Yue Pan
yuepan@student.ethz.ch

Assignment 11

1.CONDENSATION Tracker Implement

For this task, please refer to the uploaded codes.

Color Histograms:

The color histograms are used as the observation in this task. The histogram is counted in a neighborhood (bounding box) of the estimated position of the tracked object. It is then concatenate into a single feature vector, which is used for the calculation of chi-square feature distance between adjacent frames.

Derive matrix A:

For the no motion model:

$$A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \tag{1}$$

$$\underset{2\times k}{p}' = \underset{2\times 2}{A}\,\underset{2\times k}{p} + \begin{bmatrix} \Delta x & \Delta y \end{bmatrix}^T \tag{2}$$

For the constant velocity model:

$$A = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3}$$

$$\underset{4\times k}{p}' = \underset{4\times 4}{A}\,\underset{4\times k}{p} + \begin{bmatrix} \Delta x & \Delta y & \Delta \dot{x} & \Delta \dot{y} \end{bmatrix}^T \tag{4}$$

This is because the constant velocity would also contribute to the block of distance.

2.Experiments

Video 1:

Firstly, I tested the CONDENSATION algorithm on video 1, the simple dataset with uniform background. For this dataset, I didn't do enough ablation study. I only changed the model type (no motion and constant velocity model) and the histogram updating parameter α. The parameter settings are listed in Table 1 and the corresponding results are shown in Fig.1 to Fig.4. It is shown that both the no motion and constant velocity model with the default parameter settings managed to track the hand on this dataset. Results of constant velocity model seems to be a bit better than no motion model's (more area of the hand instead of the arm can be tracked). In order to have a more comprehensive comparison and analysis of different parameter settings, the algorithm is then tested on more challenging datasets.

Video 2:

Video 2 is a dataset with more clutters and occlusions. I tried more groups of parameter settings here, which are listed in Table 2. The corresponding results are shown in Fig.5 to Fig.11.

It is found that both the no motion and constant velocity model succeed when the standard deviation of position $\sigma_{pos} = 10$. However, when σ_{pos} is relatively small (=1), the no motion model totally failed (as shown in Fig.8) while the constant velocity model still works, which indicates the superiority of the constant velocity model.

Table 1: Video1 : experiment cases

parameter setting	model	α	hist_bin	particle_num	σ_{pos}	σ_{obs}	σ_{vel}
1A (Fig.1)	0	0	16	300	10	0.1	-
1B (Fig.2)	0	0.5	16	300	10	0.1	-
1C (Fig.3)	1	0	16	300	10	0.1	1
1D (Fig.4)	1	0.5	16	300	10	0.1	1

