INFO8006: Project 3 - Report

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1 Bayes filter

a. The sensor model is described by $P(E_t|X_t)$ (for $t > 0$) where the set X_t contains the unobservable ghosts positions in the maze at time t and E_t is a set containing the evidence variables which are the noisy distances between Pacman and the ghosts at time t.
A noisy distance is a normally sampled distance from a normal distribution $\mathcal{N}(\mu, \sigma)$ in the interval $[\mu - \sigma; \mu + \sigma]$ where
$\mu =$ actual Manhattan distance between Pacman and the considered ghost,
$\sigma =$ standard deviation of the rusty sensor.

b. The transition model $P(X_{t+1}|X_t)(k)$ (for $t > 0$) defines a probability distribution relying on the ghost type k. It uses the Manhattan distance d_{t+1} between Pacman and a considered ghost position (x_{t+1}, y_{t+1}) in the maze at time $t+1$ and the Manhattan distance d_t between Pacman and the considered ghost position (x_t, y_t) in the maze at time t. The positions (x_t, y_t) and (x_{t+1}, y_{t+1}) are compatible if $(x_{t+1}, y_{t+1}) = (x_t \pm 1, y_t)$ or $(x_{t+1}, y_{t+1}) = (x_t, y_t \pm 1)$ and if there's no wall in (x_{t+1}, y_{t+1}). The transition model $P(X_{t+1}|X_t)(k)$ at time t is such as

Ghost type	compatible	$P(X_{t+1}\|X_t)(k)$
$k \in${0,1,3}	True, $d_{t+1} > d_t$	$\alpha * 2^k$
	True, $d_{t+1} \leq d_t$	$\alpha * 1$
	False	0

where $k = 0$ denotes the confused ghost, $k = 1$ denotes the afraid ghost, $k = 3$ denotes the scared ghost and α is the normalization constant that is used to make the probabilities sum up to 1.

2 Implementation

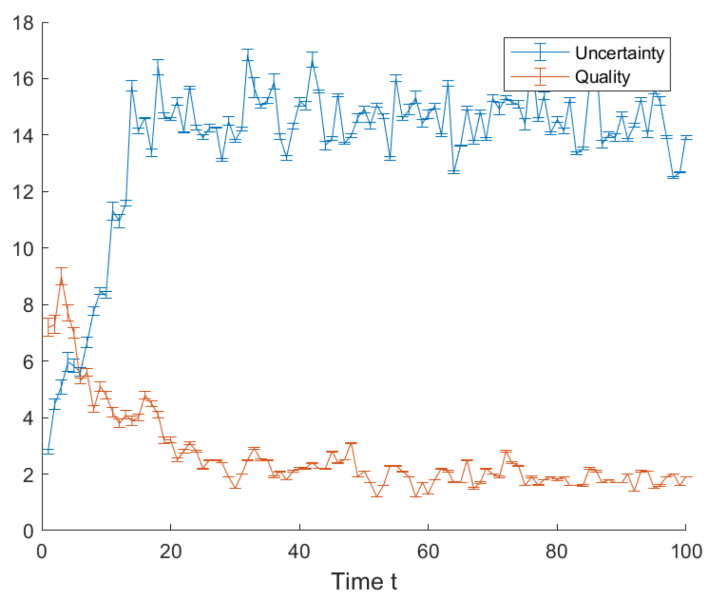
a. See `bayesfilter.py`.

