Lens Flare Removal of Deep Fusion Image

Digital Image Processing Final Project Report - Team 27

Hsing-Yu Shih
Graduate Institute of Communication Engineering
National Taiwan University
r08942161@ntu.edu.tw

CHE-WEI YU
Graduate Institute of Networking and Multimedia
National Taiwan University
r09944075@ntu.edu.tw

1 MOTIVATION

1.1 What is lens flare?

The reason for the lens flare is that the defect light transmittance of the lens glasses, which causes the incident light to be reflected inside the lens, and finally reflected on the photosensitive element (Eg. CCD and CMOS), resulting in weird colored spots. Figure 1 shows how light is reflected in the lens and the lens, which causes lens flare. [3]

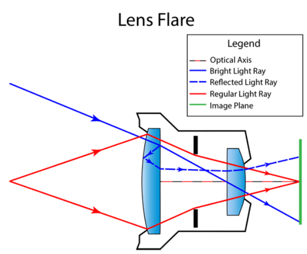

Figure 1: Causes of Lens Flare

According to the different forms of flare, it can be divided into two types: *glare* and *ghost*. When the lens is facing strong light, and part of the light enters from the edge of the lens at an abnormal angle, causing abnormal refraction and reflection, it will be glare in the image. Glare is characterized by a needle-like light around the light source. When strong light enters the lens, and the transmittance of the lens is not good enough to cause part of the light to be reflected between the lenses, ghost will appear in the image. After the lens flare is generated and reflected on the photosensitive element, it results as Figure 2. A closer look at this picture reveals a strange green spot in the lower right corner. This spot is caused by the strong light from the sun on the left reflected inside the lens.

Figure 2: Lens Glare(left) and Ghost(right)

Some people like lens flare and others don't. Some people say that this will give the image a different feel. Those who don't like it think that it cause defects in the image that are difficult to recover. Therefore, overcoming the problem of lens flare always is the goal of the photographic industry.

1.2 How to avoid lens flare?

Lens flare comes from the poor light transmittance of lens glass, so the most significant way to overcome lens flare is to use glass with better light transmittance.Therefore, in the past few hundred years, materials engineers have tried to add various elements to the glass, and even use various rare ores to make lenses, just to achieve better light transmittance. Another way to overcome lens flare is to coat on the surface of the lens with a special substance. These coatings can filter out light that is prone to flare and can also reduce the reflection of light from the lens. However, this method will lead to a substantial increase in the cost of lens manufacturing. Companies like Zeiss or Leica regard the material and coating technology of the lenses as top secrets. This is why the price of Leica lenses with good optical performance is usually tens or even hundreds of times that of mobile phone lenses. Figure 3

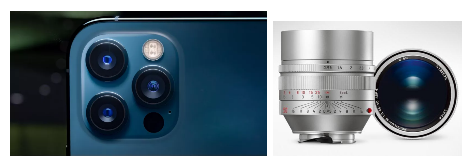

Figure 3: Iphone Lenses and Leica Lenses

That is why the camera of mobile phones is still difficult to surpass professional cameras in an era when computational photography technology is advanced. This is ultimately a question of cost considerations. If there is no cost consideration, engineers may have a way to build a mobile phone without lens flare, but this is not practical. In fact, with the advancement of lens manufacturing technology, the problem of lens flare has been reduced a lot.

1.3 HDR+ and Deep Fusion

Although it is difficult for mobile phones to surpass professional cameras in terms of material technology and photosensitive element technology, engineers still try to break through this problem from the perspective of image processing and machine learning. As the computing power of the mobile phone's central processing unit becomes stronger and stronger, it becomes feasible to realize a large number of image calculations on the mobile phone.