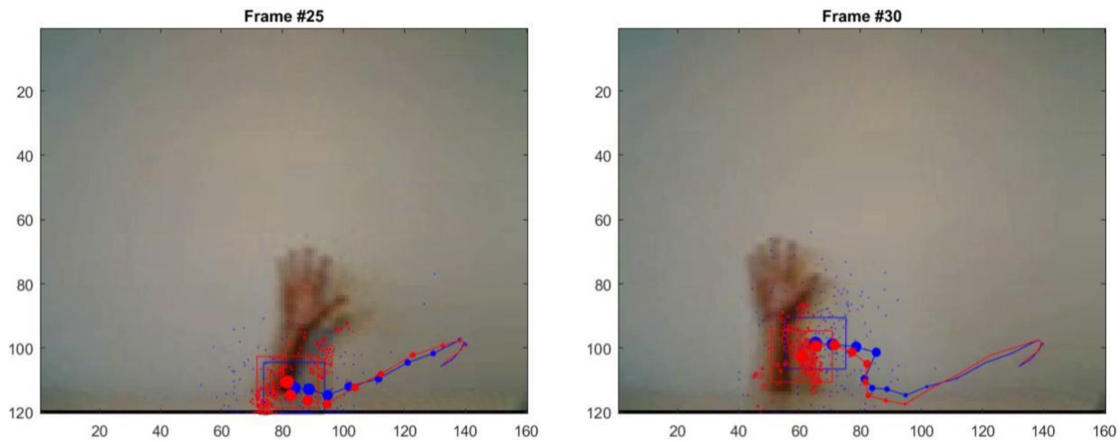

Figure 1: Results of parameter setting 1A

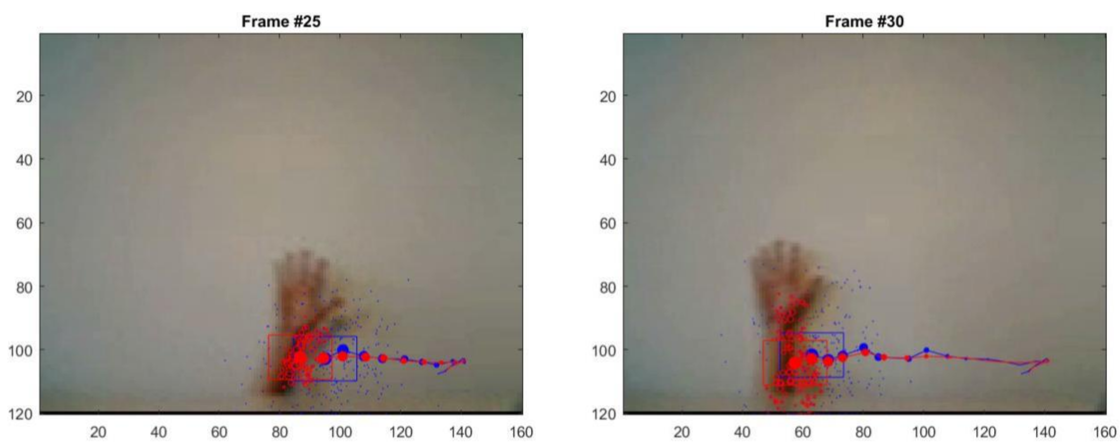

Figure 2: Results of parameter setting 1B

Besides, when the σ_{pos} is too large (for example 100), since the estimated particles would be far away from the ground truth, the observation cannot find the right way back to their right places. (refer to Fig.9). So in my opinion, $\sigma_{pos} \approx 10$ would be the best setting for the standard deviation of position.

From Fig.10 and Fig.11, it is shown that either a too large or too small standard deviation of observation σ_{obs} would result in problem of tracking. For a too small σ_{obs}, tiny changes or occlusion might mess up the tracking. As shown in Fig.11, the particles finally followed the metronome on the way instead of the hand. So I think

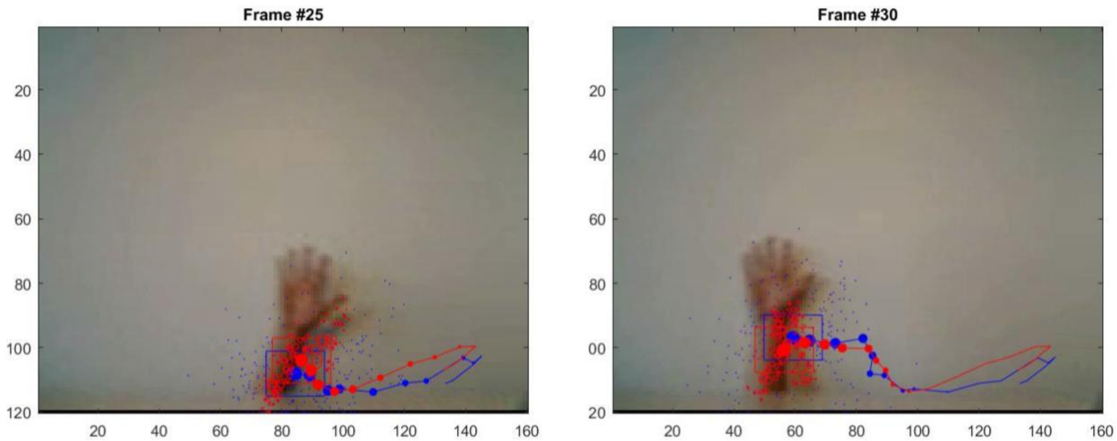

Figure 3: Results of parameter setting 1C

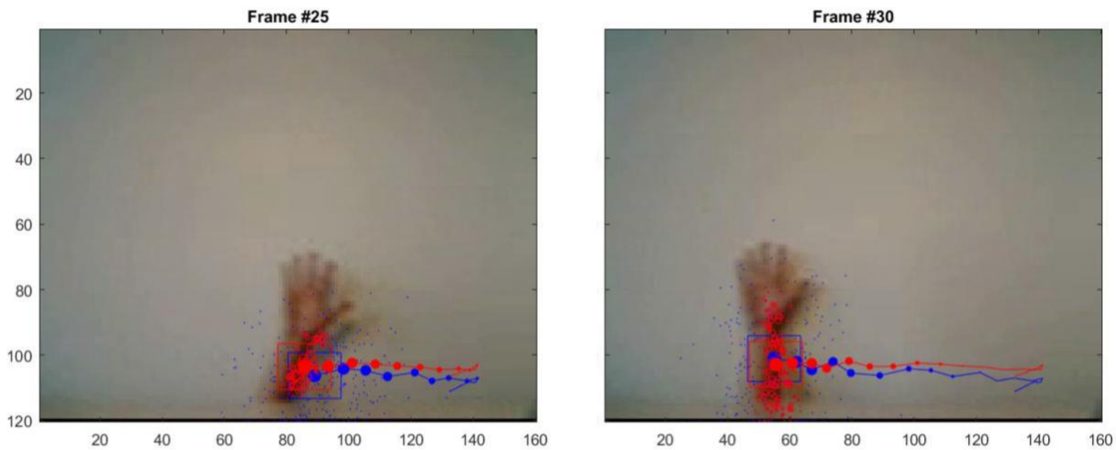

Figure 4: Results of parameter setting 1D

$\sigma_{obs} \approx 0.1$ would be a suitable setting of the standard deviation of observation.

