P2 Features Scale Warping

Siddharth Patel

I. P2.1.1 Computing Harris Corners

A. Are the features where you expected?

Yes, the features were placed where I had expected them to be in the cube image. I expected the features to occur surrounding the cube as it had sharp edges around it.

B. Are there any features in the image that you are surprised are not present? Highlight or discuss in words one or two regions of one of your images where features were detected that you did not expect (or one or two regions you thought features might exist)

Surprisingly, I was betting on the features to occur at the reflection of the cube, but there were not features on the reflection (note: I am not talking about the shadow of the cube which is right under it.) I think the features did not occur at the reflection because it is blurred and smooth. That could be one of the factors why there was no feature detection at the reflection of the cube.

C. What would happen if you used a scoring function? Plot this alternative scoring function for the light cubes base image and plot the detected features computed using it.

The trace scoring function that we are asked to compute will detect the cube no doubt, but it will also detect the corners of the image, the shadows, and even the reflection which is the most light part of the image as it is already blurred out and should not be detected technically, as you can see in the image.

D. What does this modified scoring function detect?

The modified scoring function detects the object, in this case a cube, in the middle of the image, but it also detects the entire borders of the image, the object shadow and reflection.

E. If we want to detect corners, why might we not want to use this scoring function?

If we use this trace scoring function, like I said, you end up detecting useless things such as borders, shadows and reflection. As a result, it is important not the use the trace itself and divide the trace by determinant to get a proper scoring function.

II. P2.1.2 Varying the Weight Matrix

A. Discuss the differences between these four weight functions. In particular, what happens when the filter width (or σ) is very large?

Lets start the discussion with the weight function of 5 by 5. The 5x5 weight function blurs evenly almost like a mean filter on the basis of 5x5 image window as it traverses through the entire image. The 25 weight function blurs further which results in a difficulty detecting the sharp edges therefore the 25x25 function will result in less red dots compared to the 5x5 weight function. Furthermore, the gaussian blur of five results in a sharpness at the center while blurring as it approaches the edges. Finally the 25 sigma gaussian blur will have result it even sharper center, but will be blurred more as it moves further from the center.

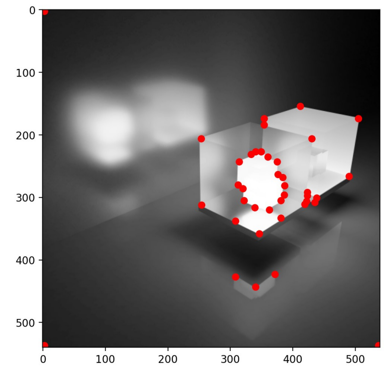

Fig. 1. Base Scoring Function

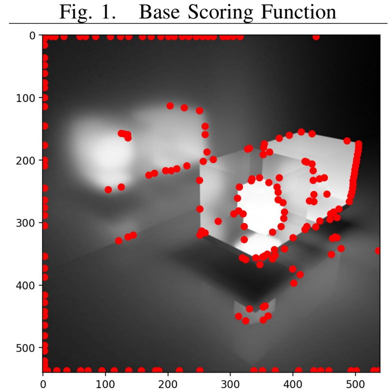

Fig. 2. Trace Scoring Function

B. What happens if we were to use a 1x1 weight matrix w=1? Why does this occur?

Because it is a 1x1 matrix which is divided by 1 itself, you are keeping the same value for everything. As a result, you are basically looking at the raw pixels traversing throughout the image. You are essentially looking at the base image. Therefore, depending on the the threshold, you are detecting the raw sharpness of the image. While you don't see a significant difference in a 5x5 kernel the reason being that each pixel balanced will be 1/25 or 0.04 which is not a significant blur from the original image, if you take the example of 25x25 kernel which has 1/625 balance per pixel

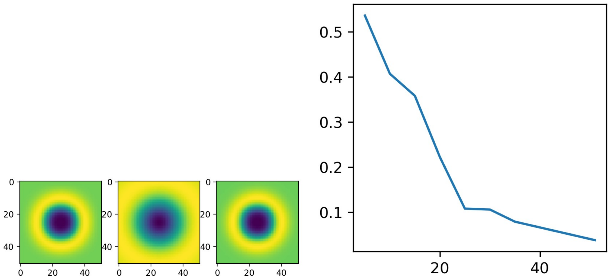

Fig. 3. Filter Response Graph and Images

resulting in 0.0016 which is a drastic blur leading to a smoothness in the image. As a result, your algorithm will have difficulty finding the sharpness in the image leading to less red dots.