"If the quality of one image is not enough, just combine multiple images together." This is the basic concept of HDR. To capture multiple images at the moment of image shooting, and then combine the good quality parts of each image through an algorithm, and finally get a high-quality and high-contrast photo. Figure 4 [4]

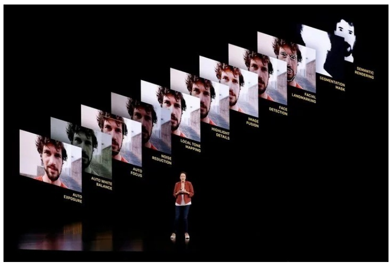

Figure 4: Iphone Lenses and Leica Lenses

Through this technology, the specifications of the components used in the mobile phone do not have to be very expensive, and satisfactory photos can also be obtained. In recent years, the Deep fusion and HDR+ technologies proposed by various mobile phone manufacturers is use deep learning models to strengthen the process of image integration.
However, such technology is not without its flaws. Because the

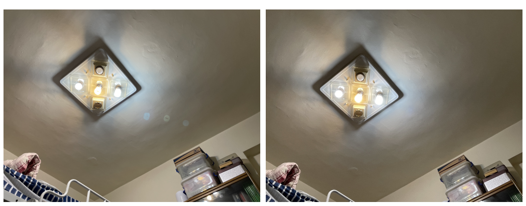

Figure 5: Image with Deep Fusion Comparison

essence of technology is to combine multiple images. If there is lens flare in the image, the algorithm will make the lens flare problem more serious. In Figure 5, the photos taken with deep fusion technology and the unused photos are compared. Both photos were taken with iPhone 12 pro. It can be found that the problem of lens flare in photos taken with deep fusion technology has become more serious. That is why the lens flare problem on mobile phones has been discussed again in recent years.

2 PREVIOUS WORK

After reading many digital image processing journals, we found that the number of studies on lens flare removal is quite small. Finally, we selected two reference papers for comparison. These two papers use traditional image processing and deep learning methods to achieve lens flare removal. The following is an introduction and comparison.

2.1 Traditional Method

Vitoria and Ballester [7] use traditional image processing algorithms to detect the position of the lens flare, and use the inpainting algorithm to remove it. Their method focused on removing *lens ghost* from images shot in *daylight*. Their method can be divided into three steps :Flare Spot Detector, Flare Masking and Reconstructor.Figure 6.

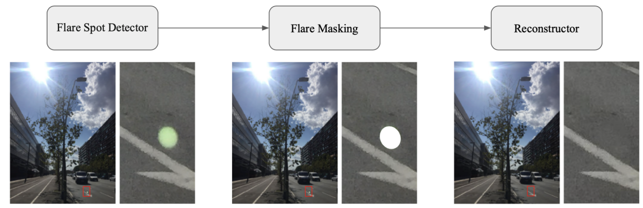

Figure 6: Image Manipulation Approach

(1) **Flare Spot Detector**
This step is to find and label the location of the lens flare in the image. First, the edge detection algorithm will be used to capture the part of the image that has obvious edges. Then calculate the numerical difference of each block to find the possible lens flare position. [7]
(2) **Flare Masking**
Make a mask for the position marked as the lens flare in the previous step and remove the lens flare.
(3) **Reconstructor**
Use the mask made in the previous step to find suitable image material for filling in the image, and use the inpainting algorithm to fill it. [5]

2.2 Deep Learning Method

Wu et al. [1] design deep learning models to remove lens flare and create a mask to retain the light source. Their methods focus on removal of lens *glare* in image taken in *daylight*. They separately collect photos and glare sample images, and combine the two images to generate training data and ground truth. Their approach can be divided into three steps: Flare-free Network, Light Source Mask and Blended. [1] Figure 7.

