CS 754 : AIP - Course Project

Difference-Based Image Noise Modeling Using Skellam Distribution

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May 10, 2020

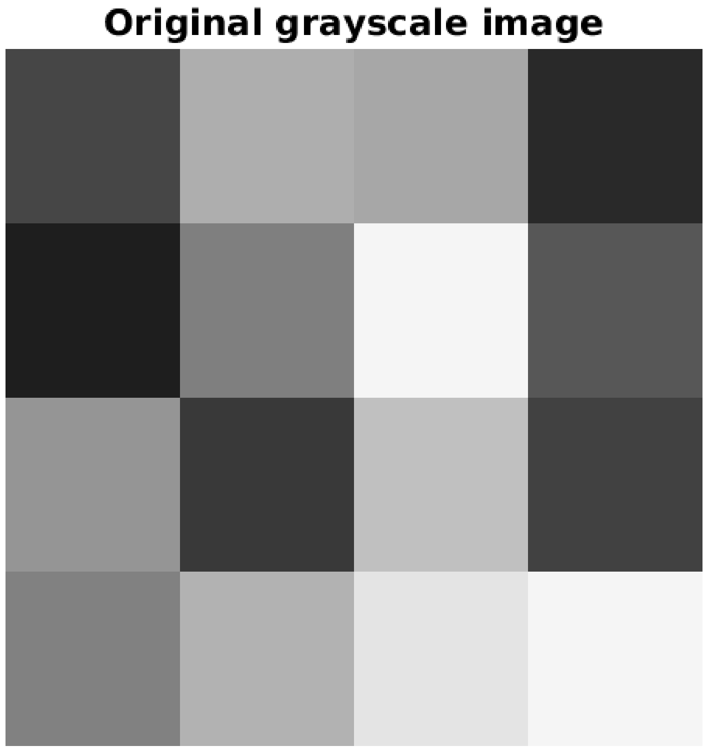
Abstract

In this project, we have shown the usage of skellam distribution in detecting edges in spatial domain and subtracting background in temporal domain. We have modelled intensity difference (or noise) as skellam distribution and computed required probabilities to generate respective masks for grayscale images and videos.

Data Synthesis

Image Data:

We have used two types of image data, synthetic and natural. For creating synthetic images, we divided the image into several patches and filled each patch with a randomly generated intensity value. We have also added 0-mean random poisson noise to the generated image.
Following is an example of our created synthetic image:



For natural images, we have taken images from this kaggle dataset

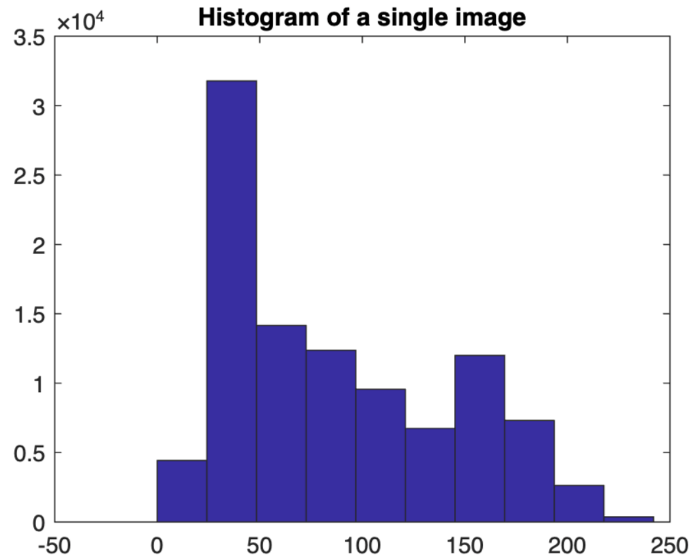
Video Data:

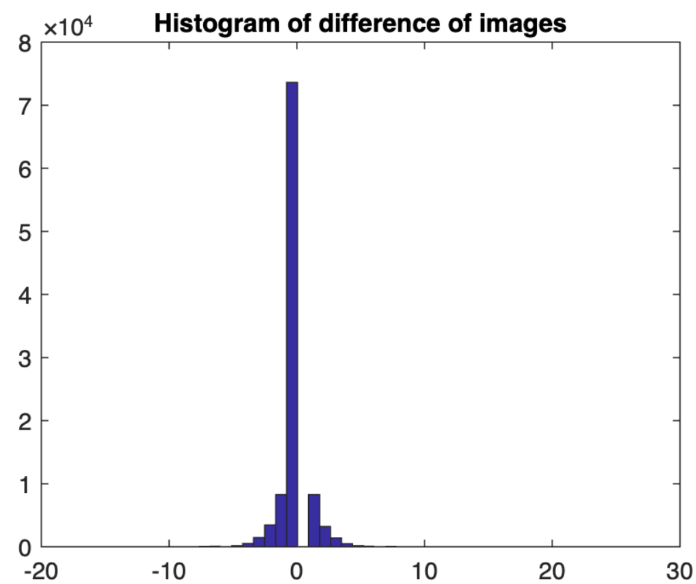
We have used two types of Video dataset. One synthetic where we created a background using the same way as for synthetic image and then simulated a moving object (black) on that background by changing its position in consecutive frames.
For natural Video we used this Dataset
The object should be small compared to background or if bigger then it should be present in only a small fraction of total frames. This is necessary because if otherwise, it will be considered in background, which is not desired.
We have also added 0-mean random poisson noise to each generated frame of the video.

Hyperparameter Tuning

We have tuned the parameters for both Background Subtraction and Edge Detection, and correspondingly chose $1 - \alpha = 10^{-5}$ as error which gives best intensity acceptance region. Patch size was also tuned in a similar fashion and chosen to be 5×5. These values may vary depending upon the nature of the image.

Motivation for skellam



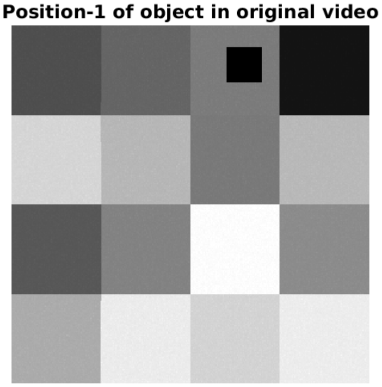


As we can see that difference of consecutive frames follows a specific distribution and we can exploit this property to detect edges. The paper demonstrates that intensity difference follow skellam distribution.

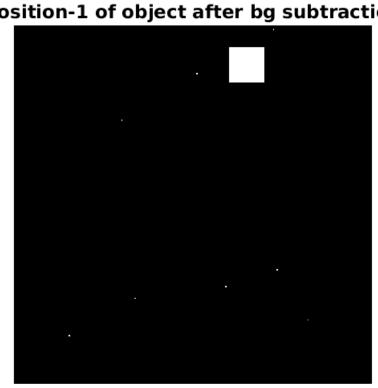
Background Subtraction in Temporal Domain

Synthetic Video

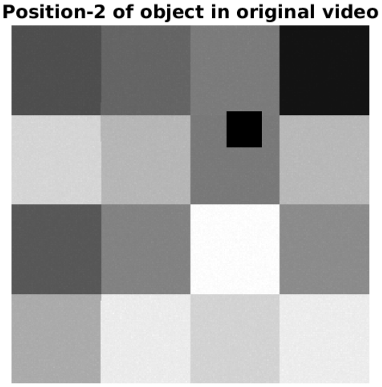
Position-1 of object in original video



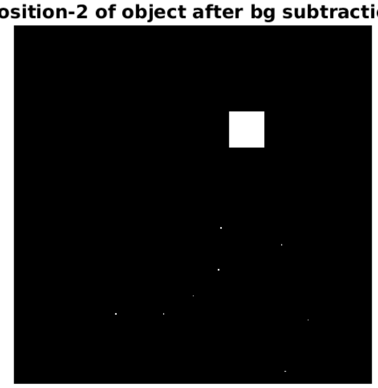
Position-1 of object after bg subtraction



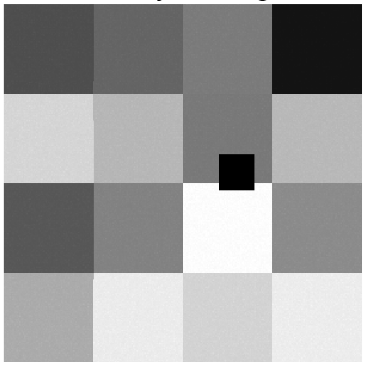
Position-2 of object in original video



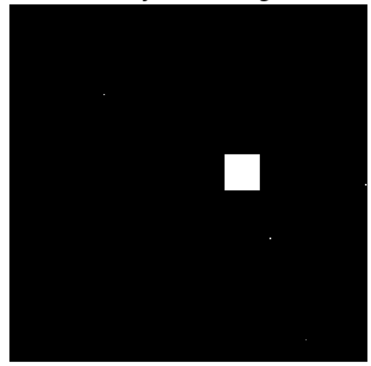
Position-2 of object after bg subtraction