III. P2.2.1 Scale-Normalized Filter Response

A. What is the relationship between the peak σ and the circle's radius?

The peak sigma represents the maximum response of the image which helps you determine the circle's radius. As a result, think of the radius using this formula: r = $\sigma * \sqrt{2}$

IV. P2.3 Image Warping

A. How do the two "bottom row" parameters control how the image is warped?

You can think of the bottom row as the z axis on a 3d plane. Any change in the bottom row will lead to the image being elongated almost like it is falling and laying flat. It will turn from a 2d image to a 3d scaled image.

There is a surprising behavior in the section when we scale the image 2 to the right. Notice how the cubes are not visible. This is due to the pixels not auto updating.

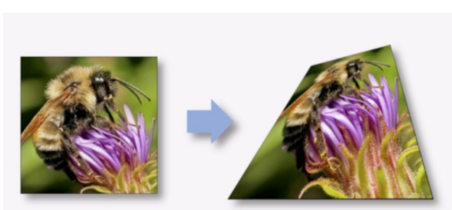

Fig. 4. Two Bottom row Parameter effects

V. P2.4 Experimenting with Some Simple Feature Descriptors

A. Which feature descriptor performs poorly on the image imgContrast? Explain why this descriptor performs worse than the others.

The Histogram perform poorly against the imgContrast function. The reason why these descriptors work poorly on the imgContrast is because this image has variation in Color change. Descriptors such as Binary are more robust/ resistant to photometric transformations as described in the lectures slides. In a histogram, however, you are more resistant to

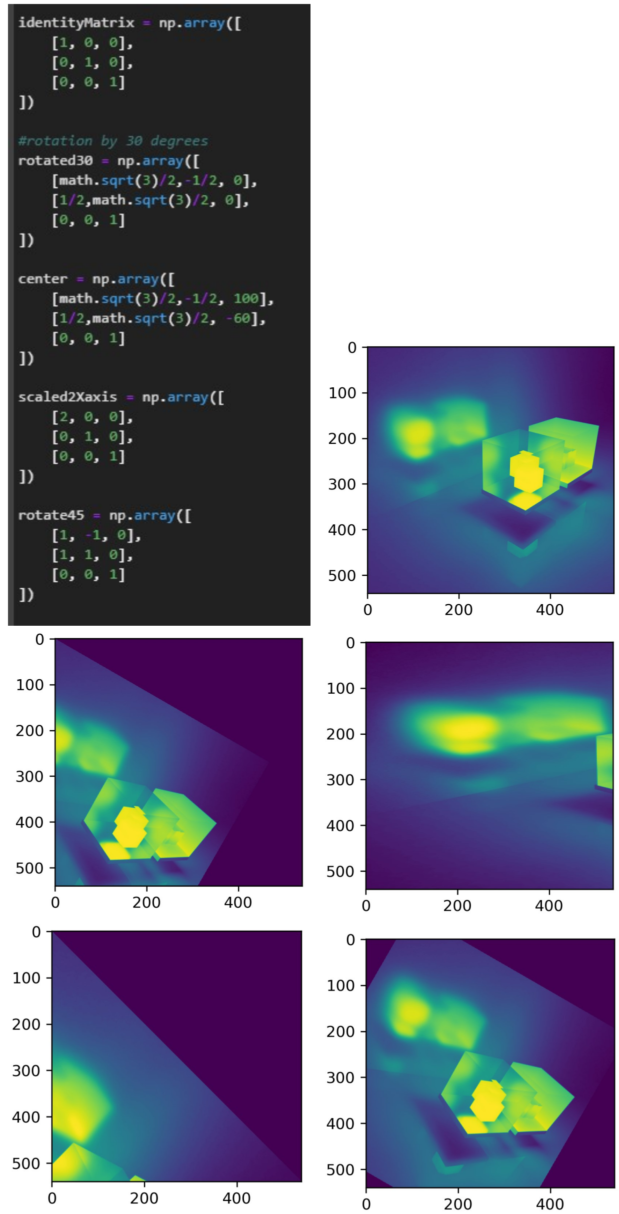

Fig. 5. All the warpings

spatial transformation, but it is really bad with color change. Therefore, it can be considered a poor descriptor.

B. Which feature descriptor performs best on the image imgTranspose? Explain why this descriptor performs better than the others.

The histogram once again is a best descriptor for imgTranspose. The reason for that is because histogram is resistant to spatial transformation as it is good with rotations and such changes. Therefore we can conclude that histogram is the best descriptor for imgTranspose.