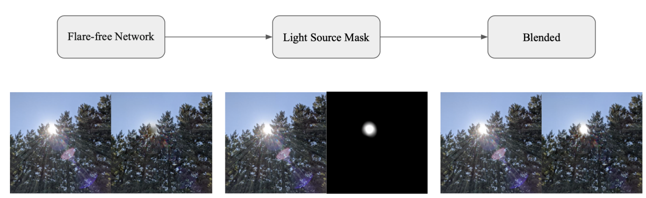

Figure 7: Deep Learning and Computer Vision Approach

(1) **Flare-free Network**
Train a CNN model to fill in the lens flare. However, this method will cause the model to mistakenly regard the light source as a lens flare and be filled together. Therefore, the next two steps are to add back the removed light source.
(2) **Light Source Mask**
In order to add the light source back, first we need a mask that can filter out the position of the light source. Therefore,

it is necessary to train another CNN model to build a light source mask.

(3) **Blended**
Finally, the light source is found using the mask of the previous step, and then the light source image is combined with the original image.

However, we found that neither of these two papers provided their source code, datasets and implementation details. Therefore, we can only construct our own algorithms with reference to their ideas.

3 PROBLEM DEFINITION

After reading a lot of information, we decided to limit the problem to the following three points:

(1) **Image taken by iPhone 12 with deep fusion**
In recent years, mobile phone cameras have made great progress, and the problem of lens flare has become less and less. It is the deep fusion technology in recent years that has caused the problem of lens flare to be brought up again. The lens flare caused by deep fusion is exactly what we want to solve. In this way, choosing the photos taken by the iPhone is a necessary condition.

(2) **Removal of lens ghost**
We observed many photos taken with iPhone 12, and we found that the appear of ghost in the lens flare problem is much greater than glare. In addition, glare can sometimes create a special atmosphere, but ghost images are very annoying. Otherwise, because the two methods are very different, we must divide the two into two different problems, and we will focus on the removal of ghosts.

(3) **Image taken at night**
After observing many pictures of ghosts appearing, we found that the chance of ghosts appearing at night is much higher than that of daylight. The appearance of ghosts usually comes from the number of light sources. In daylight, there is only one light source, which is the sun. Therefore, there is usually only one ghost in the sun, and because the sun is very far away from us, the area of the ghost will not be too large. However, at night, street lights and signboards may become the light source of ghosts, which makes the problem of ghosts much more serious at night.

Our experimental data set comes from 30 images with lens flare taken with the main camera 1x zoom of the iphone 12 pro. Each image is processed by deep fusion technology. The dimensions of each image are 4032×3024. Figure 8 shown is an image from our data set. The red circle in the upper right corner indicates the lens flare produced by the light source marked in the lower left corner. It can be seen that the flare in the shape of Chanel does affect the appearance of the photo.

4 ALGORITHM

We adopted the algorithmic architecture proposed by Victoria [7], that is, the method of lens flare removal is divided into three parts: lens flare detector, lens flare masking and inpainting. Then we implemented the three parts separately, and tried different ways of doing it.

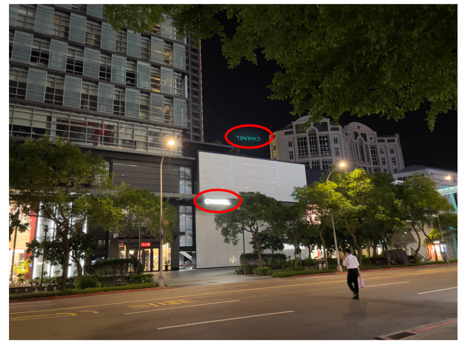

Figure 8: Example of Data set

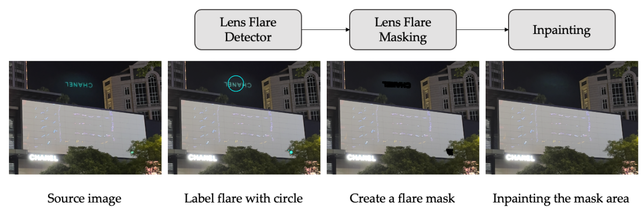

Figure 9: Our Algorithm

Figure 10: Our Hypothesis

In order to design the algorithm, we proposed three hypotheses to detect lens flare on the iPhone:

- The lens flare will be brighter than the surroundings.
- The lens flare (ghost) of iPhone 12 have a specific color.
- The shape of the lens flare should be similar to the light source. (Not always right, because over exposure)

After observing the lens flare photo Figure 12, it is believed that the flare can be regarded as a light spot like a light bulb, the color of the flare will shift to blue-green, and the appearance of the flare should be very similar to the light source. However, because the iPhone often overexposes the light source when shooting, the shape of the light source is different from the lens flare. Therefore, we did not use the last hypothesis to implement the algorithm.