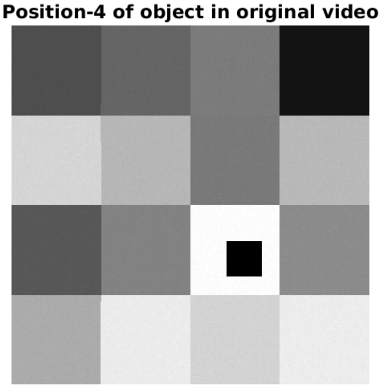
Position-3 of object in original video



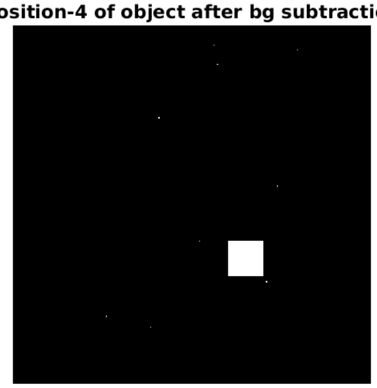
Position-3 of object after bg subtraction



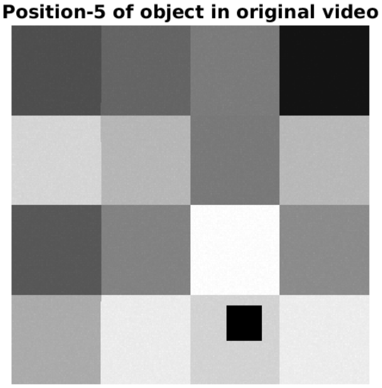
Position-4 of object in original video



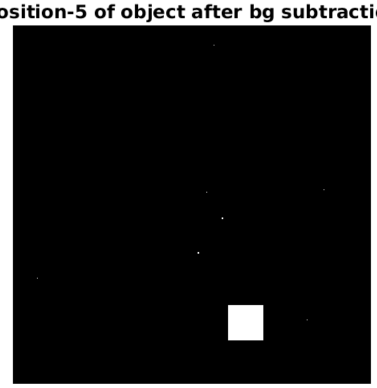
Position-4 of object after bg subtraction



