

# Filippo Ficarra: Lab 6 - Condensation Tracker

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## 1 Implementation

In this exercise we implemented the CONDENSATION algorithm, a sampled-based solution of the recursive Bayesian filter.

## 2 Results

### 2.1 Video 1

The algorithm works pretty well with the first video since the movement is very simple and the color are pretty distinguishable. The tracker worked, in a sense, with the default parameters but we, as we can see in the picture below, it tended to follow the wrist and it tended to loose the tracking almost at the end of the video, when the hand moved quicker. Below the results for the video 1 and the default parameters.

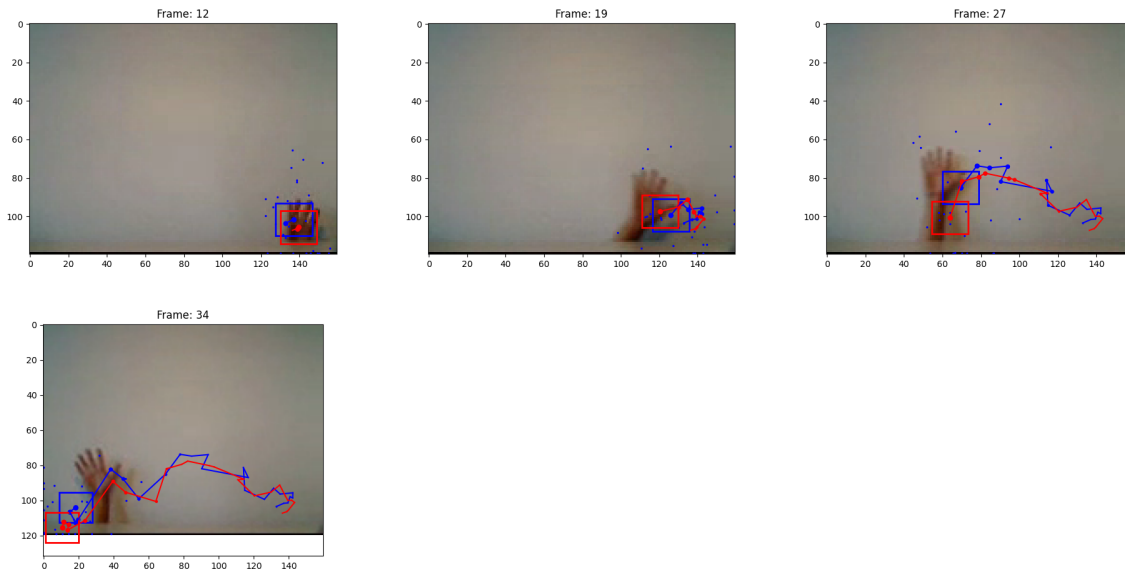


Figure 1: Video 1 with default parameters, no motion model

If we increase more the numbers of particles we should get more accurate results. As shown below the tracker gets better in the last part of the video when it doesn't loose the hand. One of the problem is that the tracker still follows the wrist, and this can be due to the no motion model or the hist\_bin, since the image contains the shadow of the hand.