4.1 Lens Flare Detector

4.1.1 Blob detection. We refer to the detection method proposed by Victoria [7], who uses the Difference of Gaussian (DoG) to implement the blob detector. In order to implement the Difference of Gaussian, we refer to Lowe's paper [2] and learned that the Difference of Gaussian uses Gaussian filters of different scales to process the image, and then calculate the difference between the results. After such processing, the area of the image that looks like a light bulb will be gradually reduced, and finally a filter can be used to detect and mark it.

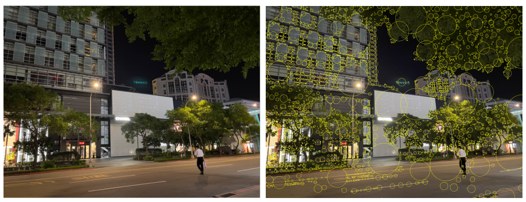

Figure 11: Results of Blob Detector

4.1.2 Blob Selector. From the results of blob detection, it can be found that the algorithm marks too many light spots as "blob", but it can be found that most of the marked areas are not real blobs. Therefore, we need an effective method to filter out the real lens flare from all the "blobs".

According to the hypothesis we obtained by observing the shadows, we found that the color of the lens flare of the iPhone 12 will be close to blue-green. We designed the following steps to make the selection:

(1) Cut the area marked as the bulb.
(2) Find the pixel with the highest RBG spatial average value in the area and brightness value (HSV space) is less than 200.
(3) Check whether the Hue value(HSV space) of that pixel is between 80-190 degrees. (Hypothesis 2)
(4) Check that the saturation value(HSV space) of that pixel is greater than 0.1 and the brightness value (HSV space) is greater than 150.
(5) Mark it as flare.

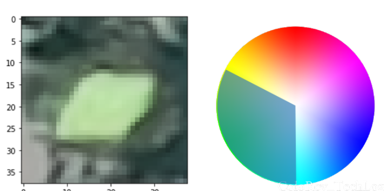

Figure 12: Crop Area and HSV Color Space

After these steps, as shown in the Figure 13, we successfully selected the most likely lens flare from a large number of "blobs".

Figure 13: Results of Blob Selector

4.2 Lens Flare Masking

Now we can successfully find the position of the lens flare from the image. Next, we will make a mask to remove the pixels where the lens flare is located. We tried the following two different methods according to different ideas:

4.2.1 Canny + Convex hull. Based on the observation of the lens flare in the image, we believe that the lens flare has a clear boundary. Intuitively, we use Canny algorithm to detect the edge of the lens flare, just like the result shown in the middle of Figure 14. When we have the edge of the flare, the next step we need to fill in the enclosed area enclosed by the edge. And we remembered that convex hull can be used to make a mask to cover the target object in class. So we implemented a convex hull to generate a mask to remove lens flare. It can be seen that our method can effectively create a mask to remove lens flare, as shown in the right of Figure 14, no matter the shape of the flare is ellipse or irregular text.

