Astronomy image restoration report

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July 27, 2023

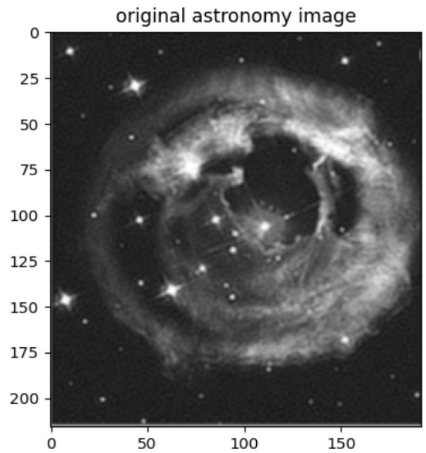
Abstract

The topic of our project is in regard to the astronomy image restoration. As we know, the process of deriving the images can be seriously disturbed so that we can have different noise on the derived images because of the special environment of the outer space, such as Moire pattern and sine periodic noise. However, it is very important and necessary for us to have clear astronomy images for scientific research. As a consequence, we need powerful restoration techniques to help restore the astronomy images effectively. The current algorithm doesn't always do a satisfactory job because sometimes it simply adopts a single method to deal with multiple kinds of noise. So finally we may not get a good result. Our idea is to design innovative algorithms which aim to improve the final derived results by the combination of multiple algorithms so that we can make the derived results clearer. Different parameters of algorithms are tuned so that we can get the optimal output of the restored image. We will evaluate the restoration effect by PSNR and SSIM value. The output of different images generated by different filters are shown in the appendix.

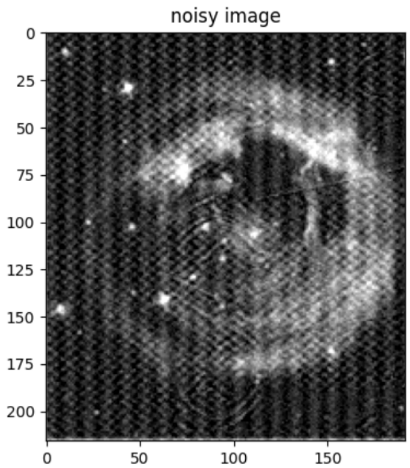
1 Introduction

As stated by Molina et al.(2001), the astronomy image restoration topic has been popular for a long period. We often suffer from all kinds of noise when we derive the astronomy images because of the special environment in the outer space, such as the capturing and signal transmission process of the image. All of these factors can cause the image to be degraded seriously, which is quite undesired. However, we do need clear images for scientific research of the astronomy, so we must find an effective way to restore the noisy images.

Even though the current denoising algorithms can remove the noise to some extent, it has limited effects in some cases. Sometimes the restored images can be still noisy or get the structure influenced by the algorithms. The main reason is that we generally have multiple kinds of noise on a single image in reality, so it can be hard to remove them with a single classical algorithm. As a result, an innovative aggregative algorithm is needed for



(a) original clear image



(b) noisy image

better restored images. For example, the figure (a) below shows a clear astronomy image, which we treat as the ground truth. Meanwhile, the figure (b) shows the noisy image which we manually added the Moire pattern, sine periodic noise and additive gaussian noise.

In this paper, we propose some innovative algorithms with the proper combination of different algorithms so that we can restore the images with potentially better effect.

1.1 Related Work

According to Kumar & Sodhi(2020), gaussian filter and median filter can effectively remove the additive gaussian noise, with the blurring effect onto the image.

Khireddine et al.(2020) propose that Wiener filter may have a good restoration effect on some of the degraded images in the frequency domain response.

In the paper of Yang et al.(2014), we also know that RL algorithm may be an effective tool in the image denoising.

The previous work solves such kind of problem mainly by single filter. For example, it may simply try a median filter or a gaussian filter in spatial domain to deal with the additive gaussian noise, or it simply applies a filter in frequency domain.

1.2 Contribution

The algorithms of the related work have roughly addressed the single pattern noise. For example, the gaussian filter or average filter can deal with the additive gaussian noise well. The notch filter can deal with the Moire pattern or sine periodic noise well, but it requires careful design of the parameters. However, they can't do a good job in face of an image degraded by multiple kinds of noise in general.

In our paper, we mainly contribute to derive an aggregative algorithm to restore the image with multiple kinds of noise effectively. We will combine the known mature algorithms with appropriate order so that we can restore the noisy image with better effect. PSNR and SSIM of each restored image are computed to evaluate the restoration effect.