Table 2: Video2 : experiment cases

parameter setting	model	α	hist_bin	particle_num	σ_{pos}	σ_{obs}	σ_{vel}
2A (Fig.5)	1	0.5	16	300	10	0.1	1
2B (Fig.6)	0	0.5	16	300	10	0.1	-
2C (Fig.7)	1	0.5	16	300	1	0.1	1
2D (Fig.8)	0	0.5	16	300	1	0.1	1
2E (Fig.9)	1	0.5	16	300	100	0.1	1
2F (Fig.10)	1	0.5	16	300	10	1	1
2G (Fig.11)	1	0.5	16	300	10	0.01	1

Video 3:

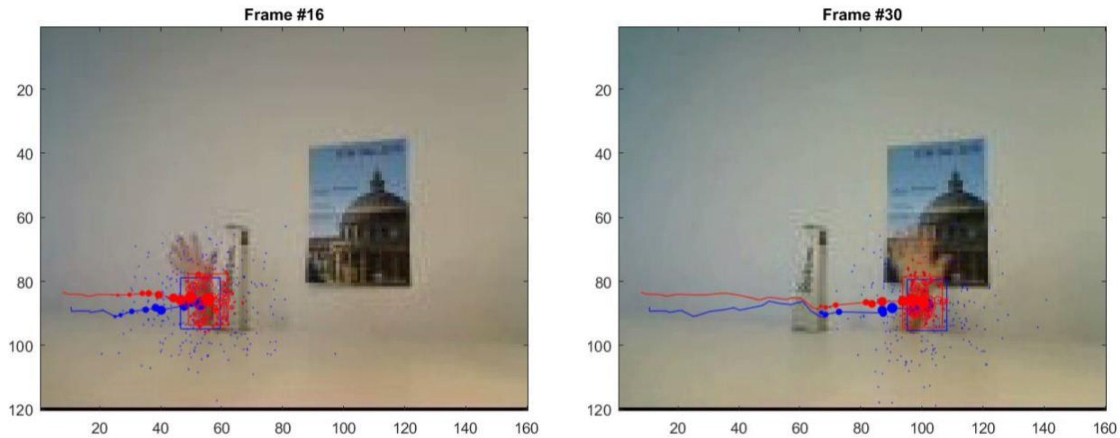

Figure 5: Results of parameter setting 2A

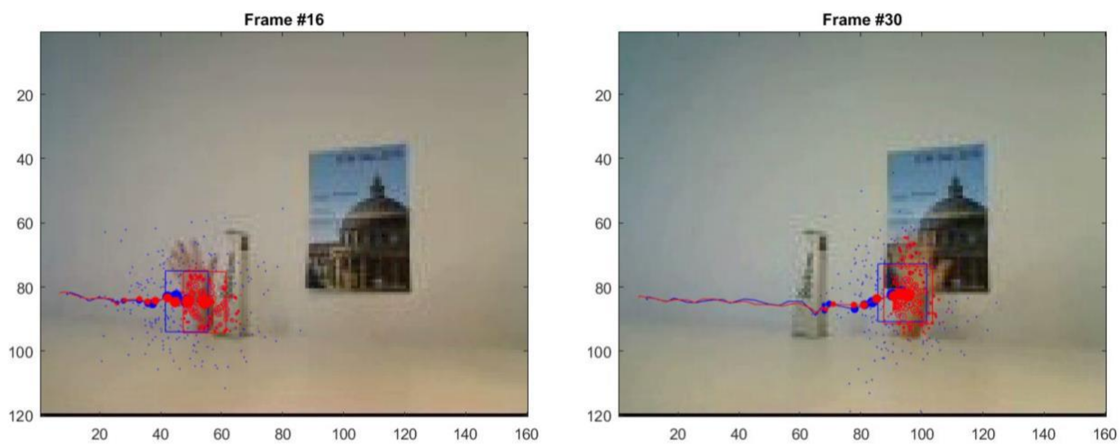

Figure 6: Results of parameter setting 2B

Video 3 is a dataset with a bouncing ball. I tried some other groups of parameter settings here, which are listed in Table 3. The corresponding results are shown in Fig.12 to Fig.19.

