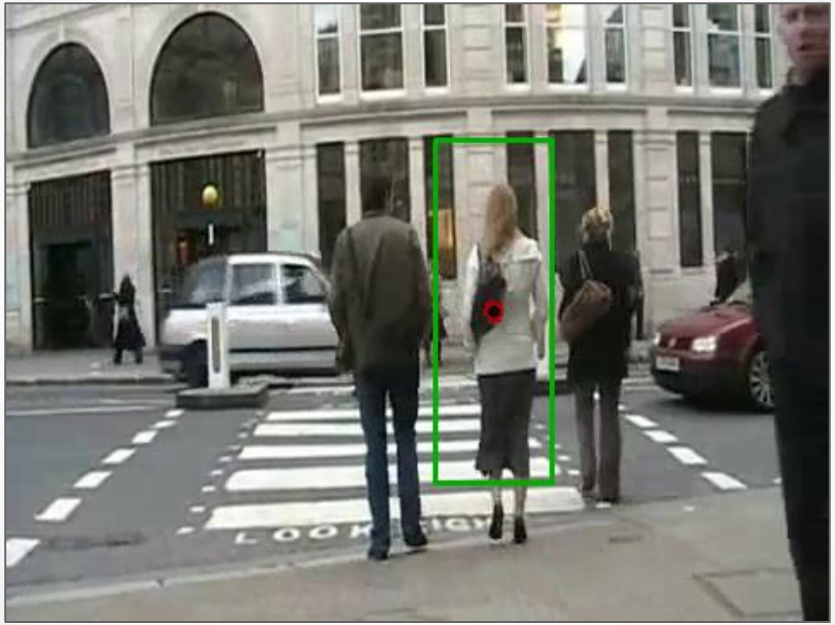
Computer Vision (Spring 2021) Problem Set #5

Josh Adams
Jadams334@gatech.edu

4a: PF Occlusions

ps5-4-a-1

4a: PF Occlusions (cont.)

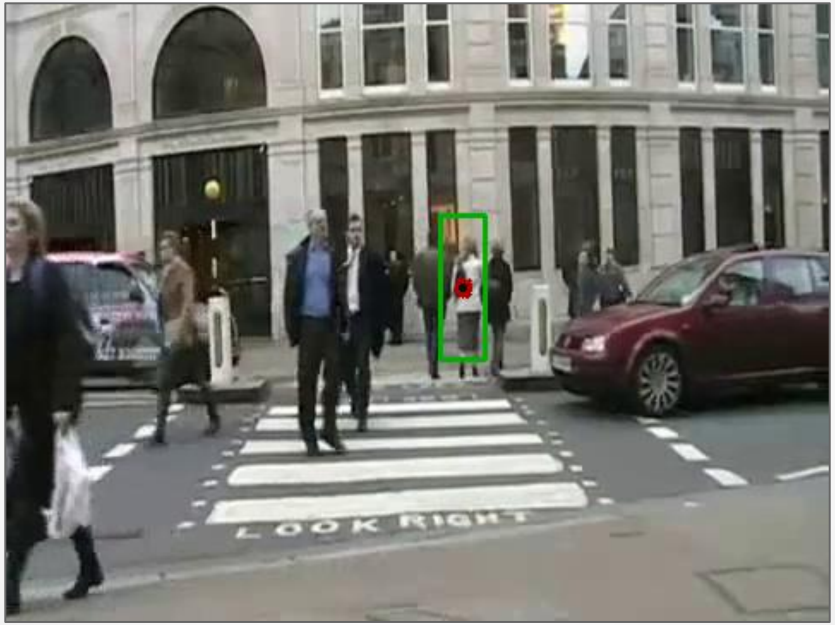


ps5-4-a-2

4a: PF Occlusions (cont.)

ps5-4-a-3

4a: PF Occlusions (cont.)



ps5-4-a-4

4: Text response

Describe what you did. How did you modify the Particle Filter class to continue tracking after occlusions?

To be able to track occlusions I used two different approaches combined. The first was to keep track of previous templates, particles, and weights. Using those I create a running average of N previous templates and weights. I then create two estimate templates, one called template_A, using the average X and average Y of the particles and the second called template_B, being the particle X and particle Y associated with the highest running average weight. I compare the current template with template_A and template_B. The comparison is based on Peak signal to noise ratio (PSNR) and structural index similarity (SSIM). If either of the two are better representations of the template when compared to the very first template used, scaled as needed, then I set the current template to be the best template. This approach works really well for improving your template. When there are occlusions, it will just not update your template and you basically have the best template to the point of the occlusion. The problem for this approach is when the pedestrian is moving away, such as in this example, and now is much smaller than they were in the previous template. What happens is now that the pedestrian is no longer occluded but is much smaller than they were when the previous template was stored. The error produced by comparing the pedestrian and template is too large for algorithm mentioned above to update the template, thus the pedestrian is lost, and tracking fails. How I overcame this obstacle was to use the previous templates, weights, and particles to calculate estimated pixel displacement. The estimated displacement was calculated by taking the derivative in both X and Y directions between the average N template and the newest template being added to the template container. The average change in the standard deviations of the particles X and particles Y is also used to help with estimating the size of the template. Even though the template is not being updated I can estimate my expected change based on the previous templates. This allows me not only to follow the trajectory of the occluded pedestrian but resize the template to what is estimated. Using these combined methods allowed for the newly resized template to be a much closer fit to the pedestrian once they were no longer occluded and this allowed the first algorithm to being updating the template once more.

5: Tracking multiple targets

ps5-5-a-1

5: Tracking multiple targets (cont.)

ps5-5-a-2

5: Tracking multiple targets (cont.)

ps5-5-a-3

5: Text response

Describe what you did. How different it was to use a KF vs PF? Which one worked best and why? Include details about any modifications you had to apply to handle multiple targets.

I think
my answer is ...

6: Challenge Problem

ps5-6-a-1

6: Challenge Problem (cont.)

ps5-6-a-2

6: Challenge Problem (cont.)

ps5-6-a-3

6: Challenge Problem Text response

Describe what you did. Did this task present any additional challenges compared to the previous sections? Include details about any modifications you had to apply.

I think
my answer is ...