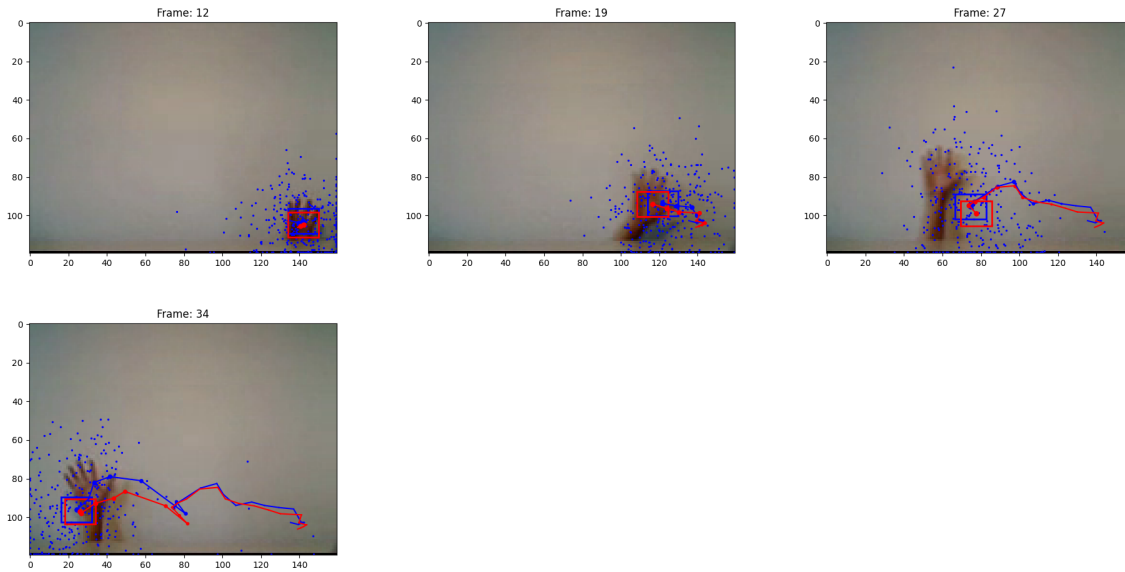


Figure 2: Video 1 with default parameters, no motion model, 300 particles

What happens if we play with other parameters like the number of bins? Below I show that reducing the number of hist\_bins impact on the tracking and make it fail. This is due to the fact that we are grouping very different colors together, and this makes the algorithm not robust to light changing for example.

