Advanced tracking

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I. Introduction

In this project, we implement a Kalman filter and a particle filter tracker, each based on appropriate motion models. We evaluate the Kalman filter using synthetically generated trajectories, and test the particle filter on the VOT14 dataset. Additionally, we analyze the impact of key parameters such as the number of particles and the choice of color space for constructing the visual model.

II. Experiments

A. Kalman filter

First, we implemented the Kalman filter and tested its performance using different motion models and parameter settings on a spiral trajectory.

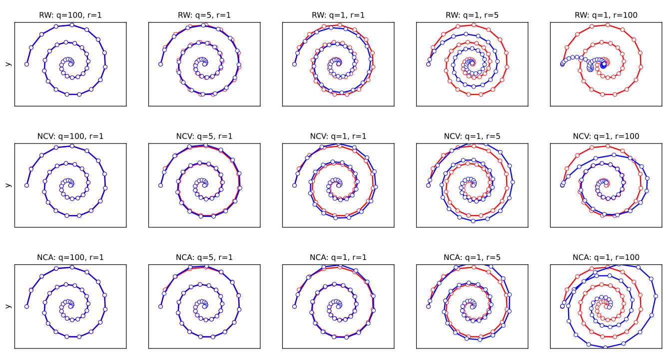

Figure 1: Kalman filter tracking results on a spiral-shaped trajectory. The red line shows the ground truth, the blue line shows the predicted trajectory.

From Figure 1 we can see that, when the process noise is high and measurement noise is low (e.g., q = 100, r = 1), all three models adapt quickly to changes in the trajectory and track the motion accurately. However, as the measurement noise increases and process noise decreases (e.g., q = 1, r = 100), the filter becomes overly reliant on the motion model. This causes the predictions with the Random Walk model to significantly differ from the ground truth, as it lacks predictive motion structure. In contrast, NCV and NCA showed better performance.

B. Additional Trajectories

To compare model performance, we evaluated the Kalman filter on two additional trajectories. For both curves, similar performance was observed as in the spiral-shaped trajectory. The RW model performed the worst, with increasing observation noise and decreasing process noise. In this case, the NCA model performed slightly better than NCV, as we can see from Figures 2 and 3, where it better handled the directional changes.

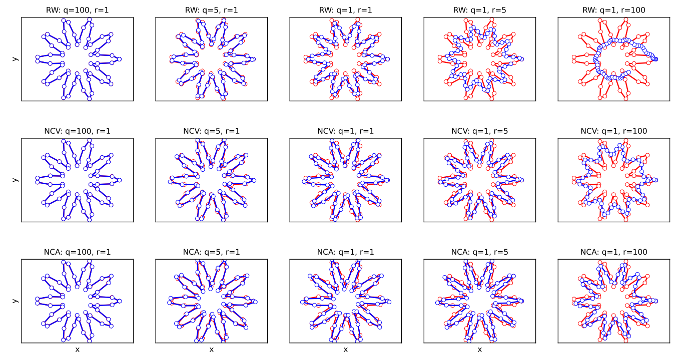

Figure 2: Kalman filter tracking results on a star-shaped trajectory.

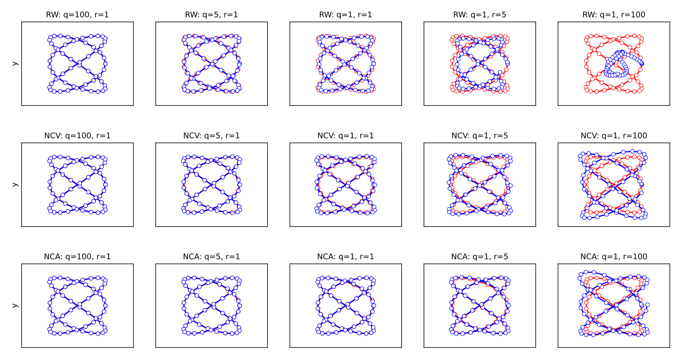

Figure 3: Kalman filter tracking results on a loop-shaped trajectory.

C. Particle Filter Tracker

For the particle filter implementation, we achieved the best results by setting the process noise parameter as $q = 0.1 \cdot \min(\text{width}, \text{height})$, which ensured that the noise is proportional to the target size. The histogram update rate was set to $\alpha = 0.0005$, and the likelihood parameter to $\sigma = 0.1$. For the visual model, we used a histogram representation with 16 bins, weighted by an Epanechnikov kernel with kernel size 1. Using 100 particles.

Table I: Performance of the Particle Filter Tracker on VOT14 Dataset.

Average Overlap	Total Failures	Average Speed [FPS]
0.51	38	110.62

Most of the failures occurred due to drifts, sudden motion changes, occlusions or when the visual model was too similar to the background, as in sequences like fish1, hand1, davis, and motorcross. Examples of failure cases are shown in Figure 4.

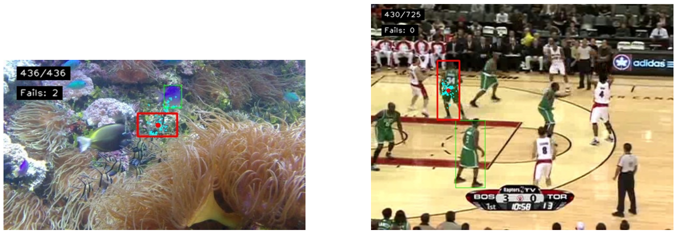

Figure 4: Failure cases of the particle filter, with shown particles.

