Project 2

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Image Processing - Spring 2018

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Problem 1. Applying Robert's Operator to a gray Scale picture.

Solution Robert's operator was quick to compute. The computations are mainly additions and subtractions - in order to determine the value at a pixel.However it is sensitive to noise, since it is a small kernel.

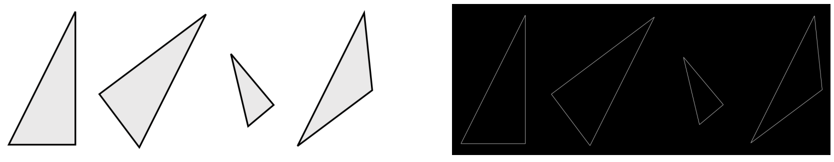
Figure 1 shows basic application of Robert's operator. Figure 2 shows another application of Robert's operator in a clean image and Figure 3 shows how Robert's operator does not work well on a noisy image. Clearly shows how a noisy image can spoil the result for the Roberts operator. In this case, we can apply thresholding to improve the results of a noisy input image.

In this way we have demonstrated this operators sensitivity to noise in an image.

Problem 2. Applying Sobel Operator to image.

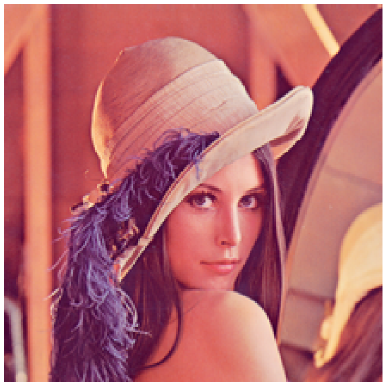
Solution In this case, I took a simple image with shapes in it, to see how each sobel operator performed on the image. Then I also visualized the combined effect of convolutions x and Y. Please see the results in the Figure 4 to Figure 9.

It can be seen that the convolution X is more prominent for the vertical edges, very faint lines can be seen for horizontal edges, where as the convolution Y filter is prominent for the horizontal edges. Squaring these kernels, causes the faint edges detected become a little more prominent. The combined effect of these filters, can see that all edges are identified.



(a) Original Image (b) Robert's Operator Output

Figure 1: Application of Robert's Operator



(a) Original Image

(b) Robert's Operator Output

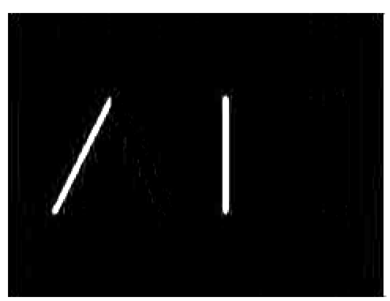
Figure 2: Application of Robert's Operator on clean image

(a) Original Image

(b) Robert's Operator Output

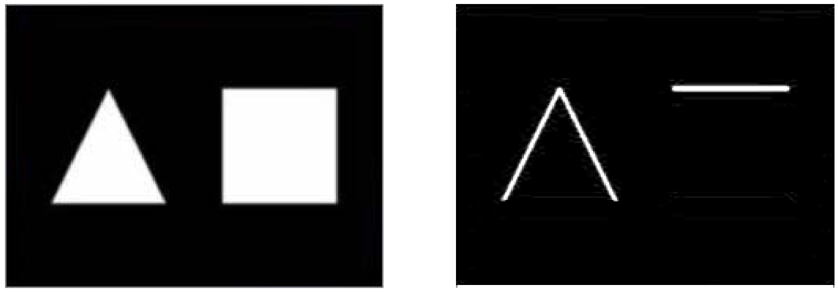
Figure 3: Application of Robert's Operator on noisy image

