Comparison of Denoising Algorithms for Demosaicing Low Lighting Images using CFA 2.0

Chiman Kwan and Jude Larkin

Applied Research, LLC, Rockville, Maryland, USA

Abstract

In modern digital cameras, the Bayer color filter array (CFA) has been widely used. It is also widely known as CFA 1.0. However, Bayer pattern is inferior to the red-green-blue-white (RGBW) pattern, which is also known as CFA 2.0, in low-lighting conditions in which Poisson noise is present. It is well known that demosaicing algorithms cannot effectively deal with Poisson noise and additional denoising is needed in order to improve the image quality. In this paper, we propose to evaluate various conventional and deep learning based denoising algorithms for CFA 2.0 in low lighting conditions. We will also investigate the impact of the location of demosaicing, which refers to whether the denoising is done before or after a critical step of demosaicing. Extensive experiments show that some denoising algorithms can indeed improve the image quality in low lighting conditions. We also noticed that the location of denoising plays an important role in the overall demosaicing performance.

Keywords

Bayer pattern, RGBW pattern, CFA 1.0, CFA 2.0, color filter array, demosaicing, denoising, pansharpening, deep learning

1. Introduction

Bayer pattern [1] was invented in the early 1980’s and is still a very popular color filter array (CFA) for digital cameras. The Bayer pattern as shown in Figure 1(a) is also known as CFA 1.0 in the literature. Even for planetary explorations, NASA has adopted the Bayer pattern in the Mastcam imagers onboard the Mars rover Curiosity [2]-[5].

Aiming to improve the Bayer pattern in low lighting conditions, Kodak researchers [6,7] invented a red-green-blue-white (RGBW) CFA pattern, which is also known as CFA 2.0, as shown in Figure 1(b).

Figure 1. Two CFA patterns. (a) CFA 1.0; (b) CFA 2.0.
Figure 1(b). Half of the pixels in CFA 2.0 are white and the remaining pixels share the R, G, and B colors. Due to the presence of white pixels, the camera sensitivity is increased and hence the performance of CFA 2.0 in low lighting conditions should be better than CFA 1.0. Extensive experiments in [8] showed that CFA 2.0 is in indeed better than CFA 1.0 in low lighting conditions, where Poisson noise is dominant. Figure 2 shows a clean color image and two noisy images with different levels of Poisson noise. It can be seen that the noise can seriously affect the visual quality of the images. In low lighting conditions, demosaicing methods alone are not sufficient in suppressing the noise. Although there are some joint demosaicing and denoising algorithms such as [9] in the literature, those algorithms are tailored to only Gaussian noise. In an earlier paper [8], we developed new demosaicing algorithms for CFA 2.0. In the process, we also investigated the impact of denoising on the overall image quality. However, the denoising investigation in [8] was limited to only one method, the block matching in 3D (BM3D), even though the performance BM3D is reasonable.

![Fig 2](image-url)

Figure 2. Comparison of clean and noisy images with different levels of Poisson noise.

To the best of our knowledge, joint denoising and demosaicing for CFA 2.0 is underdeveloped in the literature. In this paper, we will thoroughly investigate different algorithms in dealing with Poisson noise. We focus on CFA 2.0 because it was concluded in our earlier papers [8][10]-[12] that CFA 2.0 has better performance in low lighting conditions. Since only one denoising algorithm was used in [8], we would like to investigate how much performance we can further improve if we adopt other conventional and new denoising algorithms. In particular, we applied six conventional and one deep learning algorithms for suppressing Poisson noise. Two signal-to-noise (SNR) levels (10 dB and 20 dB) of Poisson noise were introduced into clean Kodak images. Moreover, three denoising configurations were also investigated. This is because, in our earlier paper [8], we observed that the location of denoising can have very different overall performance in the final demosaiced images.

Our contributions are as follows. First, we thoroughly compared seven denoising algorithms for low lighting images. Some filters can improve the image quality quite significantly. Second, three denoising configurations were studied. One configuration works better than others. Third, we are the first team to carry out denoising and demosaicing studies for CFA 2.0.

The rest of this paper is organized as follows. Section 2 summarizes the methods, data, and performance metrics. In Section 3, we present the denoising results for two noisy conditions. Finally, we conclude the paper with a few remarks and future directions.