Similar conclusions of video 2 can be drawn from video 3. Besides, there are some more analysis of the setting of α, the number of histogram's bin, the number of particles and the standard deviation of velocity.

From Fig.16, it is shown that when the number of histogram's bin is too small (for example 4), the algorithm may fail. It's because that only 4 bin of histogram would only generate a 12-dimensional vector, which is not enough descriptive to act as the observation for tracking. When the bin number reach 16 (or even larger, like 64), the tracking is successful.

As for the particle number, the result of 30 particles is a bit messy but still successful. When the particle number is even smaller than 30, the algorithm might failed since the sample number would be not enough to represent the distribution. Under such cases, the tracking result would be less stable. When there are plenty of particles (for example, larger than 500), the tracking result would be more robust but more time-consuming.

For the value of α, since the target color histogram is updated as $CH_{target} = (1 - \alpha)\, CH_{target} + \alpha CH_{E[St]}$, when

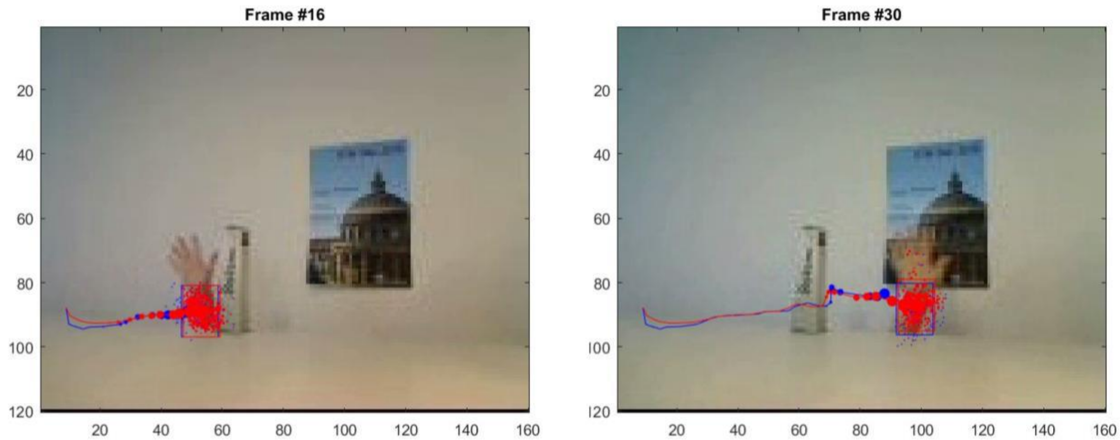

Figure 7: Results of parameter setting 2C

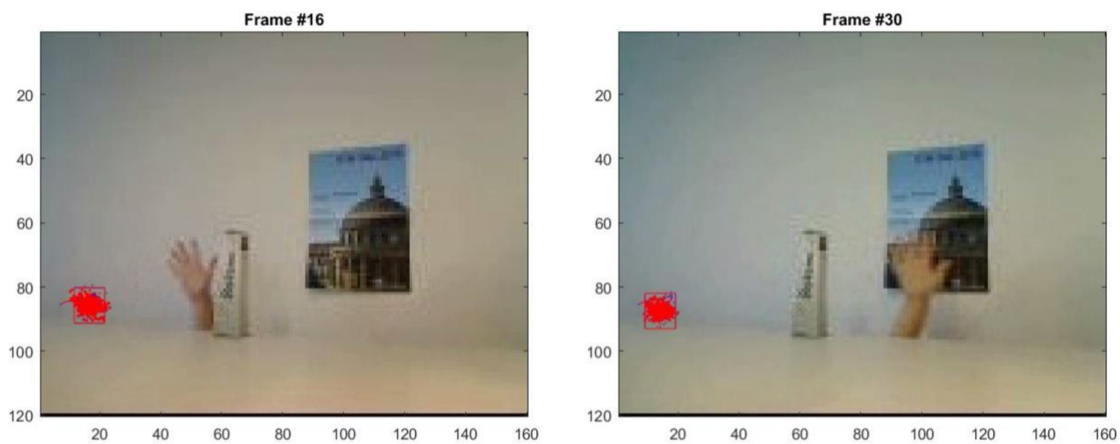

Figure 8: Results of parameter setting 2D

$\alpha = 0$, the initial target color histogram would not change any more. When $\alpha = 1$, the target color histogram would only depends on the newly estimated neighborhood. So it's a better choice to select α between 0 and 1 so that the target color histogram would be more robust.