(a) Original Image



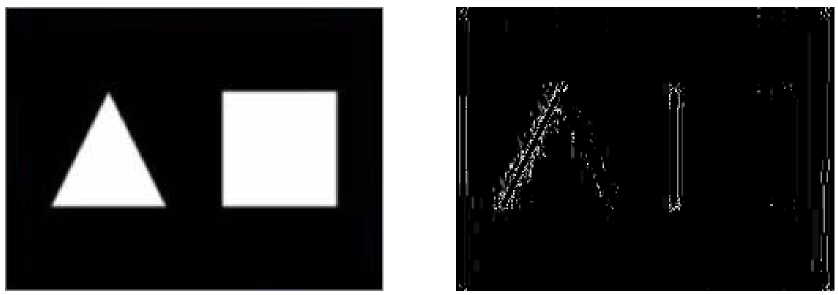
(b) Sobel's Operator Output

Figure 4: Convolution X output



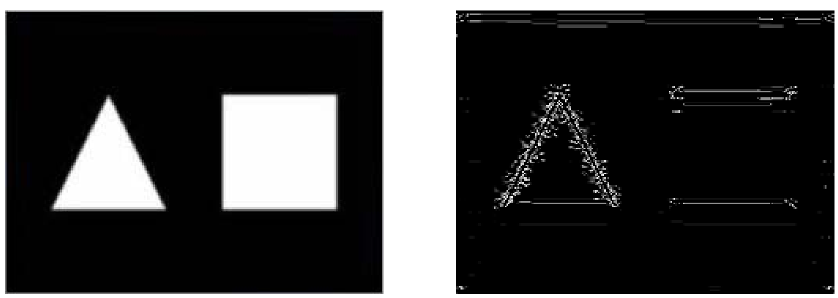
(a) Original Image (b) Sobel's Operator Output

Figure 5: Convolution Y output



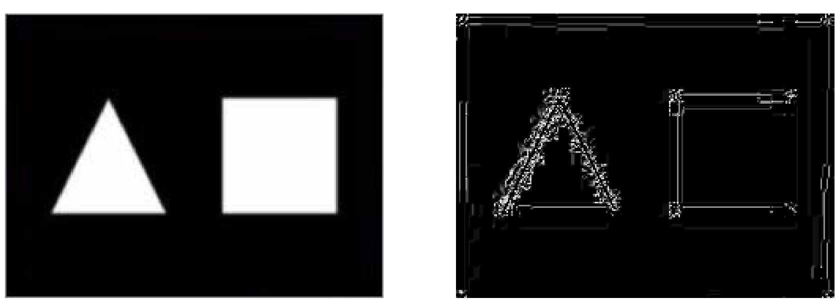
(a) Original Image (b) Sobel's Operator Output

Figure 6: Convolution $\mathrm{X}^2 output$



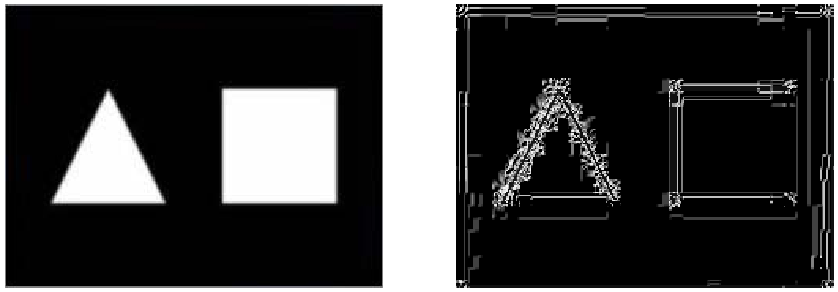
(a) Original Image (b) Sobel's Operator Output

Figure 7: Convolution $\mathrm{Y}^2 output$



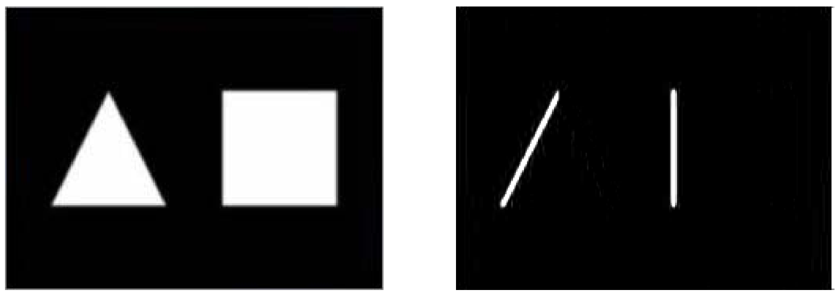
(a) Original Image (b) Sobel's Operator Output

Figure 8: $\mathrm{X}^2 + Y^2 output$



(a) Original Image (b) Sobel's Operator Output

Figure 9: Square root of X$^2 + Y^2 output$



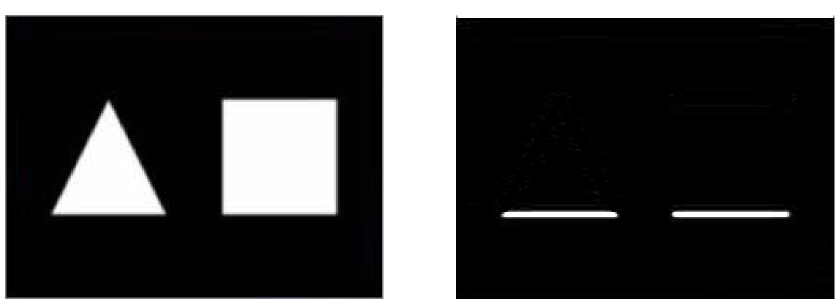
(a) Original Image (b) Prewitt's Operator Output

Figure 10: Exaggerate boundary on vertical

Problem 3. Applying Prewitt Operator to image.