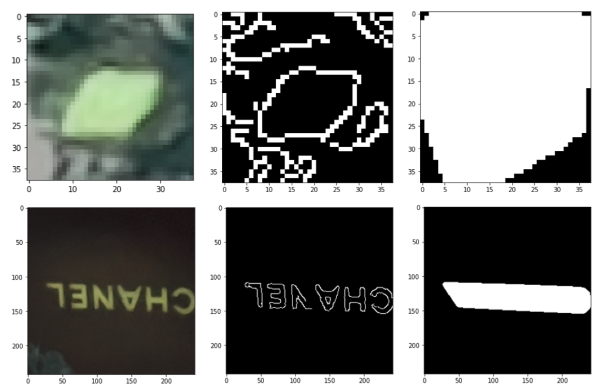

Figure 14: Results of Canny and Convex Hull

4.2.2 HSV space filter. It can be noticed from the Figure 14 that the range of the mask we used canny+convex to block the light spot is too large, which is beyond the area where the flare is located. So we started to think about another way to make the mask, and make the mask close to the original size of the flare. We consider that the lens flare of the iPhone has a certain color, so we can also design a rule to filter out the pixels with flare in the cropped image. Therefore, we convert the image to HSV space and filter out the RGB range values as shown in the left of Figure 15.

It can be seen from the right of Figure 15 that the mask made after such processing is more similar to the original outline and size of the flare.

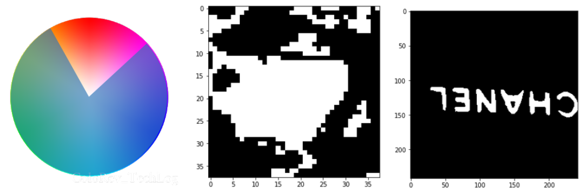

Figure 15: Results of HSV Space Filter

4.3 Inpainting

In the previous step, we made a mask that can remove the lens flare. When the lens flare is removed, there will be many holes in the image. Therefore, we must fill in the holes to make the image look normal. We have tried two different inpainting techniques, one is the traditional algorithm, and the other is the algorithm based on deep learning.

4.3.1 Fast Marching Method. We refer to the method proposed by Telea [6], which is an inpainting technique designed based on the Fast Marching Method. This method searches for a certain range of filled pixel values around the pixel to be filled, and calculates the gradient according to the pixels in this range, and finally finds a value that is most suitable for filling. The result of inpainting is shown in the Figure 16. It can be found that if filling in an image with a single background, the effect is quite good. For example, the flare of the chanel shape in the Figure 16 can be completely filled. However, for areas with a more complex background, unnatural seams will appear in the image after filling.

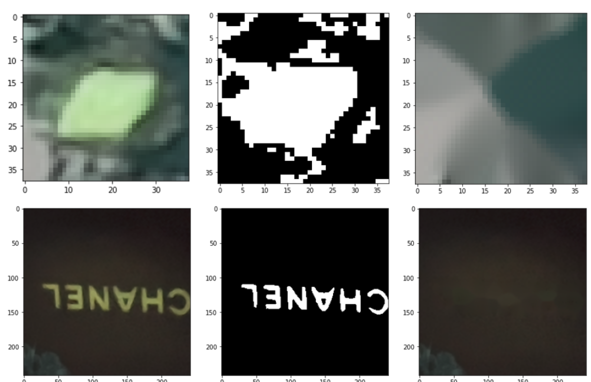

Figure 16: Results of Inpainting Based on Fast Marching Method

4.3.2 U-net method. In order to achieve a better inpainting effect, we refer to the deep learning method mentioned in the paper in Wu's paper [1]. In his research, an architecture called U-Net is used, which can be regarded as an improved version of auto-encoder. The architecture of the model is as shown in the figure. In this architecture, the original image and latent are concatenated in each layer. This approach allows the model to focus more on filling the loopholes during training.

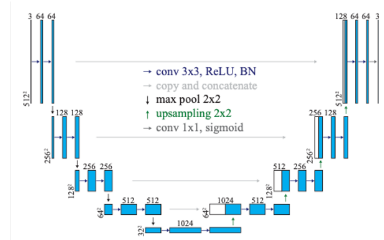

Figure 17: U-Net Architecture

In order to train the U-Net model, we selected two images from the data set as training data and test data.

