Exercise 4: Advanced tracking

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I. Introduction

In this exercise we look into the kalman and particle filter. We implemented the kalman filter for random walk (RW), nearly consant velocity (NCV) and nearly constant acceleration (NCA) motion models. We show kalman filter on a few simple curves to analyse how motion model parameters affect the filter. Then we implemented the particle filter and show performance as number of failures, average overlap and average FPS for their parameter choice. We compare particle filter tracker using different motion models (RW, NCV and NCA) on VOT14 dataset.

II. Experiments

A. Kalman filter

We show kalman filter at work on three different curves. We show how parameters q (system covariance) and r (observation covariance) affect RW, NCV and NCA motion models. In Figures 1, 2 and 3 we observe that using a large observation covariance and low system covariance results in poor performance. Kalman filter always succeeds when using a high system covariance (q = 100). In all three plots we show the original curve with red and the tracked curve with blue.

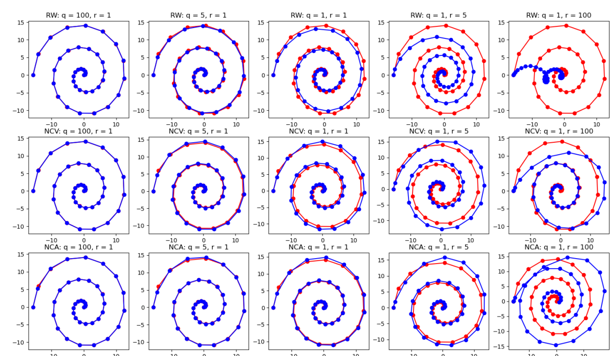

Figure 1: Example of kalman filter on a spiral curve with RW, NCV, and NCA motion models.

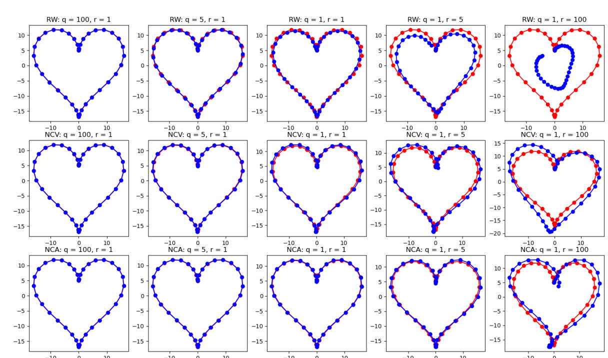

Figure 2: Example of kalman filter on a heart shaped curve with RW, NCV, and NCA motion models.

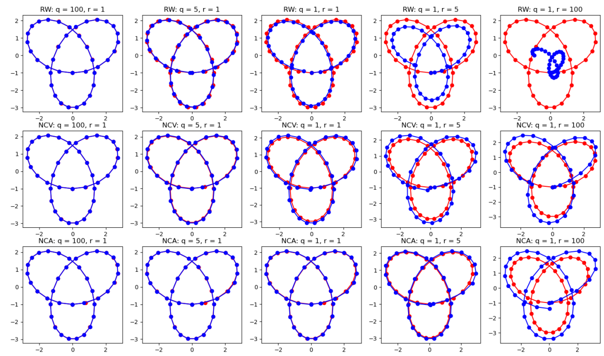

Figure 3: Example of kalman filter on a trefoil knot curve with RW, NCV, and NCA motion models.

B. Particle filter

We implemented particle filter using color histogram as a visual model. To compare histograms we used hellinger distance. To obtain tracking performaces we integrated our tracker with toolkit-lite. As default parameters for all three motion models we decided to use:

1) **number_of_particles** = 70,
2) **number_of_bins** = 16,
3) $\sigma = 1$ for epanechnik kernel and $\sigma = 4$ for hellinger distance,
4) $\alpha = 0.01$,
5) **q** = 0.1 * mean of the size of bounding box.

Table I: Results for all three motion models used on VOT14 dataset.

	Failures	Overlap	FPS
RW	59	0.43	59.7
NCV	43	0.46	66.9
NCA	281	0.52	46.9

In Table I we observe that NCV motion model gives us the best trade off between number of failures and average overlap. This is expected since most video sequences have a target that moves almost with constant velocity. RW also performs quite good with 16 more failures. However NCA model performs really bad, since it assumes that the target is accelerating. We must note that the overlap is better for NCA since the overlap measure partially depends on the number of failures (with each fail, the bounding box resets creating a better overlap). We also observe that the speed of tracking does not change drastically with the change of motion model.

C. Motion model parameter influence

In this section we will show how q and alpha parameter impact tracking based on number of failures and average overlap. We use default parameters listed in previous section.

1) Parameter alpha: Updating our reference histogram with every iteration allows the algorithm to adapt to our target that might change over time. Alpha parameter controls the update speed.

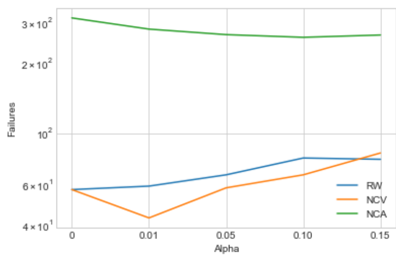

Figure 4: Parameter **alpha** influence on number of **failures** for RW, NVC and NVA motion models.