D. Effect of process noise q

We experimented with tuning the process noise parameter q. When using a constant value, we observed that increasing q reduced the number of failures up to $q = 10$. However, further increasing it caused performance to drop.We also tuned q by making the process noise proportional to the target size, using both the mean and the minimum of the height and width. The best performance was achieved using the minimum, with a scaling factor of 0.1.

Table II: Effect of q parameter on the tracker perfromance

q value	Average Overlap	Failures	Speed [FPS]
0.1	0.44	76	115.12
1.0	0.51	54	116.37
5.0	0.50	43	92.77
10	0.52	41	61.54
50	0.54	51	95.28
0.01 * min (h, w)	0.48	58	90.72
0.1 * min (h, w)	0.51	38	110.62
0.01 * mean (h, w)	0.48	55	73.25
0.1 * mean (h, w)	0.51	40	78.13

E. Modelling with different motion models

Using different motion models, from Table III we can see that NCV performed the best, followed by RW. However, NCA surprisingly performed the worst, with 214 failures. We additionally tried tuning the parameters, but the number of failures did not decrease.

Table III: Different motion model assumtpion.

Model	Average Overlap	Failures	Speed [FPS]
RW	0.48	57	97.26
NCV	0.51	38	110.62
NCA	0.55	214	115.18

F. Effect of number of particles

To analyze the influence of different numbers of particles on the tracker performance, we tested several values in the interval [10, 1000]. As expected, using a smaller number of particles increased the FPS , and we can see that for $n > 200$, it drops below 50. From the table IV, we can see that the smallest number of failures was achieved with $n = 500$, however this comes at the cost of significantly reduced FPS. Further increasing the number of particles did not reduce the number of failures.

In our opinion, using 50 particles is sufficient, as it provides a good balance between FPS and the number of failures.

Table IV: Effect of particle number on tracker performance. For NCV model.

Particles	Average Overlap	Failures	Speed [FPS]
10	0.47	93	755.95
50	0.51	37	179.77
100	0.51	38	110.62
200	0.51	37	50.55
500	0.52	34	18.89
1000	0.51	39	11.73

G. Modelling with different color spaces

Next, we evaluate the impact of using different color spaces for building the color histogram in the visual model. To simplify implementation, for each of the models, we used the paramters which showed best performance on the NCV model.

Table V: Effect of color space on tracking performance for the three models.

Color Space	Model	Average Overlap	Failures	Speed [FPS]
RGB / BGR	RW	0.48	57	97.26
	NCV	0.51	38	110.62
	NCA	0.55	214	115.18
HSV	RW	0.47	49	82.26
	NCV	0.53	30	109.06
	NCA	0.54	204	90.16
Lab	RW	0.47	58	110.89
	NCV	0.51	44	86.53
	NCA	0.55	232	79.25
YCrCb	RW	0.48	61	86.35
	NCV	0.51	54	112.18
	NCA	0.55	240	28.36

The best performance was achieved using the HSV color space, which makes sense since HSV separates brightness from hue and is more robust to lighting changes. On the other hand, YCrCb gave the lowest performance. This is likely because YCrCb is mainly used for video compression, while in our case we process each frame independently.

Comparing the motion models, the NCV model showed the best overall performance across all color spaces.

III. Conclusion

In this assignment, the Kalman filter and particle filter tracker were successfully implemented. We further analyzed their performance by tuning parameters and comparing different motion models. The best results were achieved with the NCV model, followed by RW and NCA on the VOT14 dataset. Testing different color spaces showed that color representation does affect tracking accuracy.

Appendix

Table I: Random Walk Model

$$x = \begin{bmatrix} x \\ y \end{bmatrix}, \quad F = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, \quad \Phi = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad L = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q = q \cdot \begin{bmatrix} T & 0 \\ 0 & T \end{bmatrix}, \quad H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

Table II: Nearly Constant Velocity Model

$$x = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix}, \quad F = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}, \quad \Phi = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$L = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad Q = q \cdot \begin{bmatrix} \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^2}{2} & 0 & T \end{bmatrix},$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Table III: Nearly Constant Acceleration Model

$$x = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \\ \ddot{x} \\ \ddot{y} \end{bmatrix}, \quad F = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\Phi = \begin{bmatrix} 1 & 0 & T & 0 & \frac{T^2}{2} & 0 \\ 0 & 1 & 0 & T & 0 & \frac{T^2}{2} \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$L = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad Q = q \cdot \begin{bmatrix} \frac{T^5}{20} & 0 & \frac{T^4}{8} & 0 & \frac{T^3}{6} & 0 \\ 0 & \frac{T^5}{20} & 0 & \frac{T^4}{8} & 0 & \frac{T^3}{6} \\ \frac{T^4}{8} & 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^4}{8} & 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^3}{6} & 0 & \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^3}{6} & 0 & \frac{T^2}{2} & 0 & T \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$