Figure 18: U-Net Training Data and Testing Data

In the training and testing phases, we randomly cut out a part of the image for training, and randomly generate a rectangular mask to simulate the loopholes to be filled in the image. After training for 250 epochs with batch size 100 (Nvidia Tesla v100) , as shown in Figure 19, the model has been able to correctly perceive the images around the holes and fill in the correct pixel values.

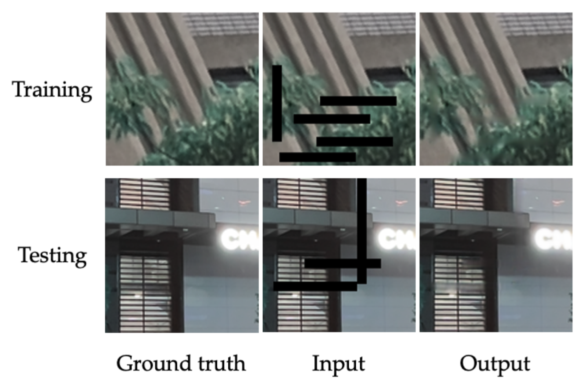

Figure 19: Training of U-Net

We apply the trained U-Net model to fill the hole after the lens flare is removed. The result is as shown in Figure 20, U-Net can correctly generate the appropriate pixels to fill in and does not produce obvious seams.

5 EXPERIMENTAL RESULTS

We combine and compare different methods, and the results are as shown in Figure 21. According to the results, the mask area

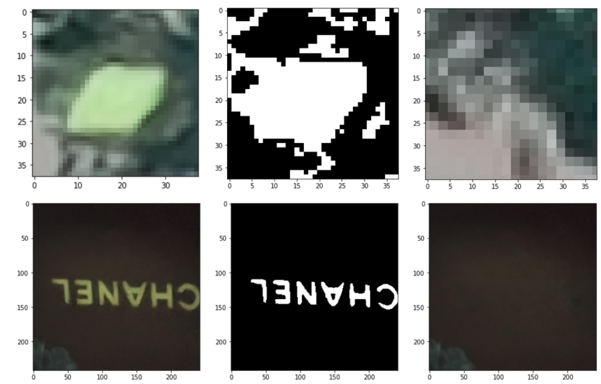

Figure 20: Results of Inpainting Based on U-Net

produced by the result of using canny + convex hull is usually larger, which will have a bad effect on inpainting. Especially in the previous step, if the blob selector regards the wrong area as a lens flare, and the area is very large, serious errors will occur in masking and inpainting. Image in Figure 21 upper left corner, notice that the house in the upper right corner is incorrectly marked as a flare and the mask generated by the canny + convex hull method is too large, which causes the result of applying the fast marching method inpainting to become very poor.

On the other hand, if the HSV space filter is used, the house in the upper right corner is marked as a flare by mistake. The mask area generated will not be too large, and there will not be too much error during inpainting. If the processed photos are viewed from a wide range of scales, the fast marching method and the deep learning method are used to inpainting on the mask generated by the HSV space filter, the difference is not too big. However, if we will look at the image details, we can find out in a complicated area such as leaves, tiles, etc., the found marching method is far less than the inpainting method of deep learning.

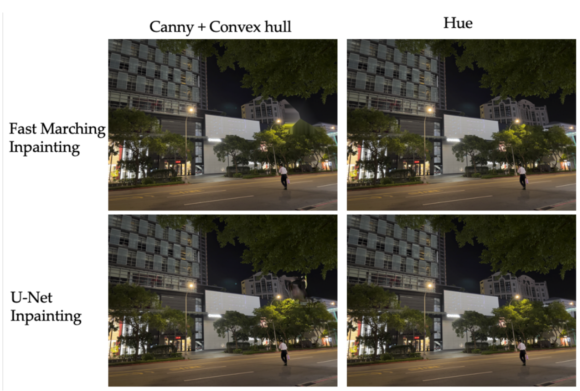

Figure 21: Compare Different Methods

Next we apply the algorithm(HSV space filter+U-Net inpainting) to images taken in different contexts, and the test is effective. We found that our algorithm still has a very good effect on the bridge with mixed street lights and car lights, and can correctly determine the location of the flare and remove it. But for those that are relatively small and low in brightness, they cannot be removed.