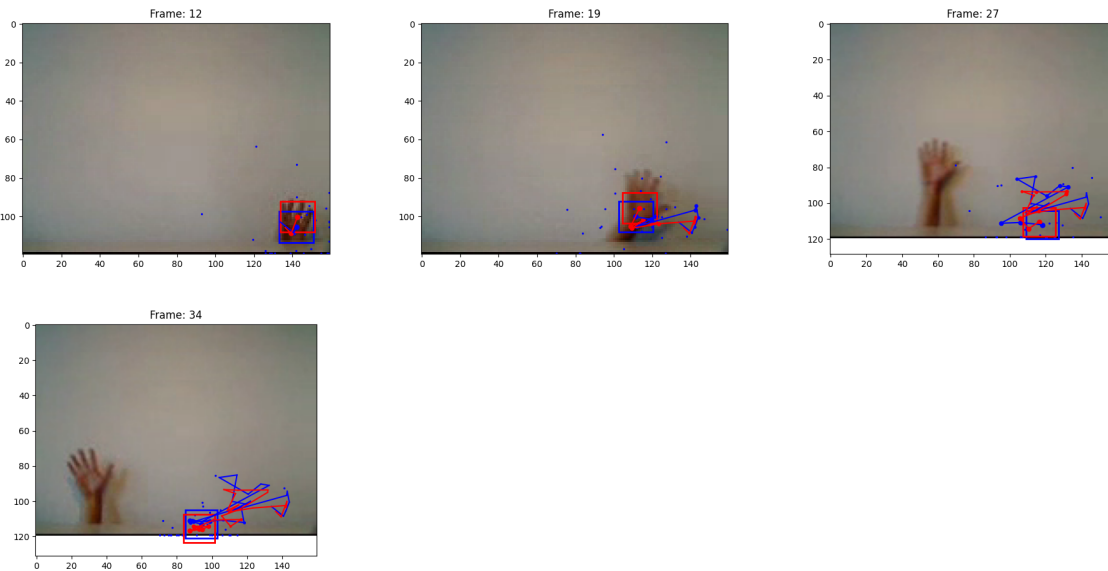


Figure 3: Video 1 with default parameters, no motion model, hist\_bin 8

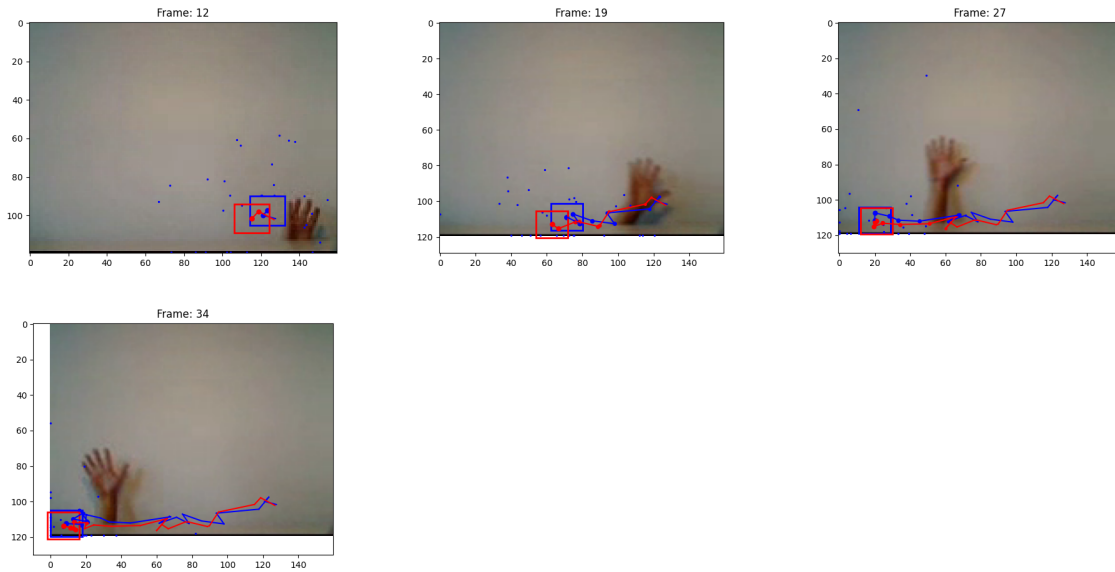


Figure 4: Video 1 with default parameters, no motion model, hist\_bin 4

If we increase the number of hist\_bins to 32 we see an improvement on the tracking. The model is able to track better the hand and not only the wrist. Also the model is more stable to the sudden disappearance of the hand at the end.

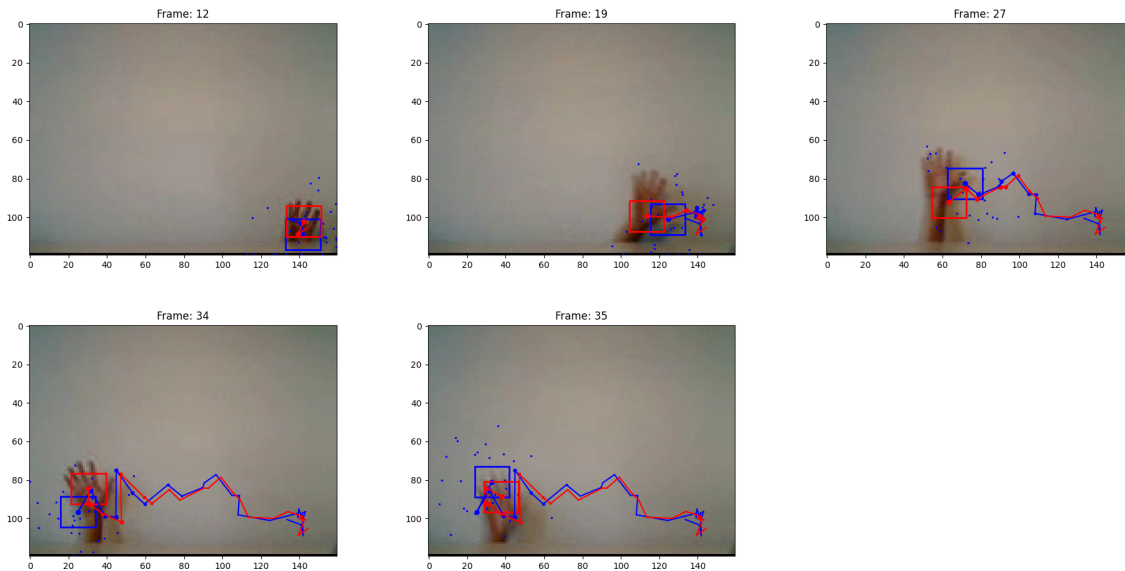


Figure 5: Video 1 with default parameters, no motion model, hist\_bin 32

While no motion model is working, thanks also to the sigma\_position, the result can be improved using a constant velocity model. The only parameter changed here are the initial velocity to  $(-1, -5)$ , so the tracker is initially directed to top left, and the sigma\_position reduced to 10.

