מרצים: פרופ' שי אבידן ופרופ' אלכס ברונשטיין

Video Processing HW3:

Particle Filter Tracking

Basic theory (just a reminder):

In the Kalman filter the density propagation changes from one Gaussian to another Gaussian distribution. What changes is the mean and variance.

This is very good if our system is linear and the noise is Gaussian. But if it isn't (i.e. cluttered data etc.) – Kalman fails.

This is where the particle filter enters - in every stage we create a new probability density function which can take any shape (not limited to being a Gaussian).

This shape is formed by sampling particles, each with a given weight and cumulative density function. This will be further elaborated in the continuation of this worksheet.

In short – we're still computing likelihood and prior probabilities and derive the posterior from them (similar to Kalman), but we're using more dynamic (non-Gaussian) probability functions to model the system.

Definitions:

For a given time stage, the system is described using the state vectors, their weights and their CDF's.

For N particles this is comprised of $\left\{s_t^{(n)}, w_t^{(n)}, c_t^{(n)}\right\}_{n=1}^N$

And in short writing we'll say that:

$$\begin{split} S_t &= \left\{ s_t^{(1)}, s_t^{(2)}, \dots, s_t^{(N)} \right\} \\ W_t &= \left\{ w_t^{(1)}, w_t^{(2)}, \dots, w_t^{(N)} \right\} \\ C_t &= \left\{ c_t^{(1)}, c_t^{(2)}, \dots, c_t^{(N)} \right\} \end{split}$$

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$$c_t^{(1)}=w_t^{(1)}$$

$$c_t^{(2)}=w_t^{(2)}+w_t^{(1)}$$
 and the weights are normalized such that
$$\sum_{i=1}^N w_t^{(i)}=1$$

$$c_t^{(N)}=\sum_{i=1}^N w_t^{(i)}$$

For example - $s_{t1}^{(5)}$, $w_{t1}^{(5)}$, $c_{t1}^{(5)}$ denotes that state vector $s_{t1}^{(5)}$ has a weight of $w_{t1}^{(5)}$ and a CDF of $c_{t1}^{(5)}$ and all this is true for time t=t1

Algorithm stages you'll implement in the assignment:

For brevity, I won't always write the time step indices. But keep in mind we're starting with the particle filter for time t-1 ('before the first image') and each new image is the next time step (t, t+1, t+2 etc. but because the images are discrete this doesn't mean much.)

Step A:

Here we will create an initial particle filter (comprised of 100 particles) for the previous time stage (t-1).

For this assignment each state vector has the following form:

$$s_t^{(n)} = \left[X_c^{(n)}, Y_c^{(n)}, \frac{\textit{Width}^{(n)}}{2}, \frac{\textit{Height}^{(n)}}{2}, X_{\textit{velocity}}^{(n)}, Y_{\textit{velocity}}^{(n)}\right] \textit{ @ time } t \textit{ and } n \in [1, 2, \dots, 100]$$

 $X_c, Y_c = coordinates$ to the center of object (the person we're going to track)

$$\frac{\textit{Width}}{2}, \frac{\textit{Height}}{2} = \textit{half of the width and height of our tracked person}$$

 $X_{velocity}$, $Y_{velocity}$ = the speed of our person in each coordinate

Hint – you don't have to change the width and height between time steps.

Now for the actual steps:

- 1. Set $s_{initial} = [297, 139, 16, 43, 0, 0]$
- 2. Create a matrix of vector states sized 6x100 by adding random additive noise to $s_{initial}$. Repeating this will create 100 particle state vectors (each column describes

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one state vector, each row describes one of the state vector components for 100 different particles). We'll call this S (with a capital S).

You can use step C (prediction) using the initial state vector for this part.

3. Load the first image and compute the normalized histogram for this image using $s_{initial}$. We'll call this normalized histogram 'q'.

This step can be confusing, so please read this carefully:

Your current frame 'I' is described in 3 dimension (width x height x 3 channels, RGB). $s_{initial}$ is 2 dimensional sized 6x1.

The histogram is computed for the pixels in the rectangle sized width x height with the centers xc and yc. You receive this information from $s_{initial}$.

Looking at this sub-portion of I, you'll notice the pixel intensities vary between 0 and 255 (8-bit). We want to quantize this to 4 bits (0 to 15).

Next we look at each new combination of I_subportion(R,G,B) and we have a total of $16^3 = 4096$ combinations of RGB values. We'll build a histogram vector such that each element in the vector describes the number of times this RGB combination appears. Do this for 16x16x16 values and reshape it a 4096x1 vector.

Normalize this vector such that the sum of all elements is equal to 1.

- 4. Repeat step 3, but this time use the first image and use the first column of *S* We'll call this normalized histogram 'p'. p is computed exactly like q was computed in the long explanation in step 3.
 - Now we compute the weights of each particle using the Bhattacharyya distance between p and q. This similarity index will be our way to determine the weights. Repeat this step for all 100 columns of S and you'll end up with

 $W=\{w_1,w_2,\dots,w_{100}\}$ were each element is the single Bhattacharyya distance value. The equation is: $w=dist(p,q)=\exp^{20*\sum_{i=1}^{4096}\sqrt{p_i*q_i}}$

- 5. Normalize vector W such that $\sum_{i=1}^{100} w(i) = 1$
- 6. Compute vector $C = \{c_1, ..., c_j, ..., c_{100}\} = \{w_1, ..., \sum_{i=1}^{j} \mathbf{w(i)}, ..., \sum_{i=1}^{100} \mathbf{w(i)} = 1\}$

We now have a complete set for our initial particle filter, normalized, weighted and with the CDFs.

Next we have to:

• sample the previous particle filter (step B)

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- predict the next particle filter and update the weights + CDF (step C)
- display the results (step D)

Step B (sampling, deterministic 'drift'):

- Repeat the following steps 1-3 for each value of $n \in [1, N]$
- 1. Generate a random value $r \in [0,1]$ from a uniform distribution.
- 2. Find the smallest value 'j' such that $c_{t-1}^{(j)} \ge r$
- 3. Set $s_t^{\prime(n)} = s_{t-1}^{(j)}$ where index 'j' corresponds with the 'j' we found in step 2.

We now have N sampled particles $S_t' = \left\{ s_t'^{(n)} \right\}_{n=1}^N$

Step C (prediction, random 'diffusion'):

Project the sampled particles from the previous step to their new location using a dynamic model and adding noise. This is done by setting:

$$S_t = AS_t' + noise$$

The noise is white additive noise (you decide what noise!).

D is a dynamic model (like in Kalman) – you may simply add the previous velocity components such that

$$S_{t} = \left[X_{c}^{(n)} + X_{velocity}^{(n)}, Y_{c}^{(n)} + Y_{velocity}^{(n)}, \frac{Width^{(n)}}{2}, \frac{Height^{(n)}}{2}, X_{velocity}^{(n)}, Y_{velocity}^{(n)}\right]_{t} + noise$$

Step D (show results):

You are required to plot the **average** particle filter rectangle in green and to plot the **maximal** particle filter (with the largest weight) in red.

There are numerous ways to achieve this type of plot.

The title of the image plot must be GROUP-XX-YY Frame number = xxx.