## 2. METHODS, DATA, AND PERFORMANCE METRICS

### 2.1. Architecture

Figure 3 shows the architecture of the proposed joint denoising and demosaicing system. Given an RGBW or CFA 2.0 image, we apply the Linear Directional Interpolation and Nonlocal
Adaptive Thresholding (LDI-NAT) [13] algorithm to demosaic a reduced resolution CFA 1.0 image. Parallel to this activity, the same LDI-NAT is applied to panchromatic image with 50% pixels missing to generate a full resolution illuminance image. We use the term panchromatic or illuminance interchangeably to represent the intensity image in this paper. After the above two steps, a denoising procedure is performed on both the panchromatic image and the reduced resolution color image. The denoised image is then going through a pansharpening process to generate the demosaiced image. Finally, another post-filtering is performed. It should be noted that denoising can also be done simultaneously before and after pansharpening and we call this option the hybrid denoising scheme.

Based on the above brief description, we can have three denoising configurations:

- **Pre-denoising:** This means that denoising is done before pansharpening starts. As shown in Figure 3, there are two places for pre-denoising: one for reduced resolution color image and one for the full resolution illuminance or panchromatic band.

- **Post-Denoising:** Here, denoising is done after the demosaiced image is obtained.

- **Hybrid Denoising:** This configuration basically includes both pre-denoising and post-denoising.

![Figure 3. Architecture of joint denoising and demosaicing system for CFA 2.0.](image)

**2.2. Denoising Methods**

Although there are many denoising methods in the literature, in this paper, we evaluated the following algorithms:

- **Block Matching in 3 D (BM3D) [14]:** This is a well-known denoising algorithm in the literature. The basic idea is to introduce exact unbiased inverses of the Anscombe and Generalized Anscombe transformations to deal with low-count (low photons) images. There are versions for Gaussian and Poisson noises. We used the version for Poisson and the codes can be found in [14].

- **Wavelet [15]:** The wavelet denoising consists of several steps. First, the input image is decomposed into several scales using discrete wavelet transform (DWT). Second,
thresholding is performed to the wavelet coefficients. Third, the denoising image is reconstructed from the thresholded DWT coefficients. We used the code in Matlab.

- **Diffusion:** According to [16], is a technique aiming at reducing image noise without removing significant parts of the image content. We used the Matlab codes [17], which does not specify whether the filter is suitable for Gaussian or other types of noise.

- **Median Filter [18]:** There are three variants of varying filter sizes (3x3, 5x5, 7x7). The reason for using median filters is because we observe that the noisy images have some resemblance to salt and pepper noise, which can be seen in those noisy images in Figure 2.

- **FFDNet [19]:** This is a deep learning based filtering algorithm. The first layer is a reversible downsampling operator which reshapes a noisy image into four downsampled sub-images. The second step involves the use of CNN for denoising. It has performed well on real images.

### 2.3. Demosaicing Methods

For CFA 2.0, there are not that many algorithms. In this paper, we adopted Linear Directional Interpolation and Nonlocal Adaptive Thresholding (LDI-NAT), which can be used for both demosaicing as well as interpolation [13]. It has good performance in our earlier studies [8]. We also used LDI-NAT in another earlier paper of ours [10]. As shown in Figure 3, LDI-NAT is used in two places: demosaicing the reduced resolution Bayer pattern and interpolating the panchromatic band.

In the paper [20] written by us, we proposed a pansharpening approach to demosaicing CFA 2.0. The missing pixels in the panchromatic band are interpolated. At the same time, the reduced resolution CFA is demosaiced. We then apply pansharpening to generate the full resolution color image. There are many pansharpening algorithms that can be used. Principal Component Analysis (PCA) [21], Smoothing Filter-based Intensity Modulation (SFIM) [22], Modulation Transfer Function Generalized Laplacian Pyramid (GLP) [23], MTF-GLP with High Pass Modulation (HPM) [24], Gram Schmidt (GS) [25], GS Adaptive (GSA) [26], Guided Filter PCA (GFFCA) [27], PRACS [28] and hybrid color mapping (HCM) [29]-[33] have been used in our experiments. The list is a representative, if not exhaustive, set of competitive pansharpening algorithms. Details of the above algorithms can be found in the corresponding papers and we omit the details in order to make our paper concise.