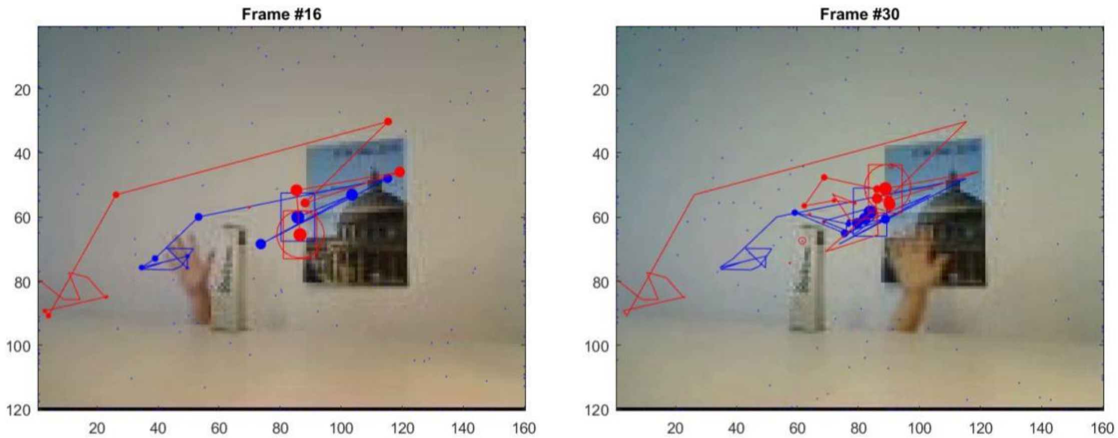

Figure 9: Results of parameter setting 2E

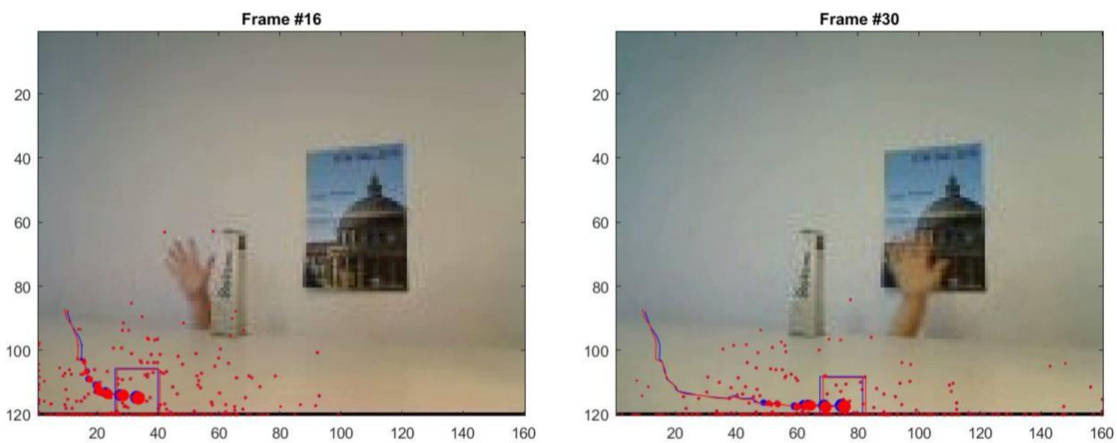

Figure 10: Results of parameter setting 2F

Table 3: Video3 : experiment cases

parameter setting	model	α	hist_bin	particle_num	σ_{pos}	σ_{obs}	σ_{vel}
3A (Fig.12)	1	0.5	16	300	10	0.1	1
3B (Fig.13)	0	0.5	16	300	10	0.1	-
3C (Fig.14)	1	0	16	300	10	0.1	1
3D (Fig.15)	1	1	16	300	10	0.1	1
3E (Fig.16)	1	0.5	4	300	10	0.1	1
3F (Fig.17)	1	0.5	64	300	10	0.1	1
3G (Fig.18)	1	0.5	16	30	10	0.1	1
3H (Fig.19)	1	0.5	16	300	10	0.1	10