Position-5 of object in original video

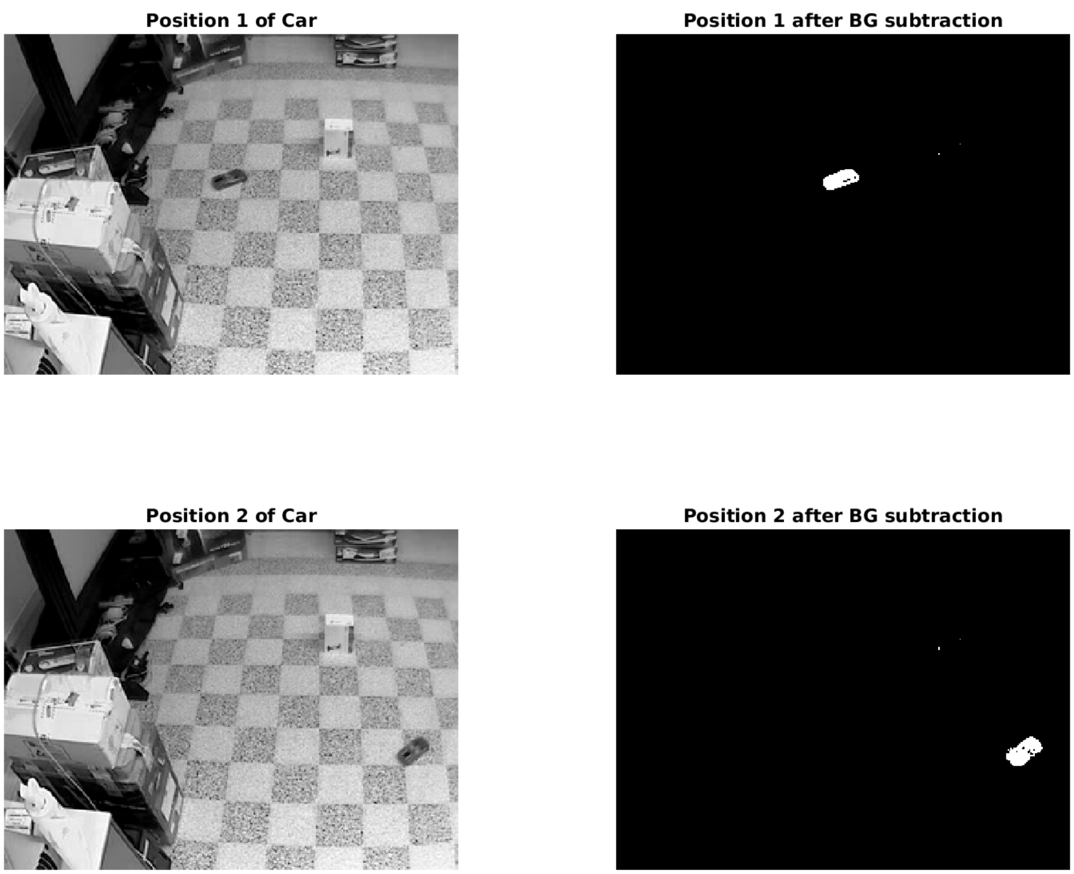


Position-5 of object after bg subtraction



Natural Video

Figure 1: Natural Background



Edge Detection in Spatial Domain

Natural Images

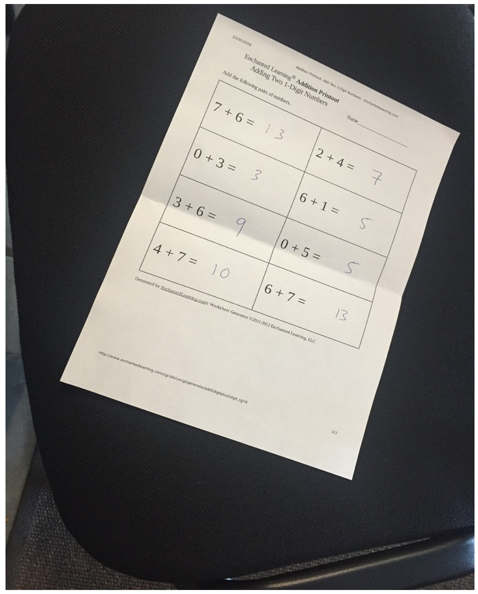


Figure 2: Original Natural Image

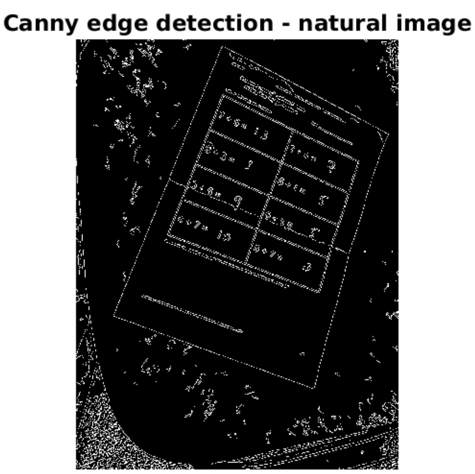


Figure 3: Canny Edge Detection

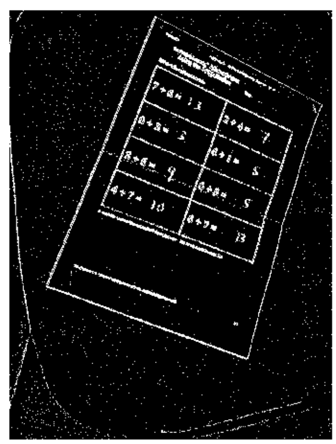