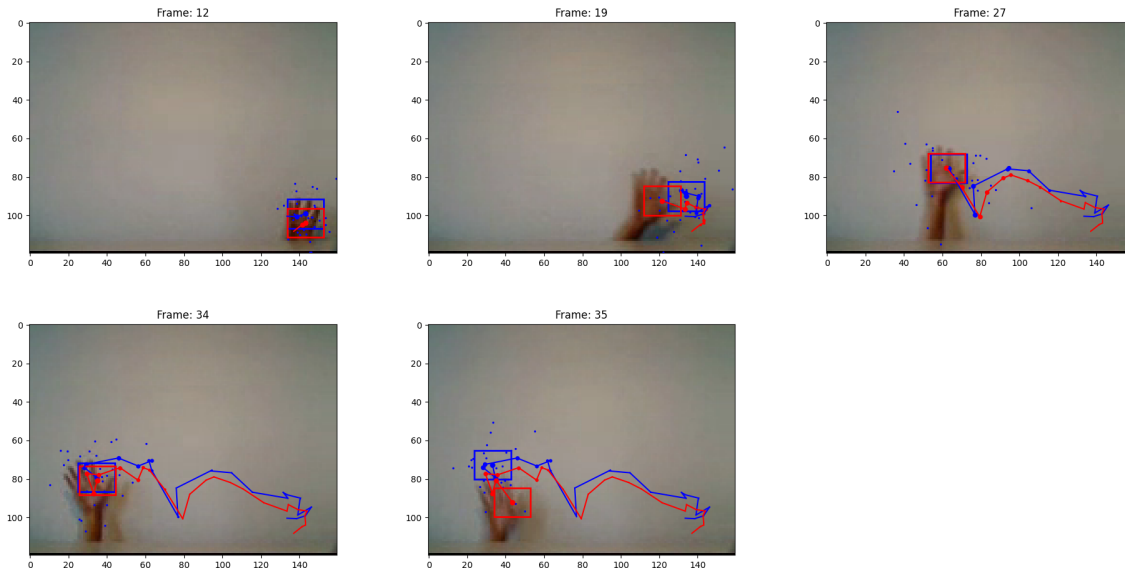


Figure 6: Video 1 with default parameters, constant velocity, initial velocity  $(-1, -5)$ , sigma\_position 10

## 2.2 Video 2

The second video was more complex than the first one, since there is an object that performs occlusion and the background is not constant as in the first video. As first model I tried the one with default parameters. Below the results.

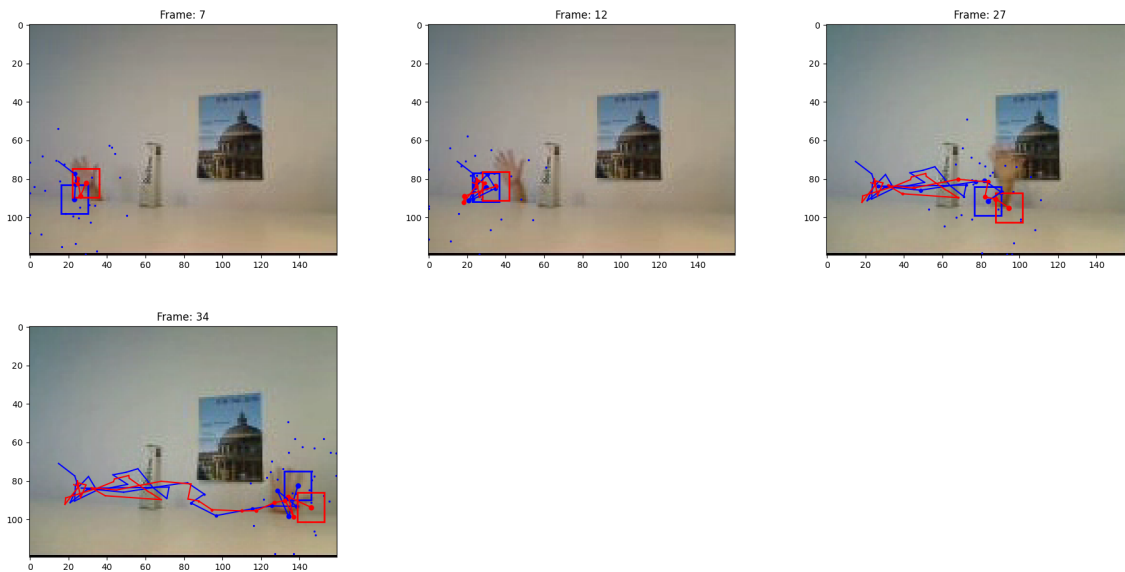


Figure 7: Video 2 with default parameters, no motion model

The model almost track the hand for the whole video. As shown in the images, we have high inaccuracy near the obstacle, but the model is still able to follow the hand.

Lets now try the constant velocity. Since the object is moving right without any y movement, we can set the initial velocity to  $(3, 0)$ .