2 The proposed algorithm

2.1 Pipeline

There are three steps in the proposed algorithm. Firstly, add different noise to the original images, including Moire pattern noise, sine periodic noise, and additive gaussian noise. Secondly, apply different kinds of algorithms to restore the noisy image. The algorithms include classical algorithms in spatial domain and frequency domain, and some innovative algorithms which combine different filters. Thirdly, calculate the PSNR and SSIM of each restored image to evaluate the restoration effect.

2.2 Classical algorithms

Some spatial filters and frequency filters are used in this project. Spatial filters include average filter, median filter, adaptive median filter and gaussian filter. Frequency filters include wiener filter, R-L algorithm filter and notch filter. Other filters except R-L algorithm are introduced in the course, so their introduction are not included in this report. The Richardson–Lucy algorithm is an iterative procedure to recover an underlying image that has been blurred by a known point spread function using Poisson distribution to model degraded images, the following equation is obtained:

$$P\left(g/f\right) = \prod_{0}^{n} \frac{a_n^{g_n} \cdot e^{-a_n}}{g_n!}$$

Differentiate on both sides:

$$\sum_{0}^{n} g_n \frac{h_{n-k}}{\sum_i^0 h_{n-i}\hat{f}_i} - 1 = 0$$

By using the multiplicative iterative algorithm, the optimal restoration estimation of the image is obtained as follows:

$$f_{k+1} = f_k \left(\sum_{0}^{n} g_n \frac{h_{n-k}}{\sum_0^i h_{n-i}\hat{f}_i} \right), k = 0, 1, \ldots N-1$$

The RL restoration algorithm needs to increase the number of iterations during image restoration to obtain the restoration effect.The restoration effect may be better than the previous methods, but it increases the computational time cost.

2.3 Innovative algorithms

The wiener filter, gaussian filter and notch filter are selected to combine with other filters, because there are still some defects in their results. The result of gaussian filter removes the periodic noise and moire pattern but they are too blurry. The results of wiener and notch filter don't remove the periodic noise. So we aim to use laplacian filter to sharpen these filters. Besides, histogram equalization is considered to enhance the contrast of the restored image for potential improvement.

3 Experiments

3.1 Datasets overview

Three datasets are used in this project. First dataset called Astronomy Picture of the Day contains 747 astronomy pictures taken by NASA since 2015. Second dataset called Top 100 Hubble Telescope Images contains 100 most popular images taken by the Hubble Telescope. Third dataset called NASA Image Of The Day Dataset contains all images on their Astronomy Image Of The Day page from 2015.01.01 up until 2022.10.03. We carefully select and compare the results of different astronomy images, and finally three typical images are chosen for the final experiment results. Additionally, only gray images are considered for simplicity.

3.2 Evaluation metric

PSNR and SSIM are used in this project. PSNR whose full name is peak signal-to-noise ratio is used to compare the strength of the required signal with the strength of background noise. It is defined by mean square error (MSE). For two images x and y:

$$MSE = \frac{1}{MN} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} \left[x\left(i,j\right) - y\left(i,j\right) \right]^2$$

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX^2}{MSE} \right)$$

SSIM whose full name is structural similarity index measure is an indicator to measure the similarity between two images. For two images x and y:

$$SSIM\left(x,y\right) = \frac{\left(2\mu_x\mu_y + c_1\right)\left(2\sigma_x\sigma_y + c_2\right)}{\left(\mu_x^2 + \mu_y^2 + c_1\right)\left(\sigma_x^2 + \sigma_y^2 + c_2\right)}$$

$$c_1 = \left(0.01L\right)^2, c_2 = \left(0.03L\right)^2$$

where L represents the range of the pixel; $\mu_x\mu_y$ represent mean values of two images; $\sigma_x\sigma_y$ represent variance of two images.

3.3 Comparison between classical and innovative algorithms

We adopt three types of innovative algorithms here, based on notch filter, wiener filter, gaussian filter respectively, and their results are compared with those of separate classical algorithms to determine whether there's improvement for the innovative algorithm.