Figure 4: Skellam Edge Detection

Figure 5: Original Natural Image

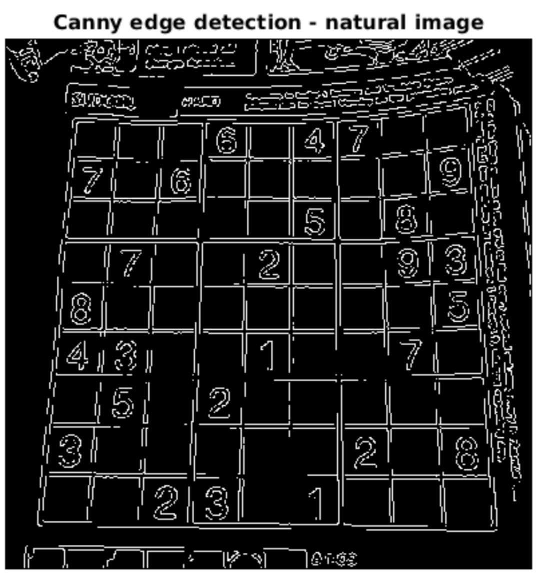


Figure 6: Canny Edge Detection

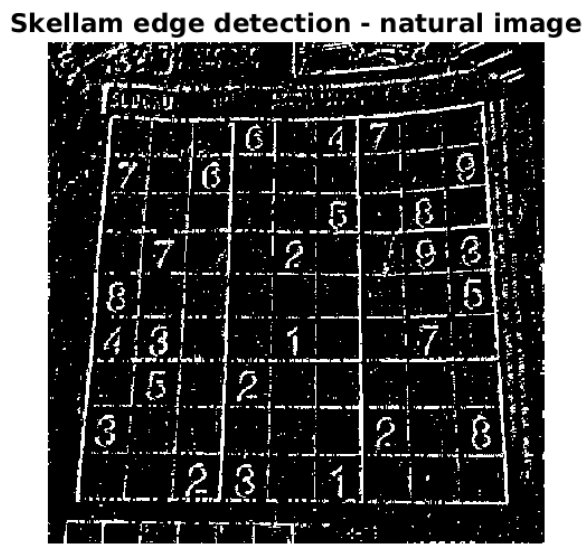


Figure 7: Skellam Edge Detection

As we can see the edges in skellam are more bright and sharp as compared to canny edge detection. Notice in Figure 3, skellam also detected edges of table which canny failed to detect.