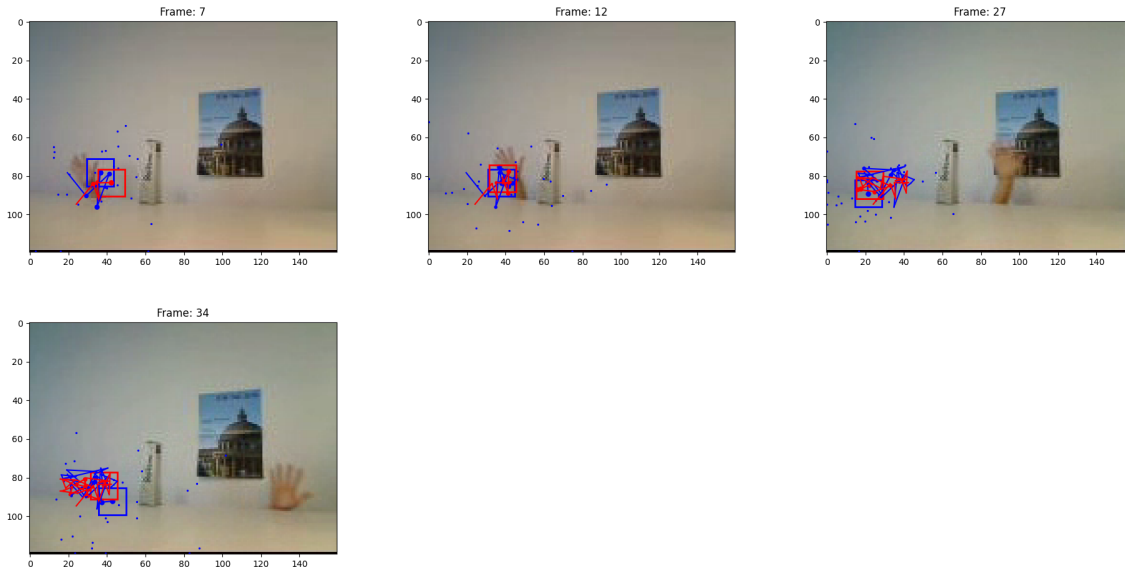


Figure 8: Video 2 with default parameters, constant velocity model, initial velocity  $(3, 0)$

This tracking fails, due to the occlusion. We can improve the tracking setting  $\alpha$  to 0.5, so that the color histogram is updated with the current histogram. Despite this change the result are not so different from the constant motion.

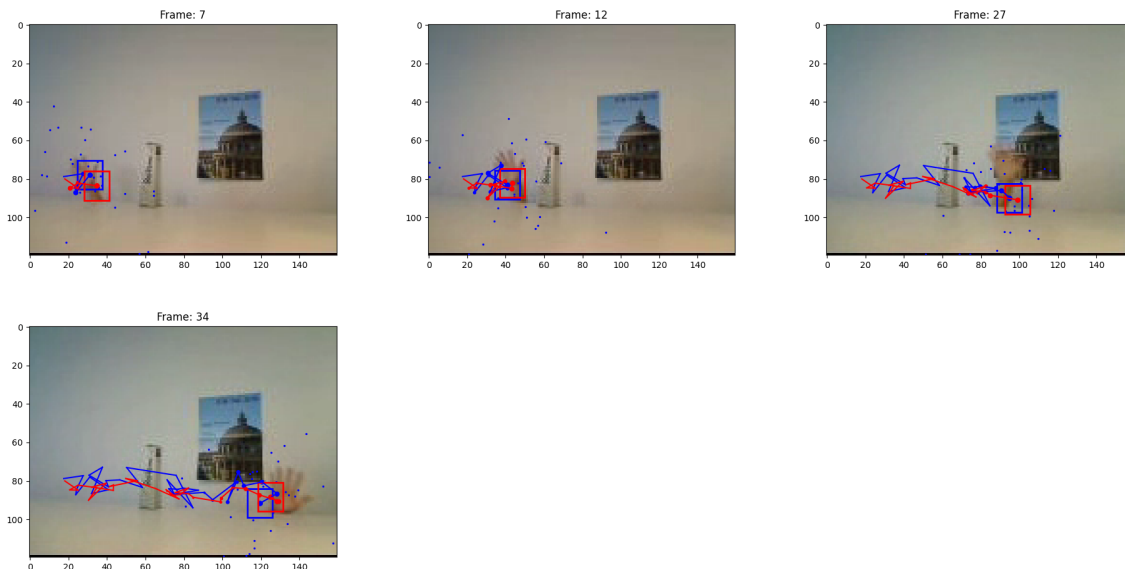


Figure 9: Video 2 with default parameters, constant velocity model, initial velocity  $(3, 0)$

If we further change the parameters we can find an optimal setting for tracking. What performed best was 300 particles,  $\sigma_{\text{position}} = 1$ ,  $\sigma_{\text{velocity}} = 0.1$ ,  $\alpha = 0.5$  and initial velocity  $(4, 0)$ . Below also a comparison of the result when using different  $\sigma_{\text{observe}}$  values.

