

Matlab Exercises

Lecture 4 – Bayesian tracking

1) Motion Model

Write a function that generates a 1D random motion of the following type:

- Brownian motion
- WNA
- Constant acceleration ($a=9.81$) + perturbation

Where $w = \text{Gauss}(0, \sigma=1)$, $\Delta t=0.1$ for all the situations.

For each case, plot a corresponding trajectory in time: $p(t)$, with $t=(0, \Delta t, 2\Delta t, \dots, N\Delta t)$, $N=1000$.

Afterwards, compute and plot the corresponding probabilistic motion models $P(s_t | s_{t-1})$ (in 1 or 2 dimensions, depending on the case)

2) Measurement model

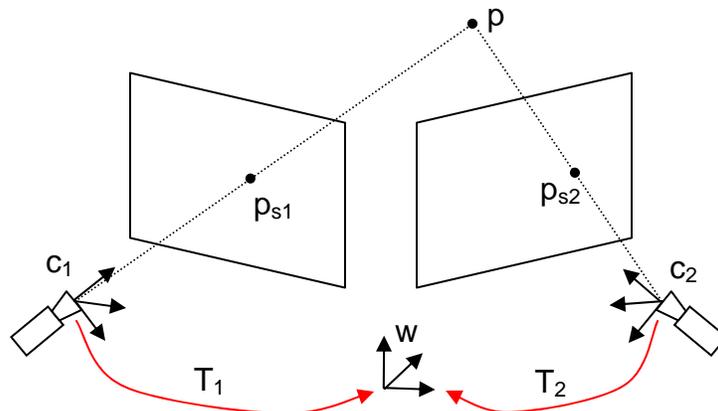
Write the measurement model $\mathbf{z} = h(\mathbf{s}, \mathbf{v})$ for the following case:

Suppose a point in space \mathbf{p} with camera coordinates (x, y, z) is being projected on the screen (x_s, y_s) , and the measurement instrument is the camera (intrinsic parameters (f, r_x, r_y)) + an image processing algorithm that identifies the screen coordinates with a Gaussian uncertainty $\mathbf{v} = \text{Gauss}([0, 0], \Lambda = \mathbf{I})$

Hint: First identify the variables \mathbf{s} and \mathbf{z} (which and how many), then write down the function $\mathbf{z} = h(\mathbf{s}, \mathbf{v})$.

3) Measurement model (stereo)

Consider the following case:



Suppose to have two cameras in a stereo configuration, and again one point in space \mathbf{p} . The two camera frames c_1, c_2 have fixed poses T_1, T_2 with respect to a world coordinate system w , so that the point \mathbf{p} transform in space as:
 ${}^{c_1}\mathbf{p} = T_1 {}^w\mathbf{p}$, and ${}^{c_2}\mathbf{p} = T_2 {}^w\mathbf{p}$ (homogeneous coordinates).

The point in space with coordinates ${}^w\mathbf{p} = (x,y,z)$ is being projected on the two screens $(x_{s1}, y_{s1}), (x_{s2}, y_{s2})$, and the cameras have the same intrinsic parameters (f, r_x, r_y) . The measurement instrument is: the 2 cameras + an image processing algorithm that identifies the screen coordinates with independent Gaussian errors $\mathbf{v}_1, \mathbf{v}_2$
 $\text{Gauss}([0,0], \Lambda=I)$.

Write down the measurement function $\mathbf{z} = h(\mathbf{s}, \mathbf{v})$.
 (Hint: the same as before: first identify the variables, then write the function)

4) **Likelihood function (edges)**

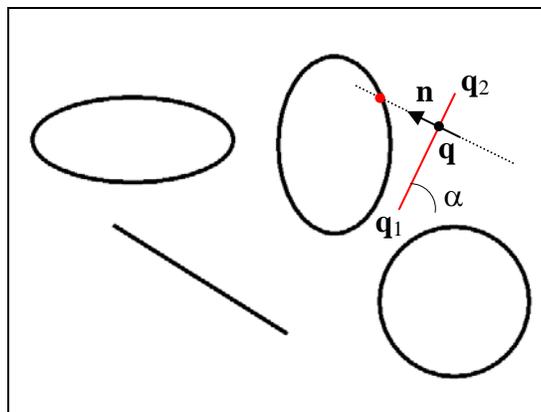
Consider now a segment model: the state \mathbf{s} is (x_1, y_1, α) the position and orientation of the segment (the length is 10).

$$\mathbf{q} = k\mathbf{q}_1(\mathbf{s}) + (1-k)\mathbf{q}_2(\mathbf{s}); k \text{ runs from } 0 \text{ to } 1$$

$$\text{where } \mathbf{q}_1 = (x_1, y_1), \mathbf{q}_2 = (x_1 + 10\cos(\alpha), y_1 + 10\sin(\alpha))$$

The measurement is the image $\mathbf{z} = I$.
 The likelihood model is an “expected image” I_{exp} given the segment hypothesis \mathbf{s} + an uncertainty model.

The expected image is an image that contains a segment exactly in the position \mathbf{s} . The uncertainty is measured by the distance along the normal direction of the nearest edge, where every point along the segment \mathbf{q} contribute independently to this error. So, we can model the uncertainty $P(\text{error})$ as a product of single uncertainties $P(\text{err}_i)$, for every point, each one given by a Gaussian centered in the segment point. In the ideal case ($I=I_{\text{exp}}$) we have the maximum Likelihood $P(I|\mathbf{s})$ (the nearest edges are exactly on the segment hypothesis).



With this model, given an image (example above) write a Matlab function that computes the Likelihood $P(z|s)$:

- take a set of 11 equidistant points in the segment ($k=0,0.1,0.2,\dots,1$)
- take the normal vector to the segment $\mathbf{n} = (-\sin(\alpha), \cos(\alpha))$
- From a point $\mathbf{q}(k_i)$, search along the normal directions $\mathbf{q}(k_i)+j\mathbf{n}$ where $j= 0,-1,1,-2,2,\dots,-L,L$ (up to a length $L=5$ in the two directions)
- Stop the search if a black pixel is found (pixel coordinates \rightarrow the points $\mathbf{q}+j\mathbf{n}$ need to be rounded to integers), or if the maximum distance L is reached
- The result is the distance of the nearest edge, l_{ok} , or L
- Now weight the distance l_{ok} with a Gaussian: $P(l_{ok}) = \text{Gauss}(0,1)$
- Finally, multiply all the 11 Gaussians, to get the Likelihood $P(z|s)$

5) Measurement model : 3D projection

Suppose we have

- a set of 3D points ${}^B p_1, \dots, {}^B p_N$ (body frame referred),
- the 6 pose parameters $\mathbf{s} = (\alpha, \beta, \gamma, t_x, t_y, t_z)$ in Euler angles + translation vector.
- A set of measured features $\mathbf{z} = (q_1, \dots, q_N)$ on the image

We model the uncertainty as N independent Gaussians: $\text{Gauss}(\text{err}_i, 1)$ where the error is the re-projection error of feature i (distance between expected and measured point).

$\rightarrow P(\mathbf{z}|\mathbf{s})$ is the product of N Gaussians.

Write a Matlab function that computes the Likelihood function $P(\mathbf{z}|\mathbf{s})$ for this case, with the 3 inputs specified above.