Synthetic Image

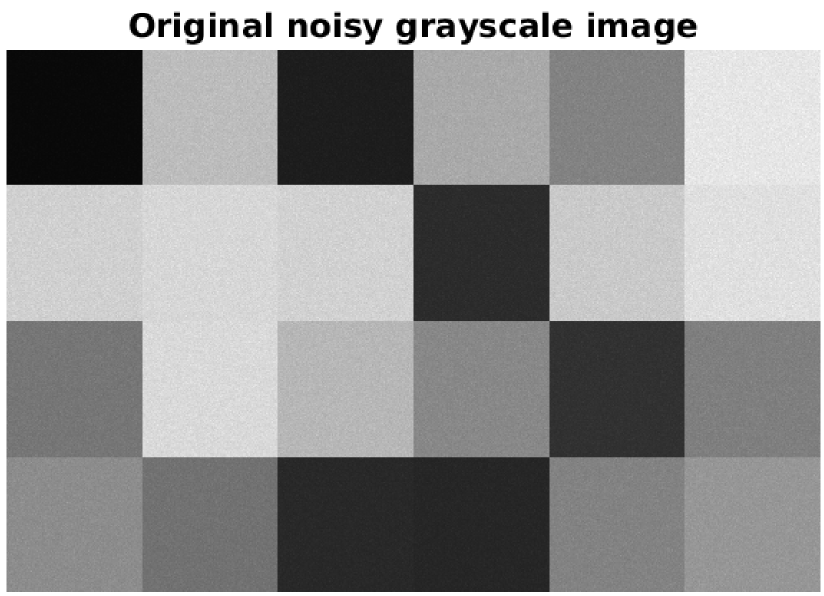


Figure 8: Noisy Synthetic Image

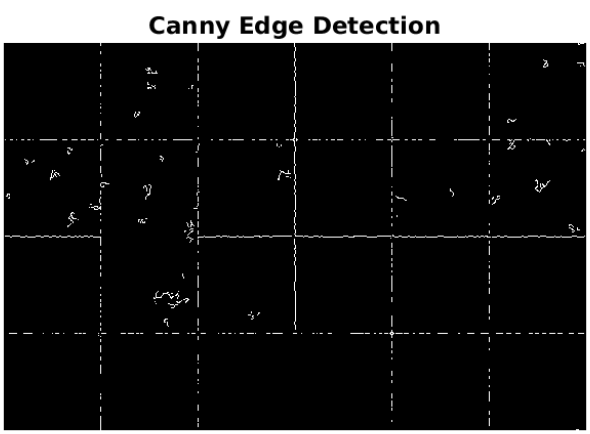


Figure 9: Canny Edge Detection

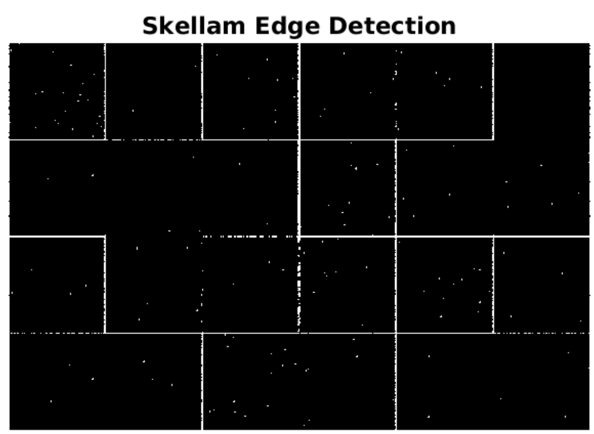


Figure 10: Skellam Edge Detection

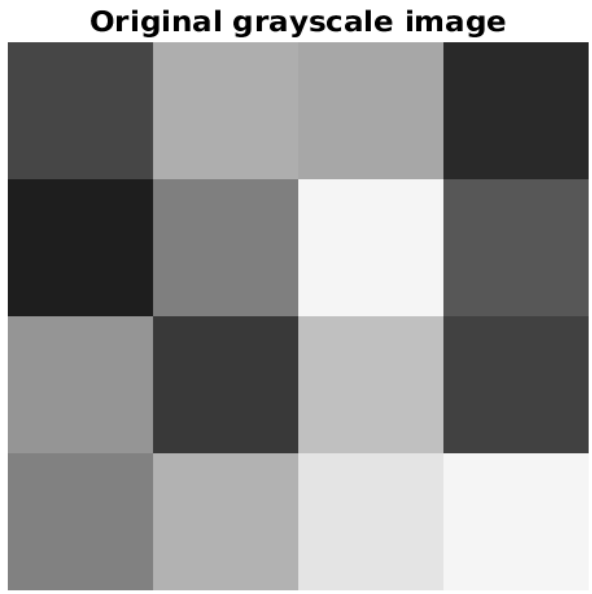


Figure 11: Synthetic Image

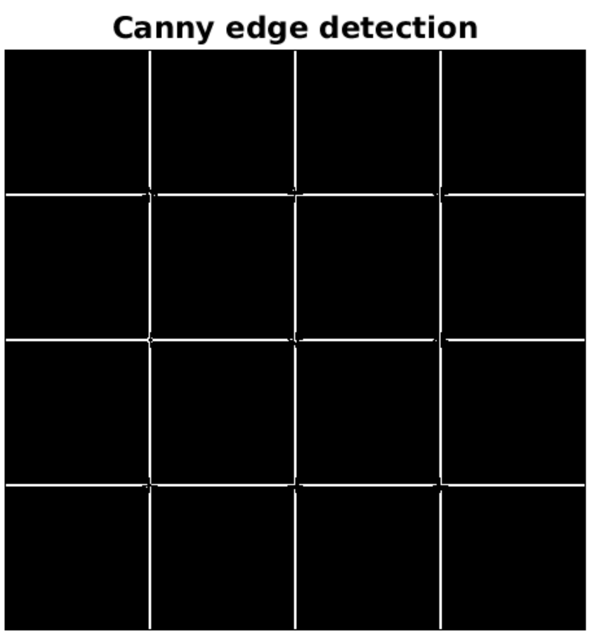


Figure 12: Canny Edge Detection

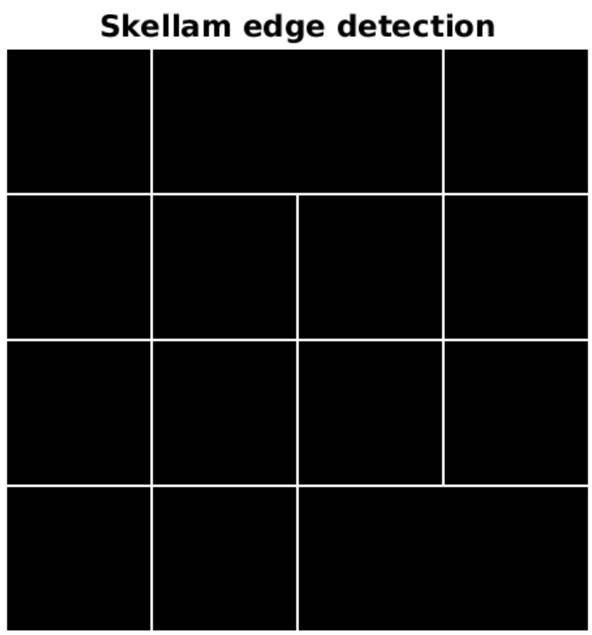


Figure 13: Skellam Edge Detection

We can see that since noise can be represented closely as skellam distribution, Our results for synthetic noisy image is better than that without noise.