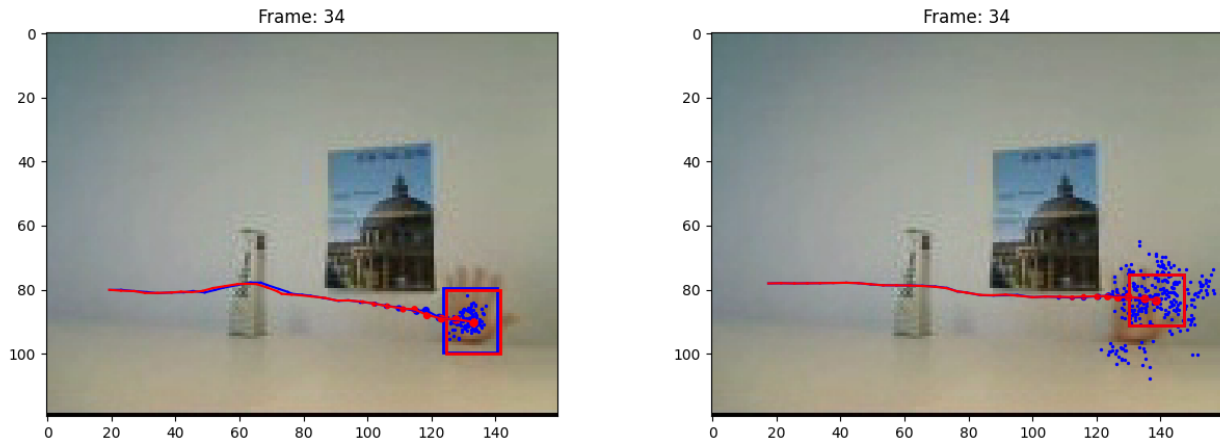


Figure 10: Best params for Video 2,  $\sigma_{\text{observe}}$  0.1 vs  $\sigma_{\text{observe}}$  1

The second image seem to be a better tracking, but the problem is that, due to the high observation uncertainty, the tracker tend to be ahead the hand and not tracking it for the middle part of the video.

If we increase  $\sigma_{\text{position}}$  to 30, the tracking result in failure as shown in the image.

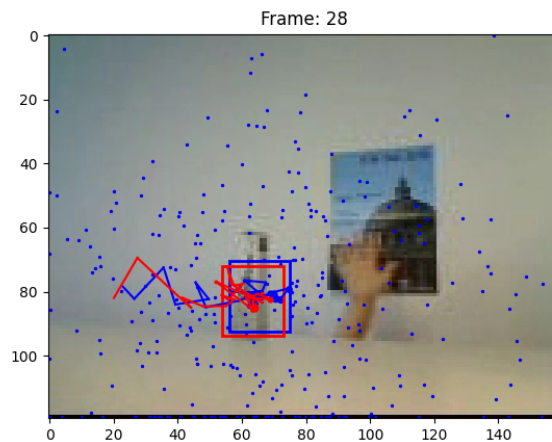


Figure 11: Best params for Video 2,  $\sigma_{\text{position}}$  30

The outcome of this experiment for now tell us that:

- Reduced system noise in the model typically leads to more confidence in the predicted motion.
- Higher system noise makes the predictions less reliable and more susceptible to errors.
- Lower measurement noise implies more accurate and reliable measurements of the object's position. This leads to better updates in the algorithm.
- Higher measurement noise introduces more uncertainty into the measurements. This makes the update less accurate.
- Constant velocity is very useful when we know that the object is moving at a constant velocity, since the assumption of constant velocity helps to estimate next frames in which the object is more likely to appear

## 2.3 Video3

I started looking at the effect of video 3 with the best parameters of the video 2. These are the results: Clearly

