Computer Vision
Fall 2016
Problem Set #7

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Important Note

Please make sure your latest ps7.py and experiment.py are set to generate the images shown in your report. We will run your algorithms again locally using the same input videos to verify these results. We will not accept modifications to these files after the deadline if running your code fails.

1a: Template used for tracking

Template image patch image - **ps7-1-a-1.png**

1a: Image frame 28 with overlaid visualizations

Image frame 28 with overlaid visualizations - **ps7-1-a-2.png**

1a: Image frame 94 with overlaid visualizations

Image frame 94 with overlaid visualizations **- ps7-1-a-3.png**

1a: Image frame 171 with overlaid visualizations

Image frame 171 with overlaid visualizations - **ps7-1-a-4.png**

1b: Image frame 14 with overlaid visualizations

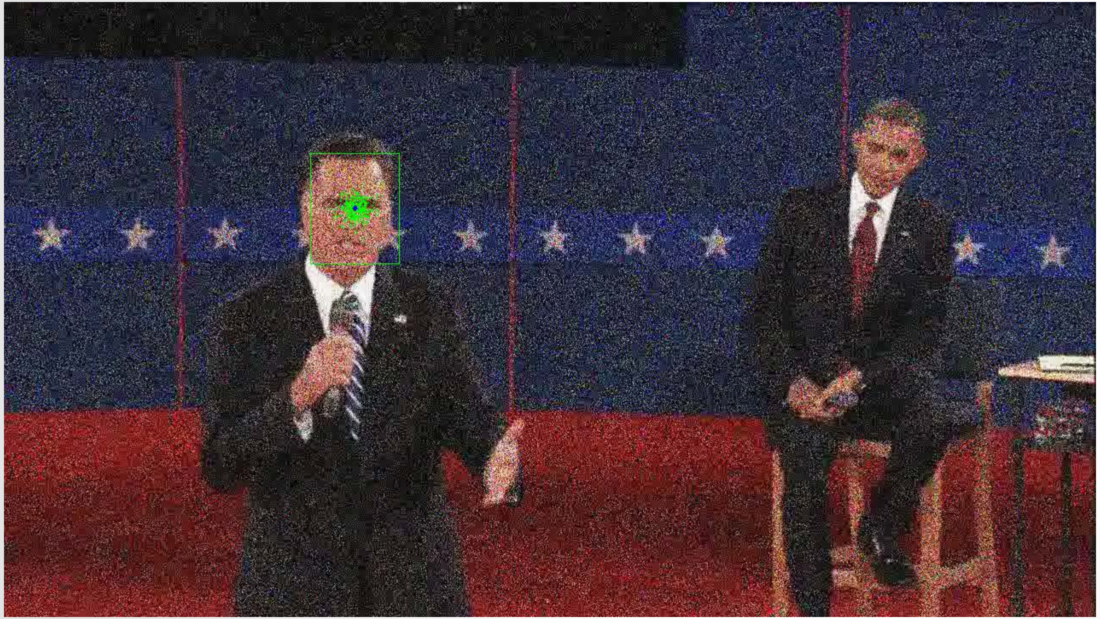


Image frame 14 with overlaid visualizations - **ps7-1-b-1.png**

1b: Image frame 94 with overlaid visualizations

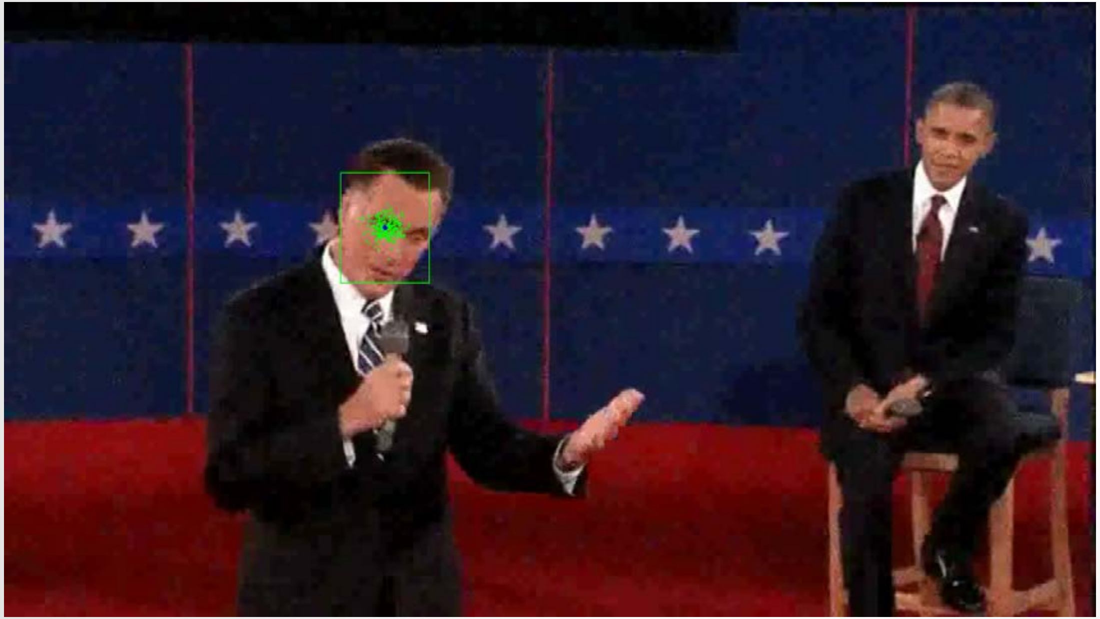
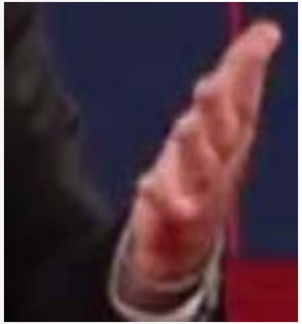


Image frame 94 with overlaid visualizations - **ps7-1-b-2.png**

1b: Image frame 530 with overlaid visualizations

Image frame 530 with overlaid visualizations - **ps7-1-b-3.png**

2a: Template used for tracking



Template image patch image - **ps7-2-a-1.png**

2a: Image frame 15 with overlaid visualizations

Image frame 15 with overlaid visualizations - **ps7-2-a-2.png**

2a: Image frame 50 with overlaid visualizations

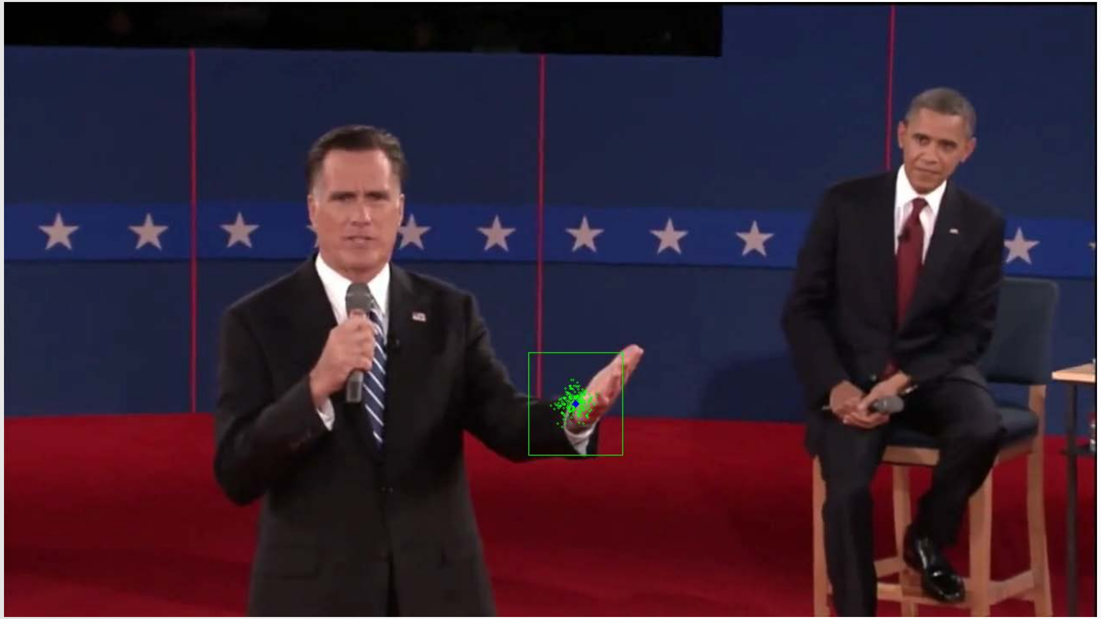
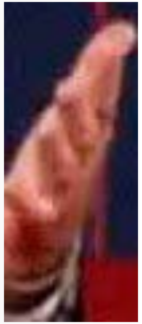