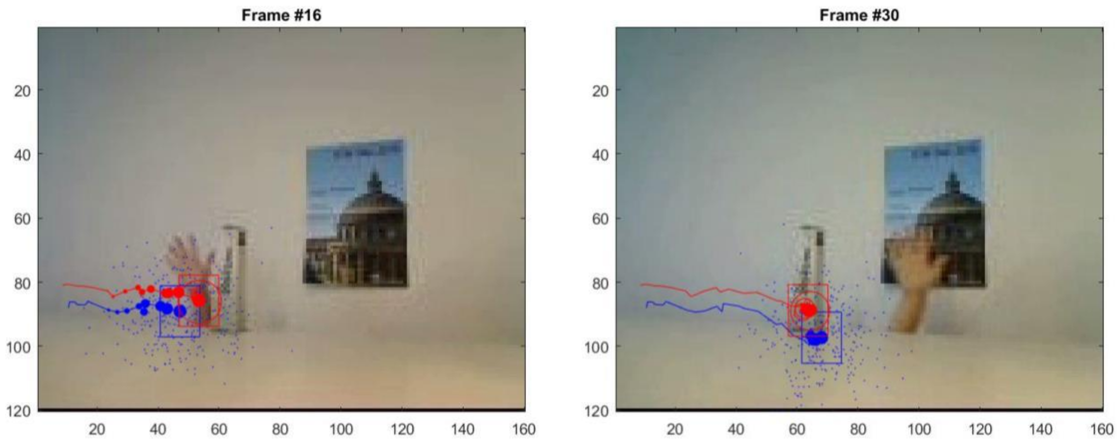

Figure 11: Results of parameter setting 2G

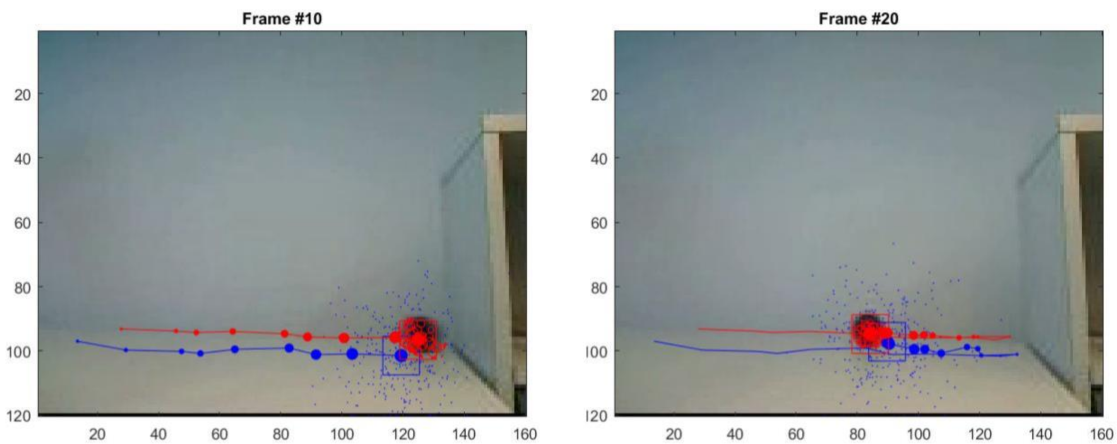

Figure 12: Results of parameter setting 3A

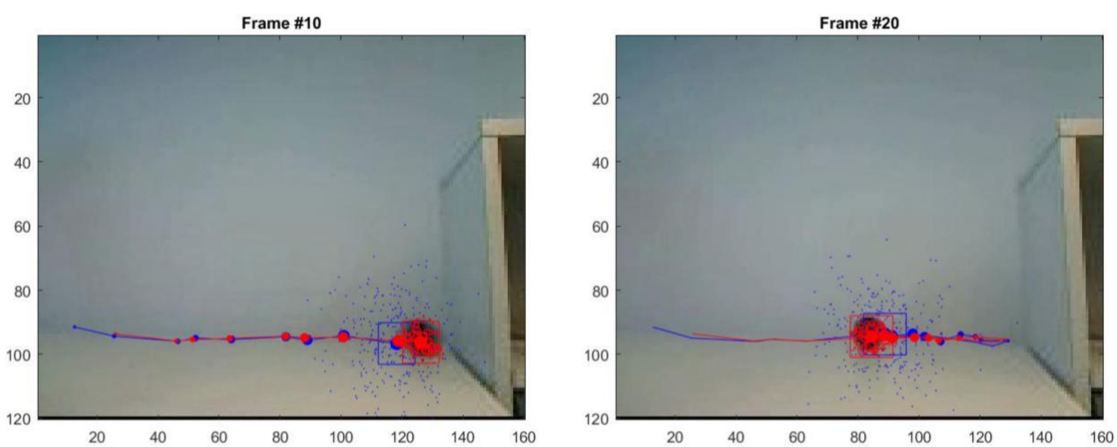

Figure 13: Results of parameter setting 3B