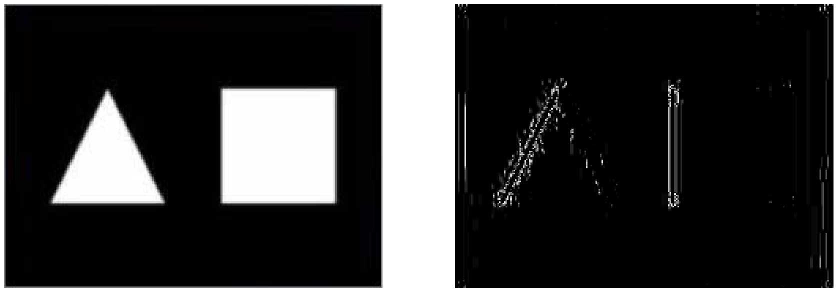
Solution A similar process was applied while studying the Prewitt operators. Figure 10 to Figure 15 show the various steps in the process. As you can see that in the Figure 10 on which we apply vertical mask, all the vertical edges are more visible than the original image. Similarly in the Figure 11 we have applied the horizontal mask and in result all the horizontal edges are visible. So in this way you can see that we can detect both horizontal and vertical edges from an image - as seen in Figure 15. The edges that are faintly visible is because of the slight noise in the input image.

Problem 4. Applying Kirsh operator to image.



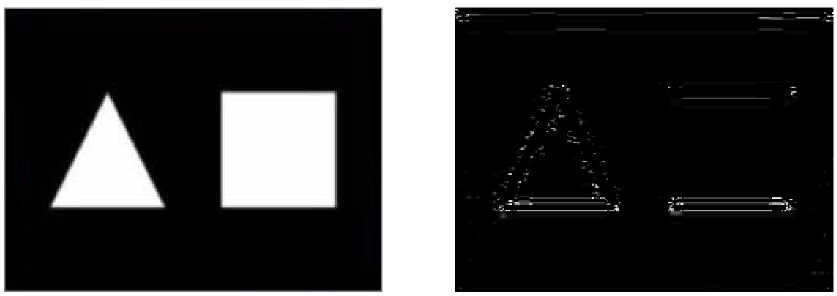
(a) Original Image (b) Prewitt's Operator Output

Figure 11: Exaggerate boundary on horizontal



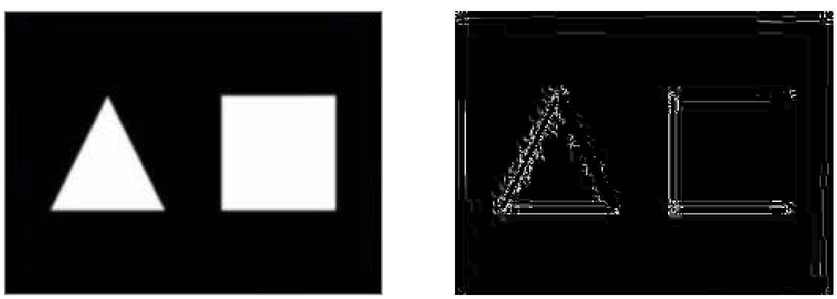
(a) Original Image (b) Prewitt's Operator Output

Figure 12: Square horizontal result



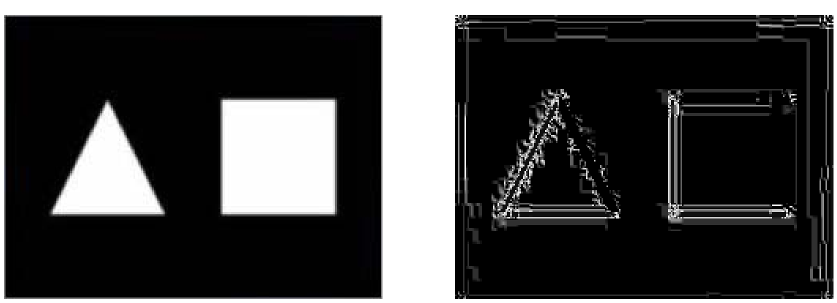
(a) Original Image (b) Prewitt's Operator Output

