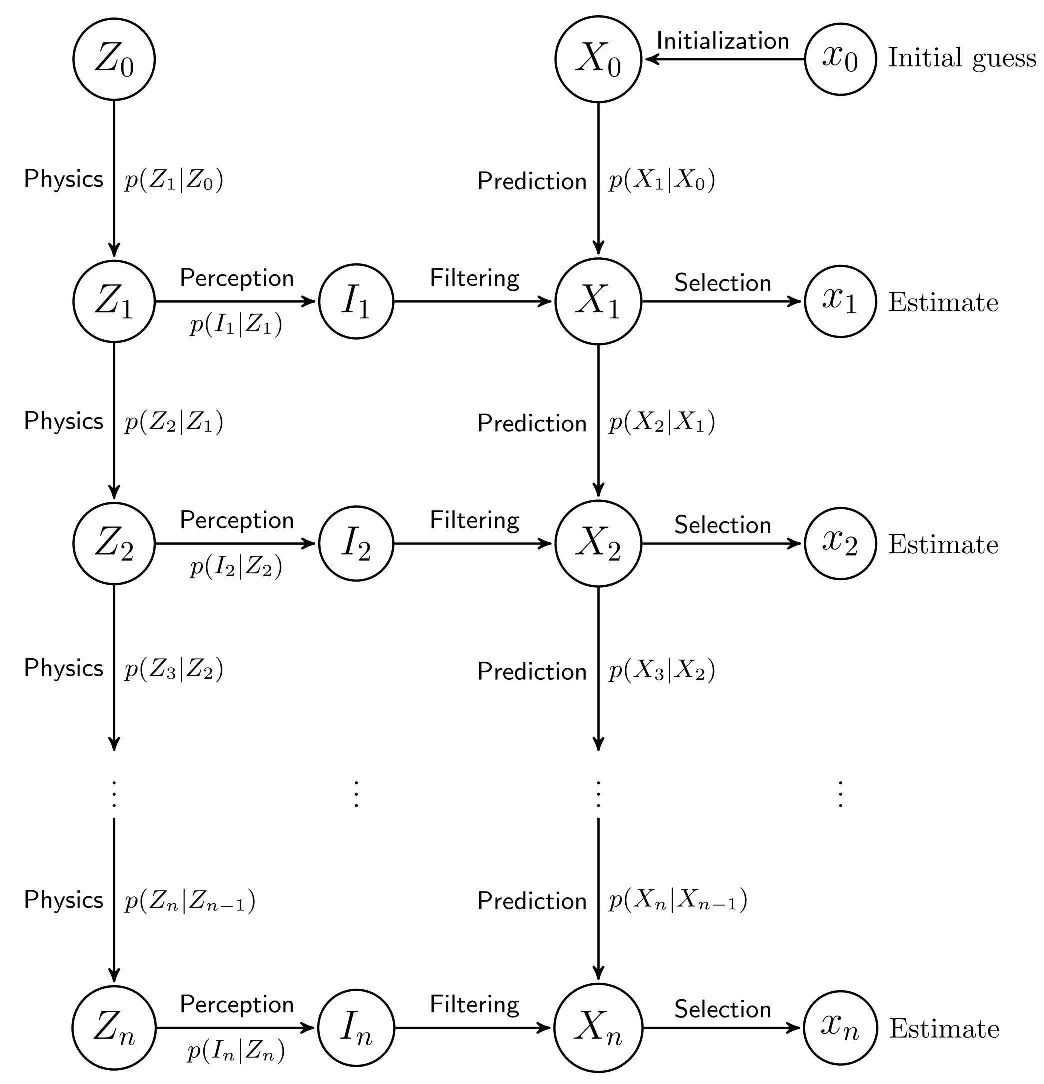
where Z_n is the system's state after step n and $p\left(Z_{n+1}|Z_n, Z_{n-1}, Z_{n-2}, \ldots, Z_0\right)$ is the probability that the system will assume state Z_{n+1} in the next step, given that the previous states were $Z_n, Z_{n-1}, Z_{n-2}, \ldots, Z_0$.
A *hidden Markov model* (HMM) describes a Markov process where one cannot measure the state Z of the system directly, but rather obtains an observation I of the state. This observation may not be deterministic, and so we have the probability $p(I_n|Z_n)$ that we will observe I_n if the current state of the system is Z_n.

The Particle Filter

The Particle Filter is a technique for simulating a process described by a HMM. It uses a finite set X_n of N hypotheses to approximate the probability function $p(Z_n)$ above. The hypotheses X_n are also known as *particles*, thereby the term "particle filter". In short terms, the particle filter does the following:

1. Predicts the next state Z_{n+1} by drawing samples X_{n+1} from $p(Z_{n+1}|Z_n)$,

2. resamples the hypotheses X_{n+1} by drawing new samples from $p\left(I_{n+1}|x^i_{n+1}\right)$



Above is an illustration of a Particle Filter working with a Hidden Markov Model. The system assumes states $Z_0, Z_1, \ldots$ with probabilities $p(Z_0), p(Z_1|Z_0), \cdots$, and we obtain the observations $I_1, I_2, \cdots$ with probabilities $p(I_1|Z_1), p(I_2|Z_2), \cdots$. Parallel to this, we have a set of hypotheses X for the state Z. The hypotheses X_n of Z_n are updated in the *prediction* step to hypotheses $\bar{X}_{n+1}$ of Z_{n+1}. The image I_{n+1} of the system is then used in the *resampling step* to select the best hypotheses from $\bar{X}_{n+1}$, yielding the *belief* X_{n+1}. Finally, we create a single hypothesis x_{n+1} from X_{n+1} that will be our estimate of the state Z_{n+1}.

Results

So far, we have run some tests on randomly generated video sequences of whisker-like objects. While the results are far from good enough for practical use, they are still quite promising.