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 by 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 discrete *Markov processes*, which are a special case of stochastic processes. For a Markov process, the next state depends only on the present state and not on past states.
An example of a discrete Markov process is that of throwing dice and summing the results: the throws and state space are discrete, and the possible states (sums) after the next throw depend only on the current state.
In mathematical terms, a discrete Markov process satisfies the following:

$$p\left(Z_{n+1} | Z_n \wedge Z_{n-1} \wedge \cdots \wedge Z_0\right) = p\left(Z_{n+1} | Z_n\right) \tag{1}$$

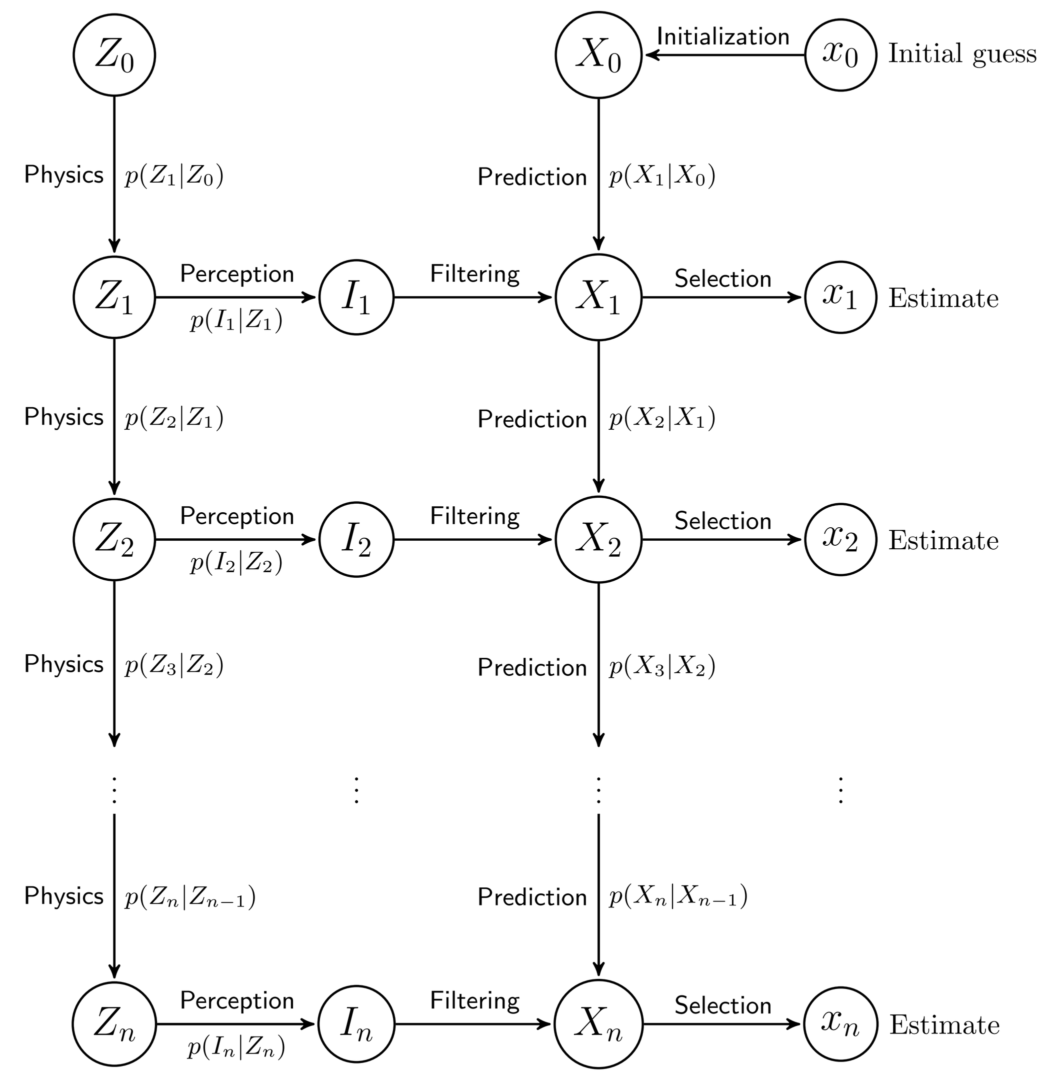
where Z_n is the system's *state* after step n and $p\left(Z_{n+1} | Z_n \wedge Z_{n-1} \wedge \cdots \wedge Z_0\right)$ is the probability that the system will have state Z_{n+1} in the next step, given that the previous states were $Z_n, Z_{n-1}, Z_{n-2}, \ldots, Z_0$.
A *hidden Markov model* (HMM) describes a Markov process where one cannot measure the state Z of the system directly - it is "hidden" - but rather obtains an *observation* I[a] of the state by some *perception*. The observation is generally non-deterministic, so we need to denote it as $p(I_n|Z_n)$ which is the probability that we will observe I_n if the current state of the system is Z_n.

[a] In this project, the observation is a grayscale *image*, which is why we use the symbol I.

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.