Image frame 50 with overlaid visualizations - **ps7-2-a-3.png**

2a: Image frame 140 with overlaid visualizations

Image frame 140 with overlaid visualizations - **ps7-2-a-4.png**

2b: Template used for tracking



Template image patch image - **ps7-2-b-1.png**

2b: Image frame 15 with overlaid visualizations

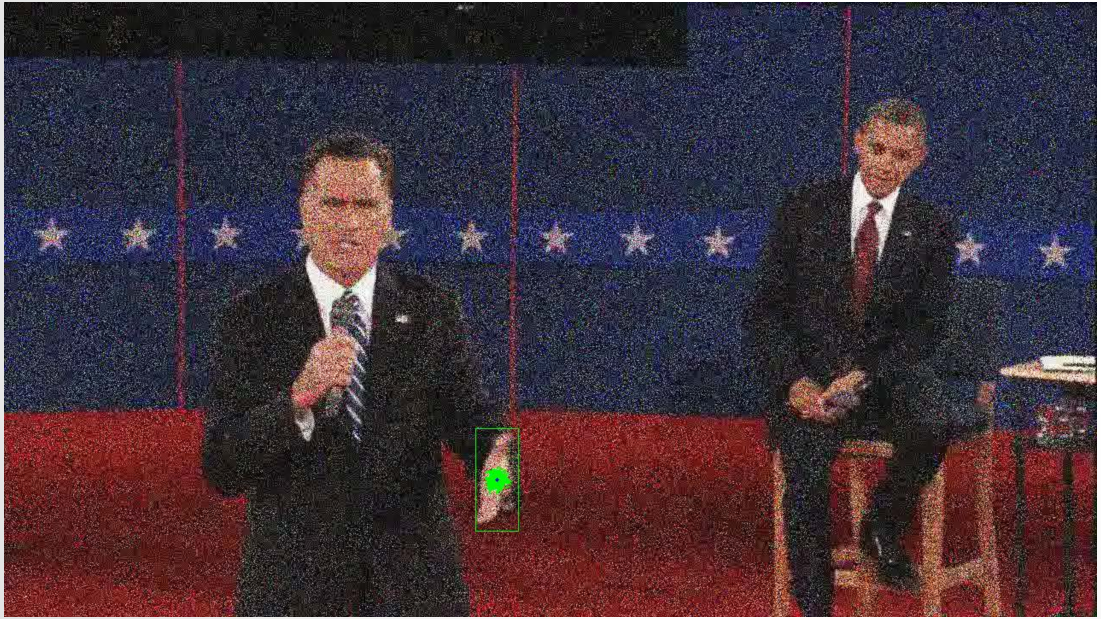


Image frame 15 with overlaid visualizations - **ps7-2-b-2.png**

2b: Image frame 50 with overlaid visualizations

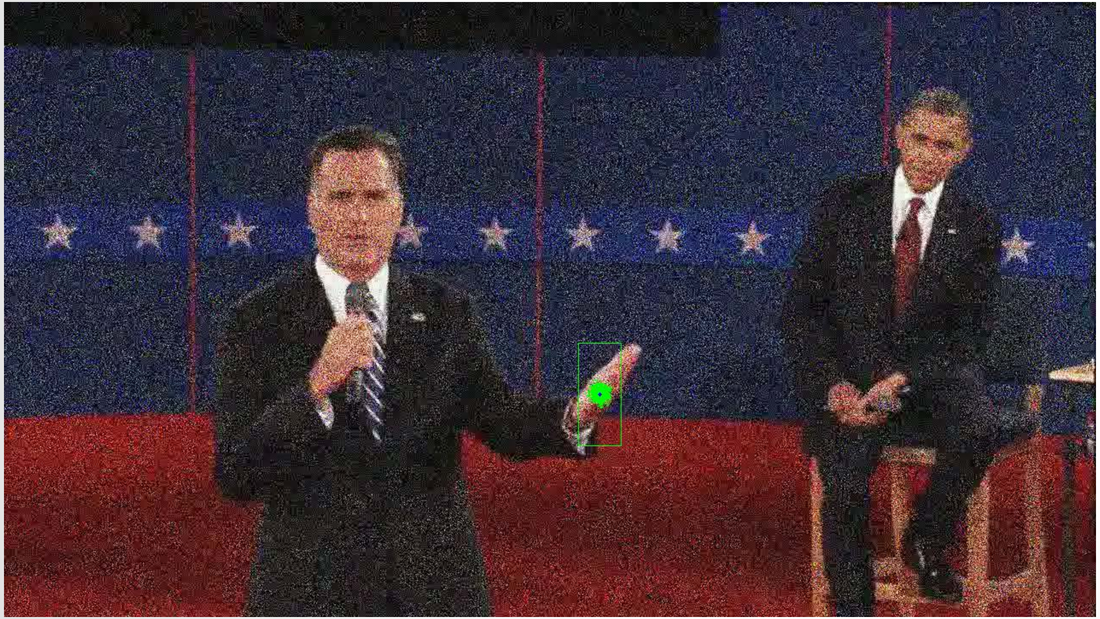


Image frame 50 with overlaid visualizations **- ps7-2-b-3.png**

2b: Image frame 140 with overlaid visualizations

Image frame 140 with overlaid visualizations - **ps7-2-b-4.png**

3a: Template used for tracking

Template image patch image - **ps7-3-a-1.png**

3a: Image frame 28 with overlaid visualizations

Image frame 28 with overlaid visualizations **- ps7-3-a-2.png**

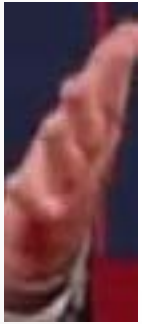
3a: Image frame 94 with overlaid visualizations