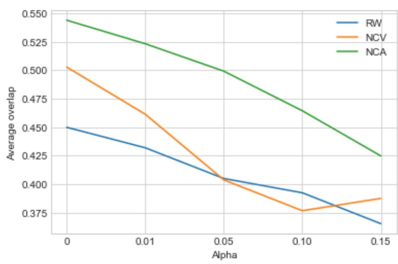

Figure 5: Parameter **alpha** influence on average **overlap** for RW, NVC and NVA motion models.

In Figures 4 and 5 we observe that using $\alpha = 0.01$ shows best results for NCV. Using a large alpha parameter might change our reference histogram too much and we lose our target.

2) Parameter q: System covariance defines how much spread we add to our particles. If the spread is too small, we might not be able to track a fast moving target. If the spread is too big, we might lose our target faster. We decided to use different q for every sequence such that q is dependent on the target size.

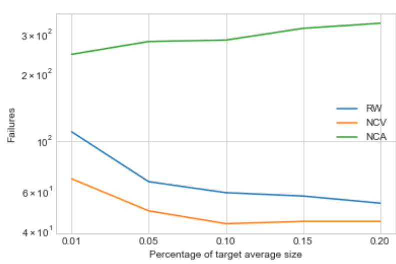

Figure 6: Parameter **q** influence on number of **failures** for RW, NVC and NVA motion models.

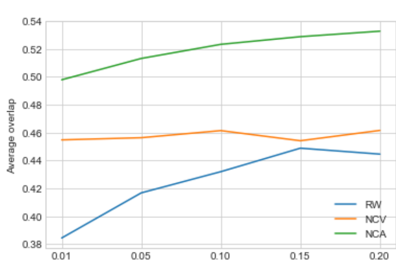

Figure 7: Parameter **q** influence on average **overlap** for RW, NVC and NVA motion models.

In Figures 6 and 7 we observe that using 10% of the mean of height and width of bounding box yiels best reults for NCV motion model. But we observe that failures still drop when increasing percentage for RW.

D. Number of particles

With increasing number of particles we increase the chance that a particle will follow the target. Since we have to compare histogram for every resampled particle, speed of tracking decreases with number of particles. In Figures 8 and 9 we show that number of failures decreases and overlap increases with increasing number of particles for all three motion models. In Figure 10 we show that FPS drop is immensely visable for RW and NCV motion models, meanwhile NCA has almost constant FPS.

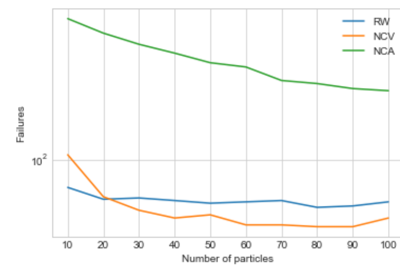

Figure 8: **Number of particles** influence on number of **failures** for RW, NVC and NVA motion models.

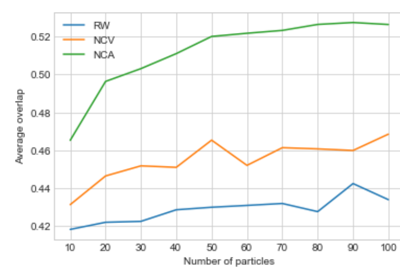

Figure 9: **Number of particles** influence on average **overlap** for RW, NVC and NVA motion models.

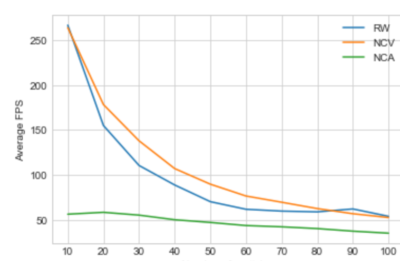

Figure 10: **Number of particles** influence on average **FPS** for RW, NVC and NVA motion models.

III. Conclusion

We have explored kalman and particle filter. We show kalman filter on different curves with using different parameter values. For particle filter we compared number of failures, average overlap and FPS for three motion models on VOT14 dataset.

IV. Appendix

Table II: Random walking motion model.

$$X = \begin{bmatrix} x \\ y \end{bmatrix} \qquad F = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

$$\phi = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \qquad L = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

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

Table III: Nearly constant velocity motion model.

$$x = \begin{bmatrix} x \\ y \\ \dot{x} \\ \dot{y} \end{bmatrix} \qquad F = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\phi = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \qquad L = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q = \mathrm{q} \begin{bmatrix} \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} \\ \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^2}{2} & 0 & T \end{bmatrix} \qquad H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

Table IV: Nearly constant accelation motion model.

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

$$\phi = \begin{bmatrix} 1 & 0 & T & 0 & \frac{T^2}{2} & 0 \\ 0 & 1 & 0 & T & 0 & \frac{T^2}{2} \\ 0 & 0 & 1 & 0 & T & 0 \\ 0 & 0 & 0 & 1 & 0 & T \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \qquad L = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$Q = \mathrm{q} \begin{bmatrix} \frac{T^5}{20} & 0 & \frac{T^4}{8} & 0 & \frac{T^3}{6} & 0 \\ 0 & \frac{T^5}{20} & 0 & \frac{T^4}{8} & 0 & \frac{T^3}{6} \\ \frac{T^4}{8} & 0 & \frac{T^3}{3} & 0 & \frac{T^2}{2} & 0 \\ 0 & \frac{T^4}{8} & 0 & \frac{T^4}{8} & 0 & \frac{T^2}{2} \\ \frac{T^3}{6} & 0 & \frac{T^2}{2} & 0 & T & 0 \\ 0 & \frac{T^3}{6} & 0 & \frac{T^2}{2} & 0 & T \end{bmatrix}$$

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