

# Advanced tracking

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## I. INTRODUCTION

With more complex object trackers it is possible to achieve better tracking performance, even when dealing with occlusions. In this report, I will explore the strengths of the Kalman filter and of the Particle filter.

## II. EXPERIMENTS

### A. Kalman filter

I implemented the Kalman filter with RW, NCV, and NCA motion models. Matrices of each motion model are listed in the following equations. In Figures 1, 2 and 3 we observe the Kalman filter with different motion models in action. With a high value of the  $q$  parameter and a low value of the  $r$  parameter, the filter is capable of correctly following the real movements. In all three figures, the filter fails, when  $q = 1$  and  $r > 1$ .

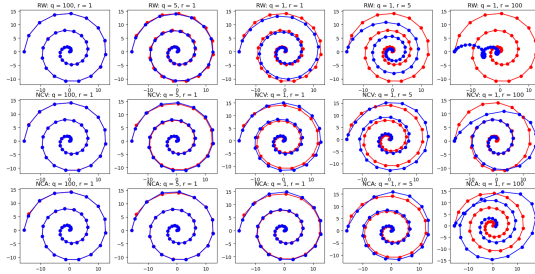


Figure 1: Example of the Kalman filter with different motion models and different  $r$  and  $q$  parameters. The red spiral represents the real movements. The blue spiral represents the movement performed by the Kalman filter.

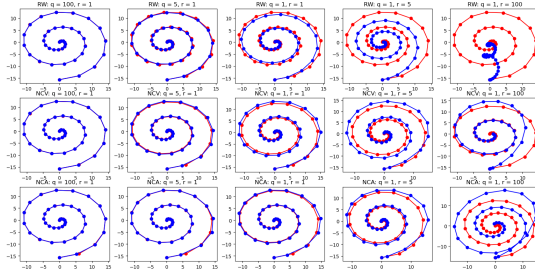


Figure 2: Example of the Kalman filter with different motion models and different  $r$  and  $q$  parameters. For this example, the axis  $x$  and  $y$  have been over-changed. The red spiral represents the real movements. The blue spiral represents the movement performed by the Kalman filter.

### B. Particle Filter

The performance of the Particle filter using the NCV dynamic model and color histogram as the visual model is shown

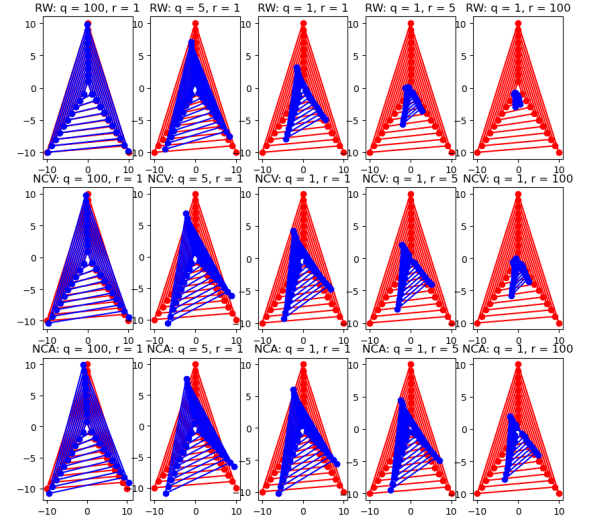


Figure 3: Example of the Kalman filter with different motion models and different  $r$  and  $q$  parameters. For this example, the represented object is an (at each iteration growing in size) triangle. The red triangle represents the real movements. The blue triangle represents the movement performed by the Kalman filter.

|          | RW      |       | NCV     |       | NCA     |       |
|----------|---------|-------|---------|-------|---------|-------|
| Sequence | # fails | FPS   | # fails | FPS   | # fails | FPS   |
| ball     | 1       | 104.2 | 0       | 122.2 | 30      | 108.8 |
| bolt     | 1       | 83.0  | 3       | 98.0  | 21      | 101.9 |
| car      | 1       | 119.1 | 0       | 122.8 | 16      | 82.6  |
| fernando | 9       | 41.6  | 10      | 45.8  | 19      | 47.2  |
| torus    | 1       | 122.5 | 0       | 121.1 | 14      | 114.6 |

Table I: Table shows the performance of the Particle filter on five different VOT14 sequences using the following parameters:  $\alpha = 0.01$ , number of bins = 16, number of particles = 100,  $q = 10$

in Table I. We observe that the particle filter with the NCV dynamic model gives the best performance among RW, NCV, and NCA. In all three cases, the tracker ran always with the same settings. When increasing the  $q$  parameter our results do not change drastically (see Table II), but the FPS on average are a little higher.