When the background in the image becomes more complicated, for example, there is a night building in the background, as shown in Figure 22 upper right corner of the group of photos. It can be found that our algorithm may mistakenly recognize the light on the windows of the building as a flare, and then remove it. In addition, for those light sources that are originally blue-green, the algorithm will also remove them by mistake. For example, in the second set of Figure 22 on the right, the part of the 101 building light in the background was recognized as a flare and removed, causing the 101 building to look abnormal.

For those lens flare with large area and high brightness, our algorithm can detect it correctly and remove it correctly. For example, in the group of photos in the lower right corner of Figure 22, our algorithm can find the halo caused by the street light and remove it.

6 DISCUSSIONS

After comparing the results of different methods, we believe that using HSV space filter to generate a mask and U-Net to fill the image is the best. HSV space filter can make the generated mask area smaller and more irregular, which is more suitable for inpainting. The inpainting method of deep learning can learn more details in the image, so it has better filling performance.

In our algorithm, we consider that the most need to improve is the accuracy of flare detection. We found that many flares could not be removed because they were not marked as flares during the detection step. In addition, most of the errors in the algorithm come from marking the wrong objects as halos, such as building windows and bluish-green signboards. In the follow-up research, we will further improve the algorithm for flare detection. We believe that there are two possible directions for improvement:

(1) Train a new CNN model to classify the detected "blobs"
(2) Because the trajectory of the flare moving in the video is very different from the background, we can be used Object tracking models such as image movement vector or yolacat++ to find the flare.

Although the above two methods are very complicated, they will be worth our time to study.

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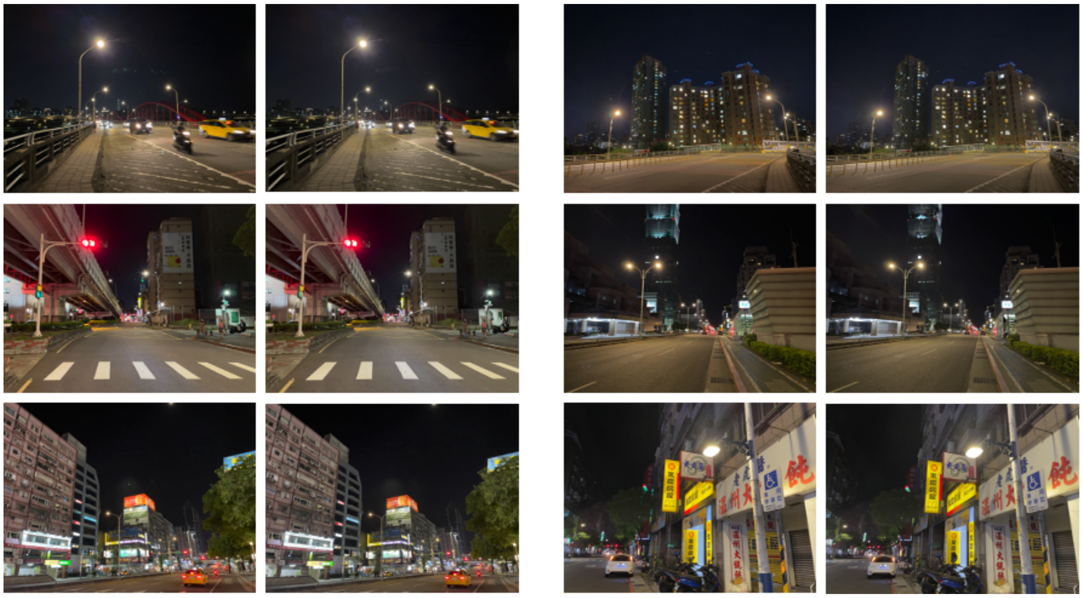

Figure 22: Algorithms on Different Image

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