3 Experiment

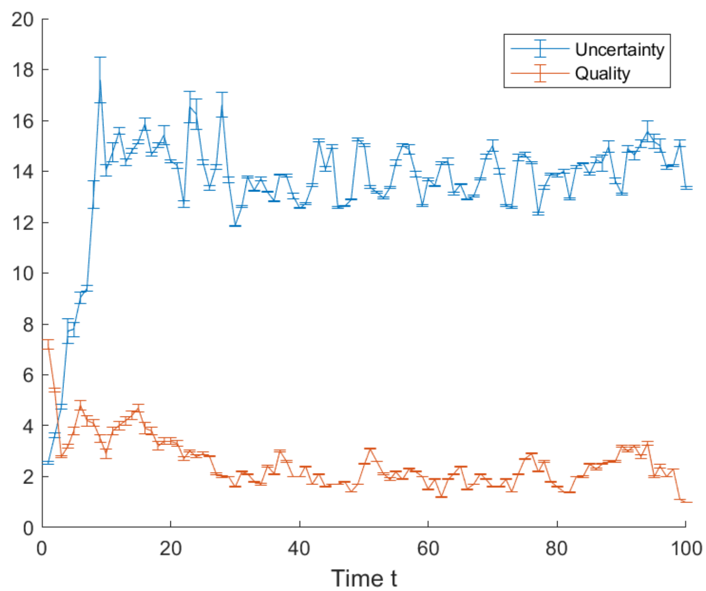
a. In order to summarize a Pacman's belief state we compute its variance. Variance measures how far the probabilities over the ghosts positions in the belief state are spread from each other (from their mean). If the variance of a Pacman's belief state is low it means that the probabilities in the belief state are close to each other so Pacman has a lesser certainty over the actual ghosts positions. The higher the variance the more certain Pacman is about the ghosts positions because the probabilities in the belief state will be more distant from each other so Pacman has a better idea of where the ghosts are and where they aren't.

b. In order to measure the quality of a Pacman's belief state we compute the Manhattan distance between the position corresponding to the highest probability in the belief state and the actual ghost position in the maze. The lower this Manhattan distance the higher the quality of the belief state.

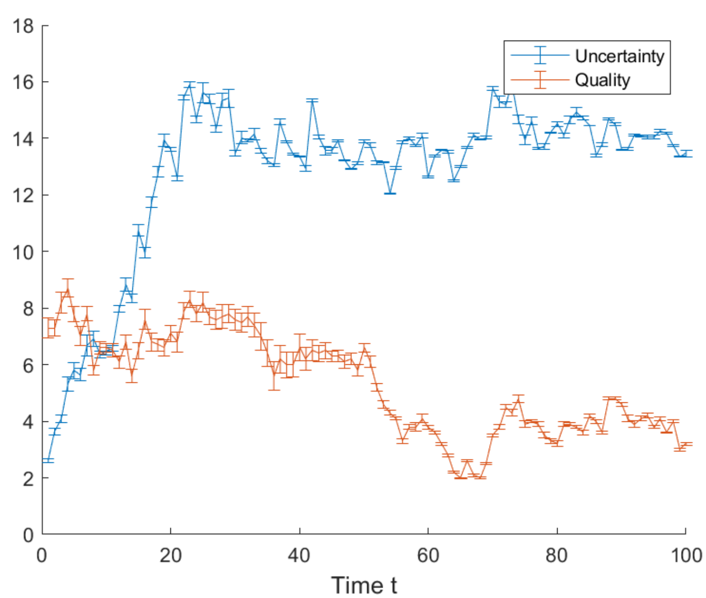
c. We did 10 trials for each ghost for each layout and plot their error bars. Note that the "uncertainty" on the graphs corresponds to the variance of a belief state at time t and "quality" corresponds to the Manhattan distance mentioned previously so a smaller "quality" is better.
Scared ghost for **large_filter** layout :



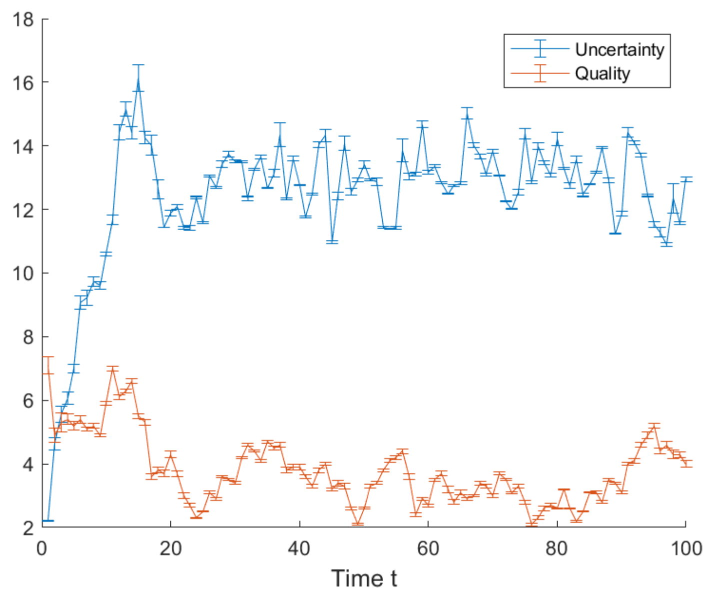
Scared ghost for **large_filter_walls** layout :