The result of notch filter and gaussian filter is relatively clearer in the first step. We consider adding laplacian filter or histogram equalization operation. The laplacian filter added with the gaussian filter is quite successful, since the result becomes sharper and PSNR increases. However, the restoration result becomes worse if we add the laplacian filter to the wiener

Table 1: classical algorithms restoration results in spatial domain

	noisy	mean	median	adaptive median	gaussian
PSNR	18.86	23.02	24.52	22.74	24.25
SSIM	0.2941	0.4405	0.5081	0.4176	0.6688

Table 2: classical algorithms restoration results in frequency domain

	noisy	wiener	R-L	notch filter
PSNR	18.86	21.93	18.57	19.34
SSIM	0.2941	0.3935	0.2853	0.3048

Table 3: Innovative algorithms based on notch filter

	notch filter	notch+laplacian	notch+histogram
PSNR	19.34	7.892	10.06
SSIM	0.3048	0.0719	0.1588

Table 4: Innovative algorithms based on wiener filter

	wiener	wiener+notch	wiener+histogram	wiener+laplacian
PSNR	21.93	21.95	10.37	17.66
SSIM	0.3935	0.3936	0.2053	0.2492

Table 5: Innovative algorithms based on gaussian filter

	gauss	gauss+notch	gauss+histogram	gauss+laplacian
PSNR	24.25	24.26	10.56	25.28
SSIM	0.6688	0.6687	0.3263	0.6374

filter, and PSNR decreases in this case.

The results of the filter combination in terms of wiener filter and notch filter are not satisfying because both PSNR and SSIM decrease after applying new filters.

Besides, histogram equalization, which is a tool to enhance the image contrast, doesn't help with the restoration results at all in all cases. The reason may be that we don't remove the noise completely, and when we do histogram equalization, we amplify the noise effect.

4 Discussion

Above all, since the noise is generated randomly, it is natural to get different value of PSNR and SSIM for the same filter in different times. However, the values are similar since the variance of the difference is not too high, so the values in the table can be a reference for experiments of readers.

It is generally hard for us to remove different kinds of noise efficiently, even with multiple filters at the same time, because the effect of one filter may influence the denoising process of other kinds of noise.

We've tried different astronomy images in our project to make the results more general, but we only include one image's information due to the space limitation. Please take a look at the source code to check two more images' restoration results. It turns out that different images have different interior features. Even though we add the noises with the same approach, the appropriate filters and corresponding parameters should be different to achieve a better result in terms of different original images.

Further research is required to try more possible algorithms and improve the effect of the restoration results of the astronomy image with multiple noises. Maybe more complex combinations of filters can get better results. Besides, we also expect colorful image restoration, where the situation can be more complex, can be considered in the future, because we have more colorful images than gray images in reality.

5 Conclusion

Generally speaking, part of our innovative algorithms makes some improvement to the final restored results of the astronomy images in terms of the PSNR and SSIM value, such as the gaussian filter together with the laplacian filter. However, those results are still far from perfect subjectively. None of the proposed algorithms truly remove all of these three kinds of noises almost thoroughly so that we can get the original clear image back.

On the other hand, we see some restored images become worse after the combination of different filters. That may be due to the noise amplification effect caused by one of the applied filters.

Besides, even though histogram equalization can enhance the image contrast, it doesn't help with the restoration effect here because as we can see, PSNR and SSIM decrease after using histogram equalization.

For the selected image, the combination of gaussian filter and laplacian filter provides the best result, who has the highest PSNR and relatively high SSIM.

6 Acknowledgement

We want to especially acknowledge the authors of digital image processing book, Gonzalez and Woods. They've really provided quite a lot of background information regarding the image restoration for us so that we can have a basic idea of the development of our project. We could have never completed our paper smoothly without their help.

Meanwhile, all the related work of the image restoration algorithms are very beneficial for our work. Thanks to all of the efforts done by the predecessors, we took advantage of them and finished our project.

