Home Work 4 – Kalman and Particle filter

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I. Introduction

The goal of this research project was to implement the Kalman filter and Particle filter for object tracking.

II. Experiments

A. Task 1 – Kalman Filter

The first step was to implement the Kalman filter, where we have three motion models, Random Walk (RW), Near Constant Velocity (NCV) and Near Constant Acceleration (NCA). For each motion model we defined the position $\mathbf{x}$, which is showed in the appendix of this paper, then the F matrix which is the transformation matrix of the position, L which represents the transformation matrix of the added noise, (ex. added noise of the velocity in the NCV model). Then we used the solution of Stengel to discretise the space and convert the matrices useful for discrete space which are the matrices Φ, the transformation matrix of the position, Q matrix which is the covariance matrix, representing the variance of the distribution, and also the H and R matrices which are the transformation and the covariance matrices respectively but of the observation model. The results showed in Figure 1 we can see how based on the importance of the models where when r is low we add much importance to the observation model (there are no variance, added error) and vice versa when q is low we add more importance to the motion model. Here we can see how the changes of the motion model are important since the NCV models shows much better results with the respect to the RW model. Also the NCA models showed great result, even better in some cases since it has the acceleration as a component.

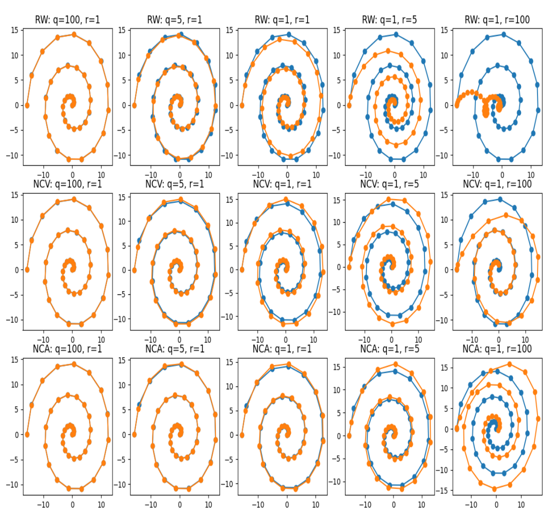

Figure 1. The performance of the kalman filter on the given function.

B. Task 2 – Particle Filter

We implemented the particle filter with 100 particles, the visual model was histogram, the motion model was nearest constant velocity, and was tested on 5 sequences as showed in the following table I.

Sequence	Overlap	Failuers	Speed
ball	0.64	1	55.71
bolt	0.61	2	47.64
car	0.40	0	55.82
david	0.49	1	41.25
drunk	0.42	0	37.98

Table I
The results on the 5 sequences

C. Task 3

Nevertheless of the shape the performance of the kalman filter is similar in both added examples of shapes (rectangular 2 and trapesoid 3).

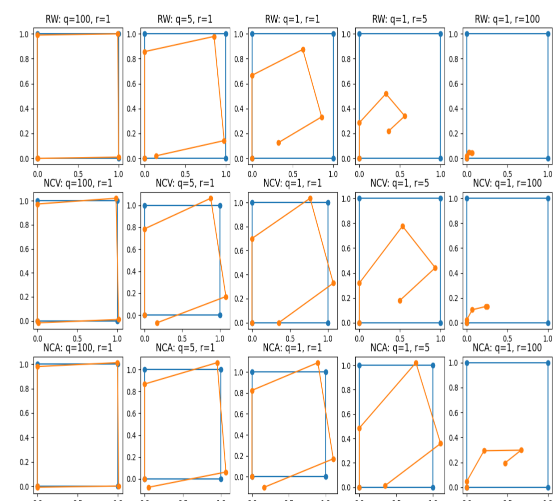

Figure 2. The performance of the kalman filter on the rectangle.

D. Task 4

As showed at the results II, we can see how the motion model impact the particle filter performance, where we can see that the filter with near constant velocity has the best number of failuers. This is most likely due to the fact most of the objects at the sequences are moving with almost constant velocity, there is not a significant acceleration, that is why even the RW model is working great. Other parameter is the q which was actually calculated by the $Q \cdot min(region-width, region-height)$ where we can see that it depends very much of the type of motion, for example larger q is better for the RW, but it is worse for the NCA, and it does not matter for the NCV.