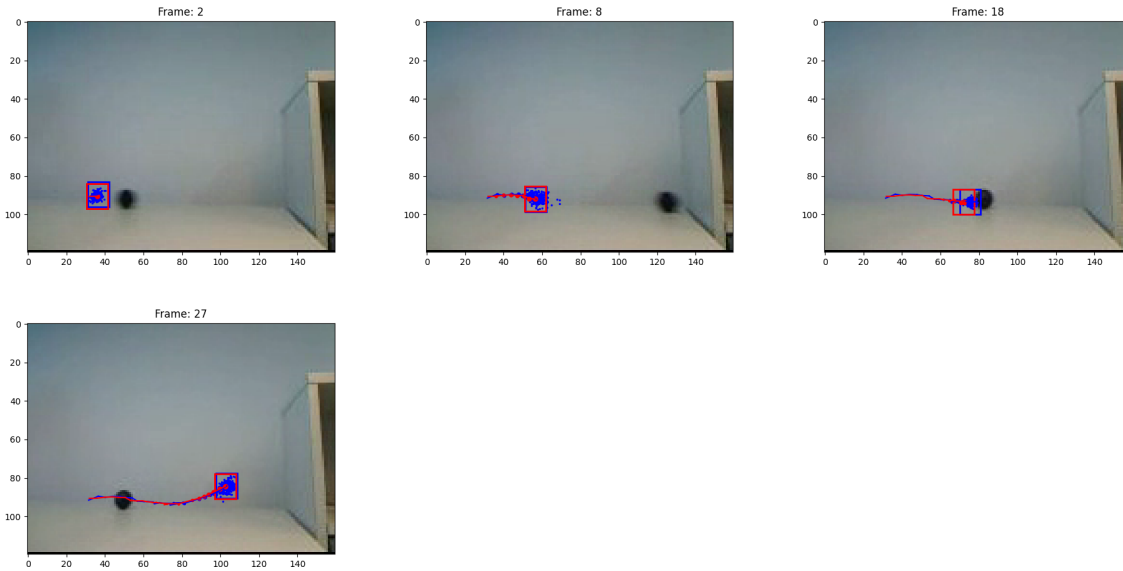


Figure 12: Video 3 with best parameters for model 2

the approach have some problems. First we notice that the initial velocity is not adequate for the video in analysis. We can improve this just increasing the velocity on the x axis to 10. We see a slightly improvement on the tracking, but still the algorithm is not capable to follow the ball for the entire video.

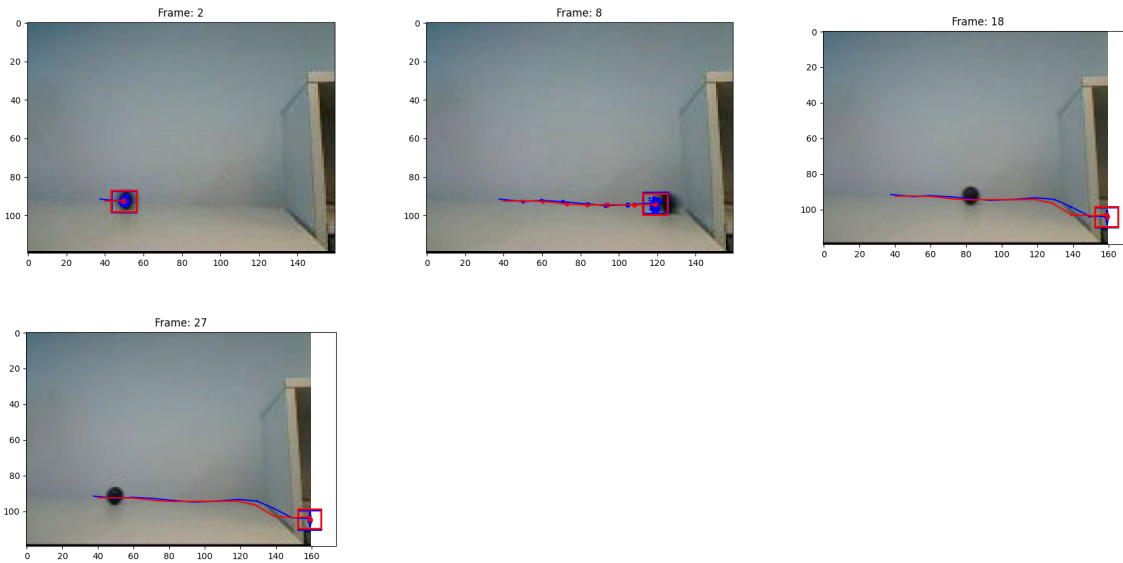


Figure 13: Video 3 with best parameters for model 2, initial velocity (10, 0)

This is because the ball changes direction suddenly, so the constant velocity is not able to follow, we can go back to the no motion model, but we need to increase the system noise.