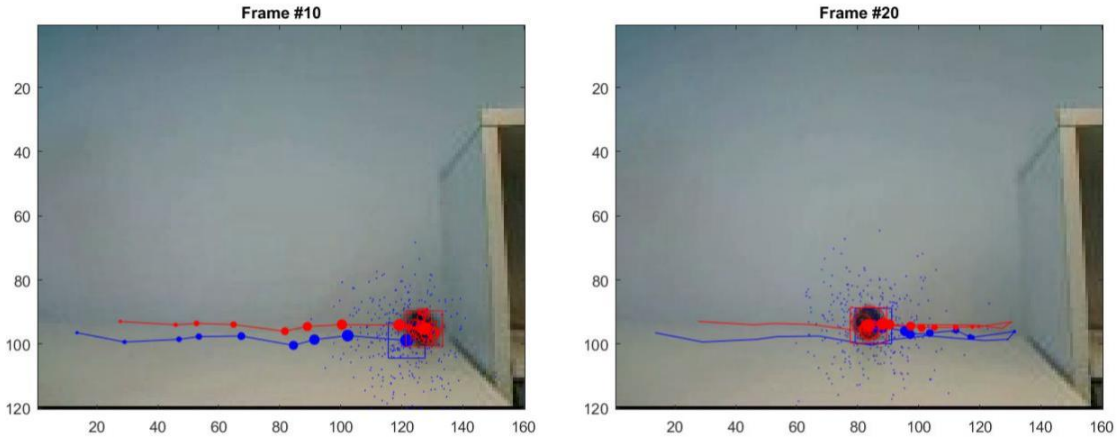

Figure 14: Results of parameter setting 3C

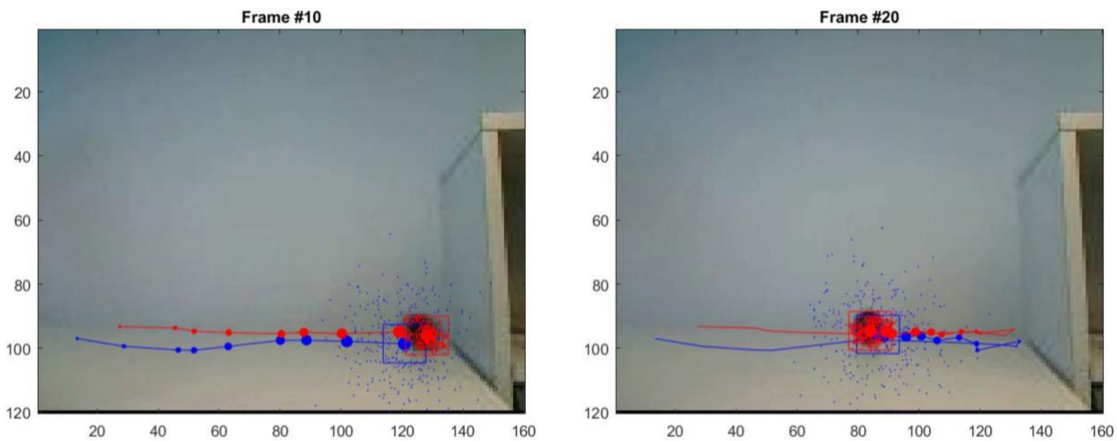

Figure 15: Results of parameter setting 3D

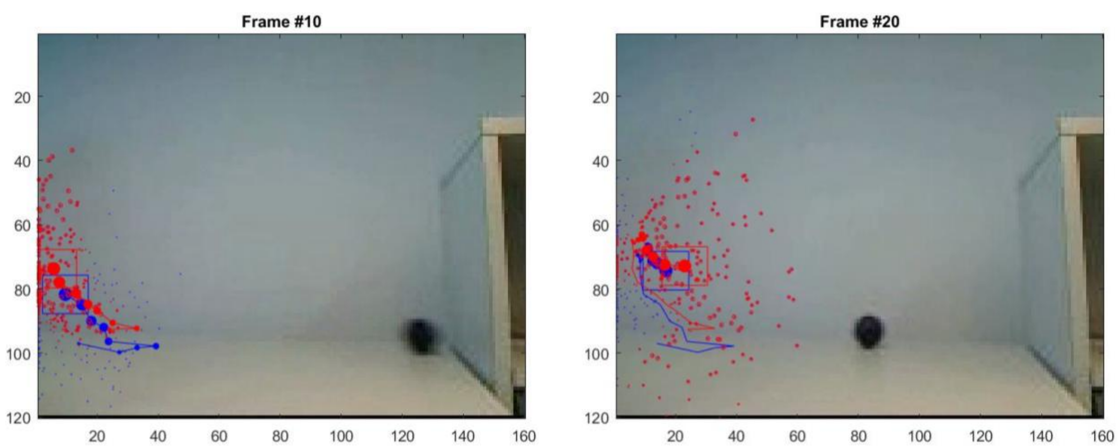

Figure 16: Results of parameter setting 3E