E. Task 5

As shown in the results section Table II, we can see how the changes of number of particles in the particle filter affects

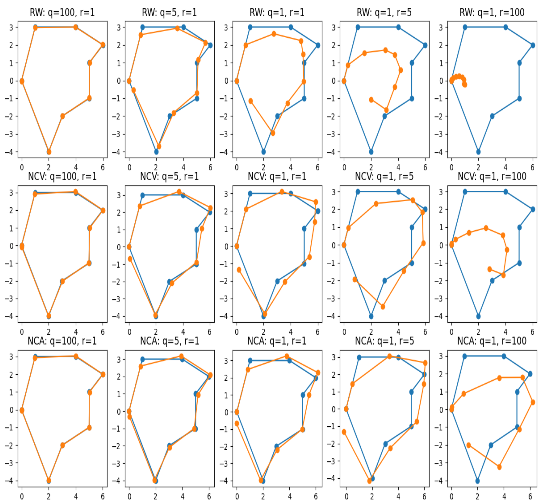

Figure 3. The performance of the kalman filter on my trapesoid.

the performance, in the RW motion model it did not affect the accuracy, but it higher particles slows down the motion model, which is expected. In the other hand at the NCV and NCA model, higher number of particles lowered the number of failuers which is improved performance and also slowed down the model, which is almost unusable for online tracking, but nevertheless it improves the performance in terms of number of failuers.

III. Results

Particles	Q	Motion	Overlap	Failures	Speed
50	0.5	RW	0.45	35	98.12
100	0.25	RW	0.41	51	49.24
100	0.5	RW	0.45	37	50.58
100	0.75	RW	0.47	34	48.98
150	0.5	RW	0.46	36	35.26
50	0.5	NCV	0.49	36	97.46
100	0.25	NCV	0.50	34	50.18
100	0.5	NCV	0.49	37	49.45
100	0.75	NCV	0.49	33	48.22
150	0.5	NCV	0.49	27	32.57
50	0.5	NCA	0.50	190	97.39
100	0.25	NCA	0.50	64	49.23
100	0.5	NCA	0.48	66	51.28
100	0.75	NCA	0.50	74	50.79
150	0.5	NCA	0.51	55	34.18

Table II
Results of the particle filter

IV. Conclusion

In conclusion we can see how the use of recursive bayesian filters such as kalman and particle filter improved the number of failures with respect to the previous object trackers, but this was with the cost of lowering the speed which is almost impossible to use for online tracking.

Appendix

$\mathbf{x} = \begin{bmatrix} x \\ y \end{bmatrix}$ $F = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ $L = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $\Phi = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $Q = \begin{bmatrix} tq & 0 \\ 0 & tq \end{bmatrix}$ $H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$ $R = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix}$

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

$\Phi = \begin{bmatrix} 1 & 0 & t & 0 \\ 0 & 1 & 0 & t \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$ $Q = \begin{bmatrix} \frac{t^3q}{3} & 0 & \frac{t^2q}{2} & 0 \\ 0 & \frac{t^3q}{3} & 0 & \frac{t^2q}{2} \\ \frac{t^2q}{2} & 0 & tq & 0 \\ 0 & \frac{t^2q}{2} & 0 & tq \end{bmatrix}$ $H = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$ $R = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix}$

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

$\Phi = \begin{bmatrix} 1 & 0 & t & 0 & \frac{3t^2}{2} & 0 \\ 0 & 1 & 0 & t & 0 & \frac{3t^2}{2} \\ 0 & 0 & 1 & 0 & t & 0 \\ 0 & 0 & 0 & 1 & 0 & t \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$

$Q = \begin{bmatrix} \frac{9t^5q}{20} & 0 & \frac{3t^4q}{8} & 0 & \frac{t^3q}{2} & 0 \\ 0 & \frac{9t^5q}{20} & 0 & \frac{3t^4q}{8} & 0 & \frac{t^3q}{2} \\ \frac{3t^4q}{8} & 0 & \frac{t^3q}{3} & 0 & \frac{t^2q}{2} & 0 \\ 0 & \frac{3t^4q}{8} & 0 & \frac{t^3q}{3} & 0 & \frac{t^2q}{2} \\ \frac{t^3q}{2} & 0 & \frac{t^2q}{2} & 0 & tq & 0 \\ 0 & \frac{t^3q}{2} & 0 & \frac{t^2q}{2} & 0 & tq \end{bmatrix}$ $H = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \end{bmatrix}$ $R = \begin{bmatrix} r & 0 \\ 0 & r \end{bmatrix}$