### C. Influence of the number of particle on tracking

In Tables III and IV are shown the results of the Particle filter with 10 and 500 particles. From Table III we observe that FPS is much higher than the FPS with 100 particles, this is because the model needs to perform less computation. In the case of 10 particles, the accuracy is a little worse than 100 particles. When using 500 particles, the FPS is much lower (see Table IV). Using 500 particles the NCA dynamic model gave the best accuracy results.

| Sequence | RW      |       | NCV     |       | NCA     |       |
|----------|---------|-------|---------|-------|---------|-------|
|          | # fails | FPS   | # fails | FPS   | # fails | FPS   |
| ball     | 0       | 124.7 | 0       | 126.5 | 45      | 110.5 |
| bolt     | 3       | 100.7 | 4       | 104.7 | 28      | 113.5 |
| car      | 0       | 139.8 | 0       | 131.7 | 21      | 91.5  |
| fernando | 7       | 48.9  | 9       | 40.3  | 23      | 53.0  |
| torus    | 0       | 128.2 | 0       | 125.6 | 21      | 119.4 |

Table II: Table shows the performance of the Particle filter on five different VOT14 sequences using the following parameters:  $\alpha = 0.01$ , number of bins = 16, number of particles = 100,  $q = 100$

| Sequence | RW      |       | NCV     |       | NCA     |       |
|----------|---------|-------|---------|-------|---------|-------|
|          | # fails | FPS   | # fails | FPS   | # fails | FPS   |
| ball     | 2       | 920.5 | 3       | 807.4 | 46      | 203.0 |
| bolt     | 1       | 703.7 | 5       | 705.6 | 29      | 191.6 |
| car      | 1       | 954.0 | 6       | 646.7 | 21      | 181.3 |
| fernando | 9       | 341.1 | 10      | 342.7 | 24      | 159.2 |
| torus    | 1       | 918.1 | 1       | 892.4 | 20      | 203.3 |

Table III: Table shows the performance of the Particle filter on five different VOT14 sequences using the following parameters:  $\alpha = 0.01$ , number of bins = 16, number of particles = 10,  $q = 10$

### III. CONCLUSION

The particle filter can be improved just by using a more complex visual model. NCV and RW dynamic models showed to work fine with a low number of particles, while on the contrary, the NCA model needs a bigger amount of particles to perform fine.

#### APPENDIX

$$X_{RW} = \begin{bmatrix} x \\ y \end{bmatrix} \quad (1)$$

$$F_{RW} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \quad (2)$$

$$\phi_{RW} = H_{RW} = L_{RW} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \quad (3)$$

$$Q_{RW} = \begin{bmatrix} Tq & 0 \\ 0 & Tq \end{bmatrix} \quad (4)$$

$$X_{NCV} = \begin{bmatrix} x \\ \dot{x} \\ y \\ \dot{y} \end{bmatrix} \quad (5)$$

$$F_{NCV} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (6)$$

$$\phi_{NCV} = \begin{bmatrix} 1 & T & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & T \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (7)$$

$$L_{NCV} = \begin{bmatrix} 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \quad (8)$$

| Sequence | RW      |      | NCV     |      | NCA     |      |
|----------|---------|------|---------|------|---------|------|
|          | # fails | FPS  | # fails | FPS  | # fails | FPS  |
| ball     | 1       | 25.9 | 0       | 26.2 | 14      | 26.9 |
| bolt     | 2       | 20.7 | 2       | 20.5 | 17      | 29.8 |
| car      | 1       | 25.3 | 0       | 24.6 | 11      | 21.7 |
| fernando | 9       | 10.0 | 10      | 9.7  | 13      | 8.8  |
| torus    | 1       | 26.3 | 0       | 25.1 | 8       | 24.2 |

Table IV: Table shows the performance of the Particle filter on five different VOT14 sequences using the following parameters:  $\alpha = 0.01$ , number of bins = 16, number of particles = 500,  $q = 10$

$$H_{NCV} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \quad (9)$$

$$Q_{NCV} = \begin{bmatrix} \frac{T^3 q}{2} & \frac{T^2 q}{2} & 0 & 0 \\ \frac{T^2 q}{2} & Tq & 0 & 0 \\ 0 & 0 & \frac{T^3 q}{2} & \frac{T^2 q}{2} \\ 0 & 0 & \frac{T^2 q}{2} & Tq \end{bmatrix} \quad (10)$$

$$X_{NCA} = \begin{bmatrix} x \\ \dot{x} \\ \ddot{x} \\ y \\ \dot{y} \\ \ddot{y} \end{bmatrix} \quad (11)$$

$$F_{NCA} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \quad (12)$$

$$\phi_{NCA} = \begin{bmatrix} 1 & T & T^2/2 & 0 & 0 & 0 \\ 0 & 1 & T & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & T & T^2/2 \\ 0 & 0 & 0 & 0 & 1 & T \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \quad (13)$$

$$L_{NCA} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 0 \\ 0 & 0 \\ 0 & 1 \end{bmatrix} \quad (14)$$

$$H_{NCA} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \end{bmatrix} \quad (15)$$

$$Q_{NCA} = \begin{bmatrix} \frac{T^5 q}{20} & \frac{T^4 q}{8} & \frac{T^3 q}{6} & 0 & 0 & 0 \\ \frac{T^4 q}{8} & \frac{T^3 q}{2} & \frac{T^2 q}{2} & 0 & 0 & 0 \\ \frac{T^3 q}{6} & \frac{T^2 q}{2} & Tq & 0 & 0 & 0 \\ 0 & 0 & 0 & \frac{T^5 q}{20} & \frac{T^4 q}{8} & \frac{T^3 q}{6} \\ 0 & 0 & 0 & \frac{T^4 q}{8} & \frac{T^3 q}{2} & \frac{T^2 q}{2} \\ 0 & 0 & 0 & \frac{T^3 q}{6} & \frac{T^2 q}{2} & Tq \end{bmatrix} \quad (16)$$