Image frame 94 with overlaid visualizations - **ps7-3-a-3.png**

3a: Image frame 171 with overlaid visualizations

Image frame 171 with overlaid visualizations - **ps7-3-a-4.png**

3b: Template used for tracking



Template image patch image - **ps7-3-b-1.png**

3b: Image frame 15 with overlaid visualizations

Image frame 15 with overlaid visualizations - **ps7-3-b-2.png**

3b: Image frame 50 with overlaid visualizations

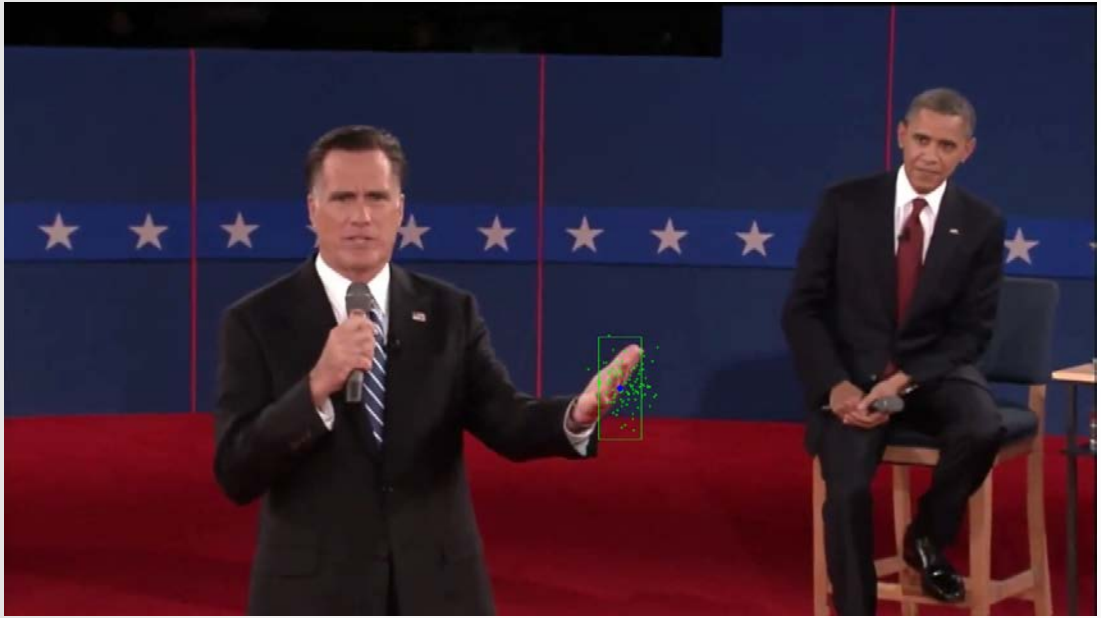


Image frame 50 with overlaid visualizations - **ps7-3-b-3.png**

3b: Image frame 140 with overlaid visualizations

Image frame 140 with overlaid visualizations - **ps7-3-b-4.png**

4: Discussion Problems

a. Using problem 1, experiment with different dimensions for the window image patch you are trying to track. Decrease the window size until the performance of the tracker degrades significantly. Try significantly larger windows than what worked in 1-a. What are the trade-offs of window size and what makes some image patches work better than others for tracking? **Describe 2-3 advantages of larger window size and 2-3 advantages of smaller window size**

The matching of the potential patches to template depends on similarity measure, which is based on pixel values at certain locations. Bigger window size include more features, resulting in at least 2 benefits. With more features, the matching can be more specific. Using an extreme example to illustrate, if we have a picture of a pair of identical twins, simply using a template of their face can not distinguish them. We will be tracking either one of them. But if they wear different clothes, and we include a piece of one twin's clothes in the template, we can specifically tracking this twin. In addition, more feature means the template matching is more resistant to changes. For example, if a template includes a forehead and hairs, even if the person turn his face, although his forehead looks narrower, it is still significantly different from his cheek due to the hairs.

On the other hand, smaller size window includes less features. This can be beneficial when the target does not closely associate with the features around it. For example, if we try to track a ball bouncing around a room, ignoring where the ball is touching at the moment may be better. Smaller window size also has obvious benefit computational wise. It takes less time to compare two small pieces.