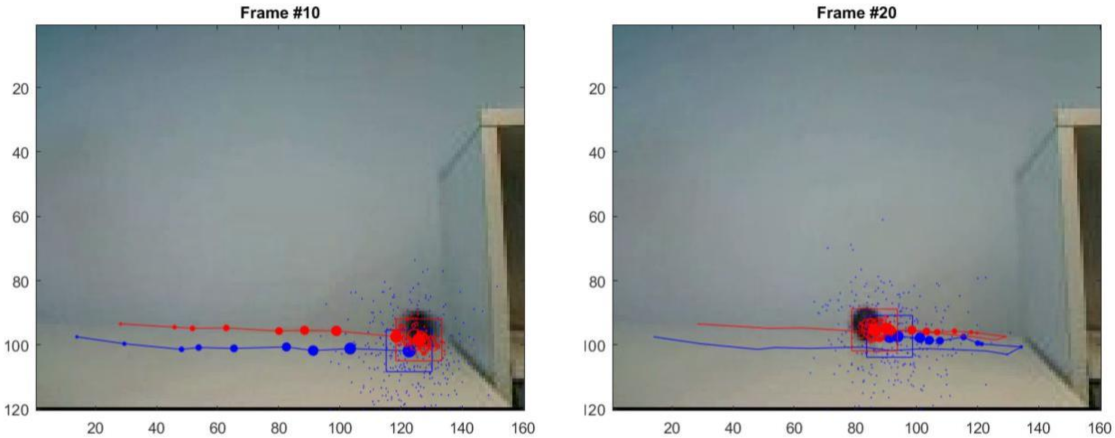

Figure 17: Results of parameter setting 3F

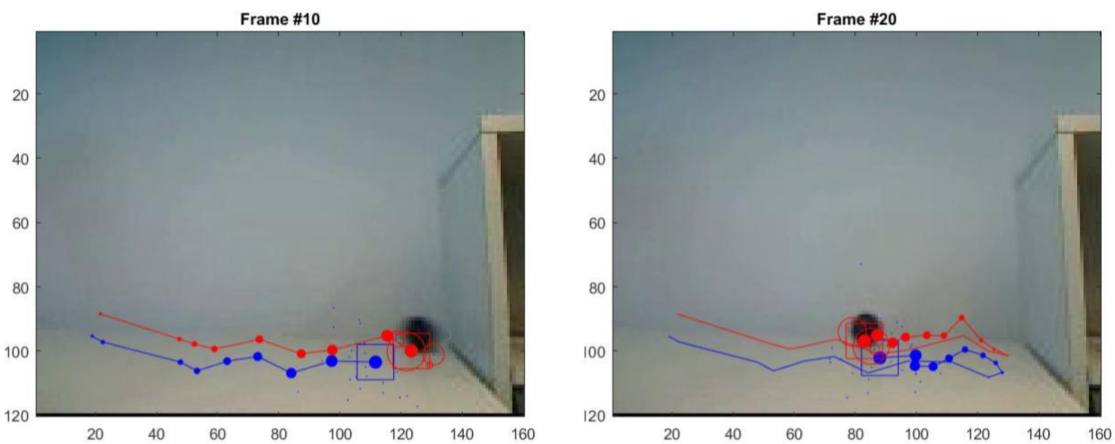

Figure 18: Results of parameter setting 3G

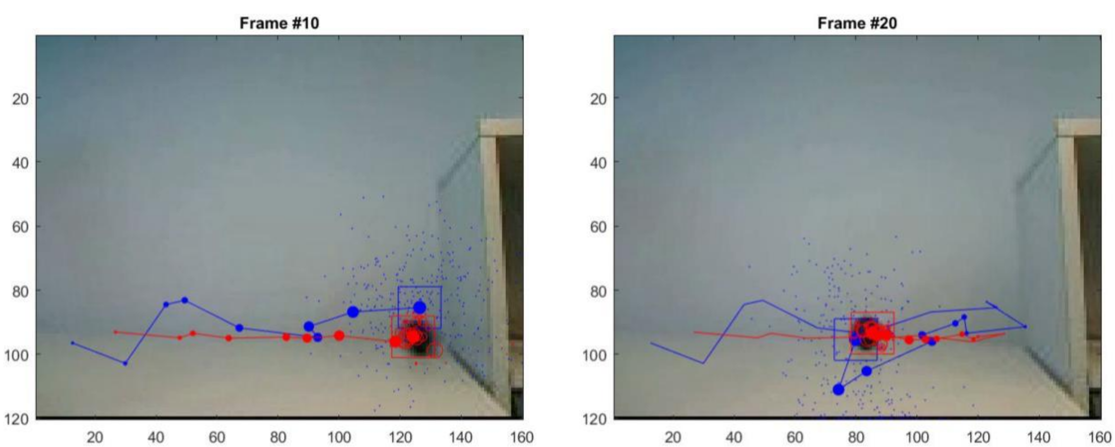

Figure 19: Results of parameter setting 3H