7 References

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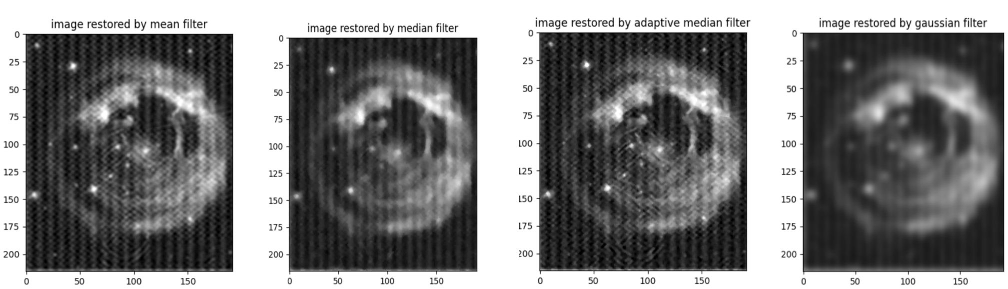
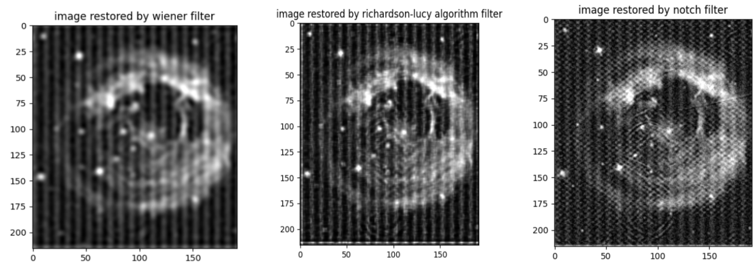
8 Appendix

Please see all the restored images of the experiments below, and the corresponding used filters are marked below each image. Similarly, due to the randomness of the added noise, the displayed image can be slightly different for the restored result of each filter.



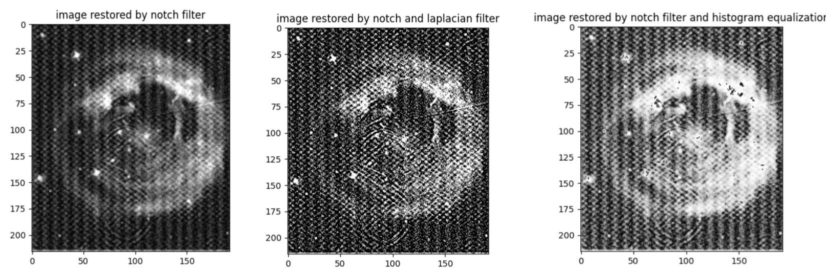
(a) mean filter (b) median filter (c) adaptive median filter (d) Gaussian filter

Figure 1: the results of classical algorithms in spatial domain



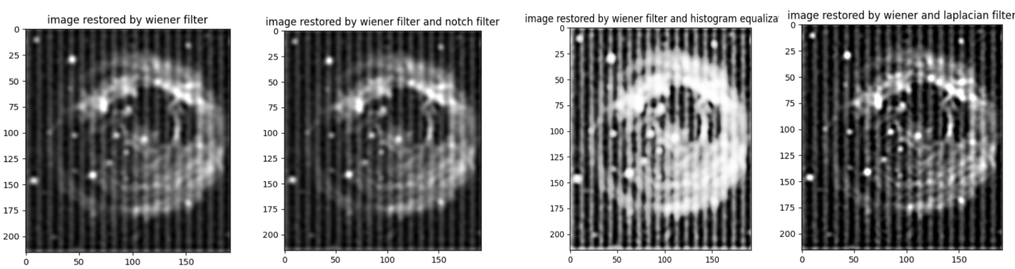
(a) wiener filter (b) R-L algorithm (c) notch filter

Figure 2: the results of classical algorithms in frequency domain



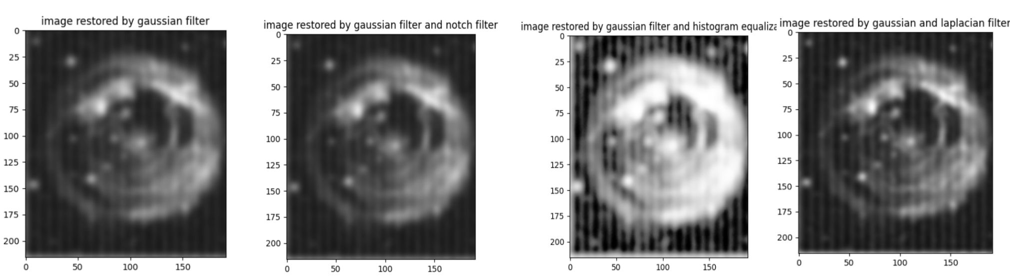
(a) notch filter (b) notch+laplacian (c) notch+histogram

Figure 3: Innovative algorithms based on notch filter



(a) Wiener filter (b) Wiener+notch (c) Wiener+histogram (d) Wiener+laplacian

Figure 4: Innovative algorithms based on wiener filter



(a) Gaussian filter (b) Gaussian+notch (c) Gaussian+histogram (d) Gaussian+laplacian

Figure 5: Innovative algorithms based on gaussian filter