4: Discussion Problems

b. Using problem 1, Adjust the σ_{MSE} parameter to higher and lower values and run the tracker. **Discuss how changing σ_{MSE} parameter alters the results and attempt to explain why.**

The equation to calculate probability of a certain particle/patch assumes normal distribution. The smaller the sigma, the narrower the bell curve. When the distribution is narrower, the difference between better fit (low MSE) and less fit (high MSE) is more significant. This result into faster convergence. When MSE is too big, the particles do not really converge, so the algorithm won't be able to identify the target. In addition, when the sigma is smaller, the algorithm "learns" faster. This leads to faster convergence, but can also make the particles easier to be trapped in the local optima in early frames and not recognize the best global match.

4: Discussion Problems

c. From problem 1 again, what happens when you try and optimize the number of particles needed to track the target. **Discuss your Optimized Particle Number and Discuss the trade-offs of using a larger number of particles to represent the distribution.**

For problem 1, I find particle number around 500 yields consistent result. Lower number such as 50 particles leads to tracking of areas such as Obama's face and Romney's hand, instead of the target (Romney's head). The particles are often trapped at local optima, and this happens in early frames. When Romney's face is correctly targeted in early frames, the later tracking has no problem even with low particle numbers.

In our algorithm, the starting location of the particles are uniform randomly distributed. If none of the initial particle locates close to Romney's face, then the "best" match would be something similar, such as Obama's head if a particle happens to be around there. Once the particles are "trapped" in these local optima, unless the sigma_dyn is huge, these particles can not jump out of the "trap". High number of particles have higher probability that the initial location of some particles can be around the correct target. Combined with a reasonable sigma_dyn, the algorithm can find the global optima, which is Romney's face.