Figure 13: Square vertical result



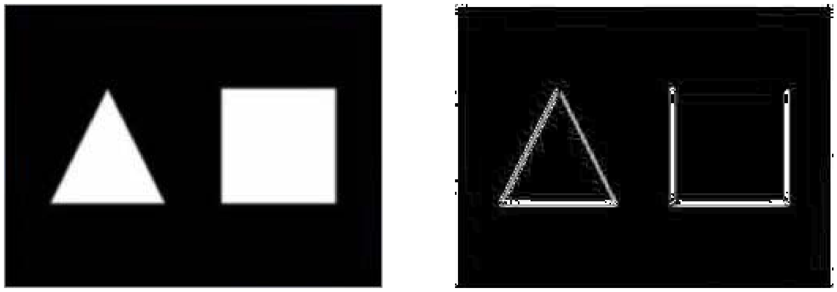
(a) Original Image (b) Prewitt's Operator Output

Figure 14: Adding squared results



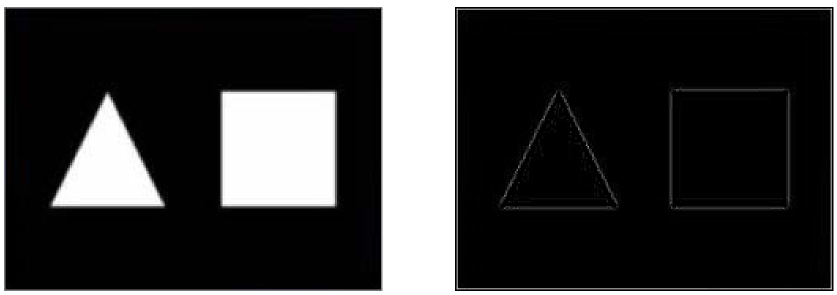
(a) Original Image (b) Prewitt's Operator Output

Figure 15: Square root of adding squared results



(a) Original Image (b) Kirsh's Operator Output

Figure 16: Result of Kirsh operator



(a) Original Image (b) Laplacian Operator Output

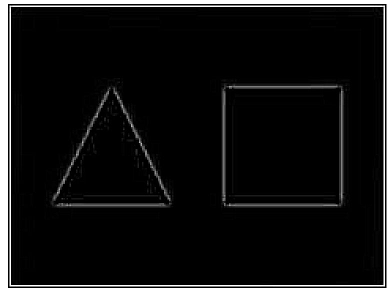
Figure 17: Positive Laplacian

Solution Kirsh operators performed significantly better than the Prewitt operators. Figure 16 will demonstrate the results. It can be clearly seen, compared to the previous operators the Kirsh operator has prominent edges, distortion of the resulting image is less. The intermeditate results of this operator are difficult to understand, and this can be seen at the time of the demonstration.

Problem 5. Applying Laplacian to an image and visualization of the laplacian.

Solution I used both the positive and the negative laplacian operators. And checked the results. Please find the Figures 17 and Figure 18 as the results for positive and negative laplacian respectively. As compared to the other operators for Laplacian operators it is observed that it did not take out edges in any particular direction. The difference between this operator and the rest is that it is a second order derivatice operator, as against the others, which are first order derivatives. Laplacian operators are highly sensitive to noise. Figure 19 and 20 is the application of the positive laplacian on a clean and a noisy image respectively. Figure 20 and 21 is the application of the positive laplacian on a clean and a noisy image respectively. It can be seen that noise affects the output of the Laplacian a lot.

(a) Original Image



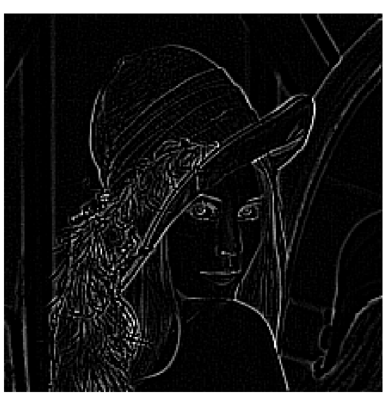
(b) Laplacian Operator Output

Figure 18: Negative Laplacian

(a) Clean Image Laplacian Ouput

(b) Noisy Image Laplacian Output

Figure 19: Positive Laplacian



(a) Clean Image Laplacian Ouput

(b) Noisy Image Laplacian Output

Figure 20: Negative Laplacian