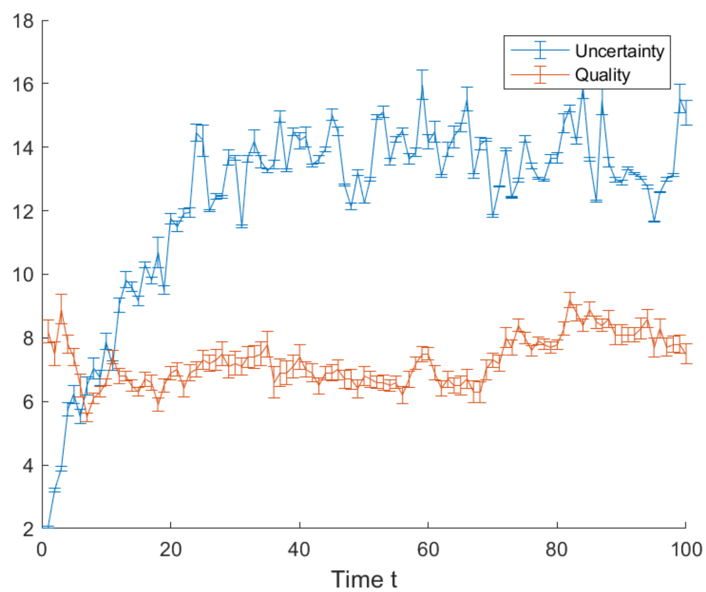
Afraid ghost for **large_filter** layout :



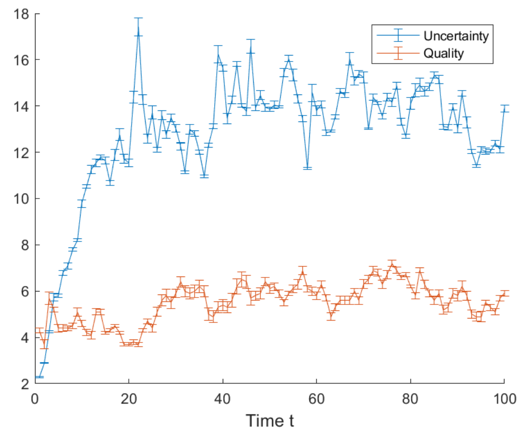
Afraid ghost for **large_filter_walls** layout :



Confused ghost for **large_filter** layout :



Confused ghost for **large_filter_walls** layout :



d. The bigger the ghost transition model parameter k the more predictable the ghosts movements will be and therefore the uncertainty will converge quicker . Indeed, we can observe on the graphs above that the uncertainty takes longer to converge for the confused ghost ($k = 0$, t∼=25) than for the afraid ($k = 1$) and scared ($k = 3$) ghosts. For $k = 1$ and $k = 3$ Pacman knows that the ghosts will try to get away from him as far as possible thus they'll go to the lower rightmost positions in the maze (since Pacman is in the left corner). The bigger the k parameter the bigger the transition model $P(X_{t+1}|X_t)(k)$ and thus by the formula

$$P(X_{t+1}|e_{1:t+1}) = \alpha P(e_{1:t+1}|X_{t+1}) \sum P(X_{t+1}|x_t)(k)P(x_t|e_{1:t})$$

Pacman's belief state $P(X_{t+1}|e_{1:t+1})$ will be more precise (we noticed that the sensor model $P(e_{1:t+1}|X_{t+1})$ is constant for a fixed seed and layout). We can also notice that for k=1,3 the uncertainty converges earlier for the large_filter_walls layout than for the large_filter because there are walls in the large_filter_walls that stop the ghosts from going to the bottom right corner. The ghosts will stay around those walls because taking another path to the bottom right corner would mean getting closer to Pacman (which s the opposite of what they want). The uncertainty thus convergences earlier.

e. Increasing the sensor variance σ changes the evidences because the noisy distances are normally sampled in a bigger $[\mu-\sigma; \mu+\sigma]$ interval. Pacman's uncertainty about the ghosts positions would then take longer to converge.

f. We'd implement the controller such that at each time t Pacman computes the sequence of actions that leads him to the shortest path towards the position corresponding to the highest probability in the belief state (highest probability of finding the ghost) and chooses the first action out of that sequence.