As expected the system noise, when increased, helps tracking in a no motion model. In the first image, due to the very low sigma\_position the tracker didn't move, while increasing its value gave an almost perfect tracking.

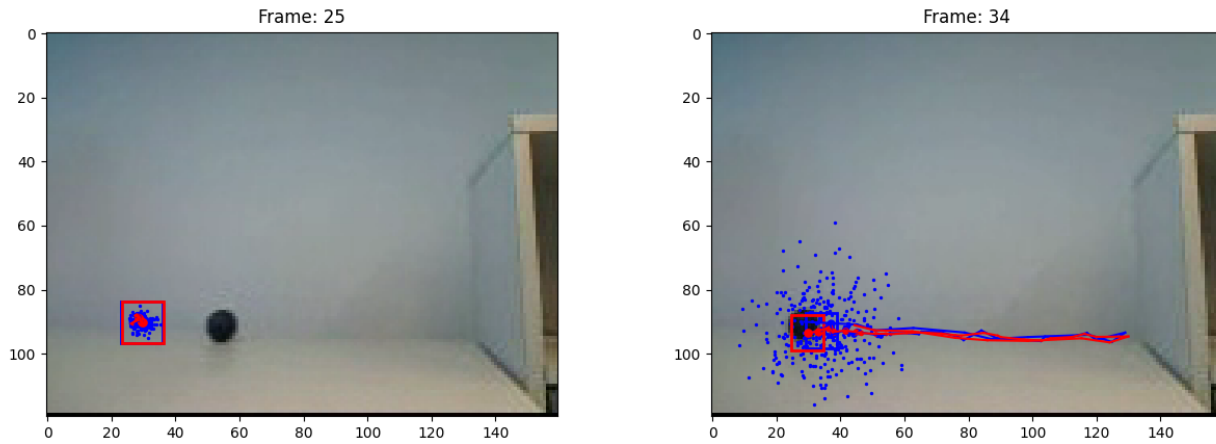


Figure 14: Video 3, no motion model, sigma\_position 1 vs 10, sigma\_observe 0.1

We can also look at the effect of decreasing and increasing the observation uncertainty.

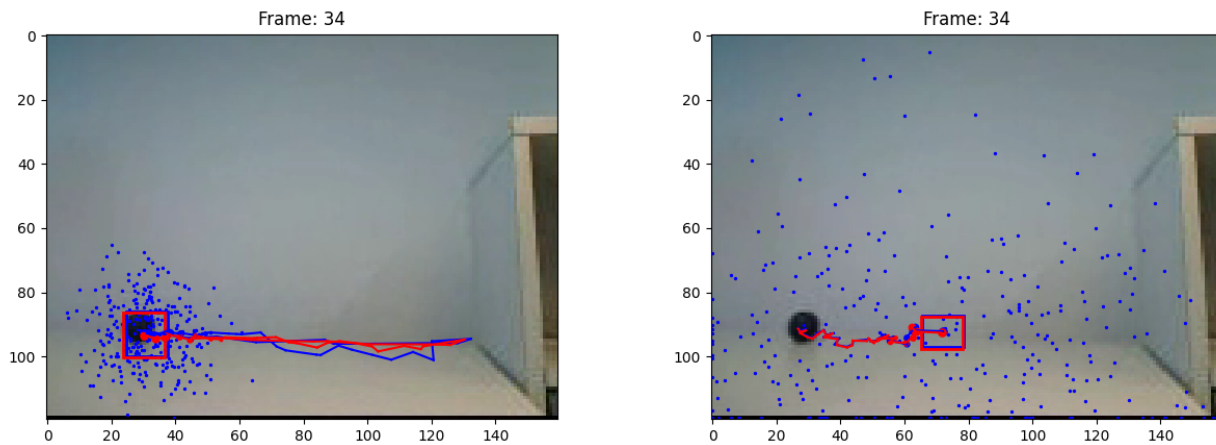


Figure 15: Video 3, no motion model, sigma\_obeserve 0.05 vs 1.0

Summary:

- Number of particles when increased makes the tracker more accurate since we have more samples from which approximate the prediction distribution
- Increasing the number of bins in a histogram color model provides a more detailed representation of color information. This for better discrimination between different colors and shades, potentially leading to more accurate object recognition and tracking.
- Allowing appearance model updating enables the tracker to adapt to changes in the object's appearance over time. This adaptation helps in handling variations in lighting conditions, occlusions etc...