### 2.4. Low Lighting Images

We downloaded a benchmark data set (Kodak) from a website (http://r0k.us/graphics/kodak/) and selected 12 images, which are shown in Figure 4. It should be noted that this dataset is well-known and has been used by many authors in the demosaicing community such as [34]-[38]. These clean images will be used as reference images for objective performance metrics generation. Moreover, they will be used for generating noisy images that emulate low lighting conditions.
The process of how we introduced Poisson noise is adapted from code written by Erez Posner (https://github.com/erezposner/Shot-Noise-Generator). Details can be found in our recent paper [10]. We include the Poisson noisy 10 dB and 20 dB images in Figure 5 and Figure 6, respectively.
Figure 5. Twelve noisy images at 10 dB from the Kodak dataset.
2.5. Metrics

We used the following four performance metrics to evaluate the various denoising algorithms:

- Peak Signal-to-Noise Ratio (PSNR) [39] Separate PSNRs in dBs are computed for each band. A combined PSNR is the average of the PSNRs of the individual bands. Higher PSNR values imply higher image quality.
- Human Visual System (HVS) metric Details of HVS metric in dB can be found in [40]. Higher values imply better results.
• HVSm (HVS with masking) [41] Similar to HVS, HVS incorporates the visual masking effects in computing the metrics. Higher values imply better results.
• CIELAB

We also used CIELAB [42] for assessing demosaicing and denoising performance in our experiments. Smaller values mean good results.

It should be noted that the HVS and HVSm have better correlation with human perceptions than the other three metrics [43][44].

3. EXPERIMENTAL RESULTS

In our experiments, we have used the default settings in all the denoising and pansharpening algorithms.

3.1. 10 dB Noisy Images

We first present the demosaicing results without denoising in Table 1. This will form as the baseline for comparing with those denoising results later. We observe that the averaged metrics in PSNR of all methods are all around 10 dB, meaning that demosaicing alone cannot enhance the image quality.

Table 1. Demosaicing results without denoising for 10 dB Poisson noisy images.

| Image | Baseline PSNR | Standard PSNR | HC PSNR | SFI PSNR | PC PSNR | GFP PSNR | GL PSNR | HP PSNR | GS PSNR | PSRA PSNR | LSL PSNR | Best Score |
|-------|---------------|---------------|---------|----------|---------|----------|---------|---------|---------|------------|----------|------------|
| Img 1  | 9.767         | 9.730         | 9.73    | 9.72     | 9.72    | 9.65     | 9.76    | 9.72    | 9.72    | 9.65       | 9.76     | 9.76       |
| Cielab| 32.99         | 34.03         | 33.7    | 34.0     | 34.0    | 33.3     | 30.9    | 33.8    | 33.7    | 33.3       | 33.1     | 35.9       |
| HV S  | 4.162         | 4.151         | 4.15    | 4.14     | 4.15    | 4.07     | 4.17    | 4.14    | 4.14    | 4.08       | 4.16     | 3.89       |
| HV Sm | 4.184         | 4.178         | 4.18    | 4.17     | 4.18    | 4.09     | 4.18    | 4.17    | 4.17    | 4.10       | 4.18     | 3.91       |
| Img 2  | 10.28         | 10.29         | 10.2    | 10.2     | 10.2    | 10.2     | 10.2    | 10.2    | 10.2    | 10.2       | 10.3     | 10.3       |
| Cielab| 23.24         | 23.55         | 23.5    | 23.6     | 23.6    | 23.2     | 22.0    | 23.5    | 23.4    | 23.2       | 23.4     | 22.0       |
| HV S  | 5.584         | 5.598         | 5.59    | 5.59     | 5.60    | 5.51     | 5.58    | 5.59    | 5.60    | 5.51       | 5.59     | 5.60       |
| HV Sm | 5.631         | 5.644         | 5.64    | 5.64     | 5.65    | 5.56     | 5.63    | 5.64    | 5.65    | 5.56       | 5.64     | 5.65       |
| Img 3  | 10.11         | 10.06         | 10.0    | 10.0     | 10.0    | 10.0     | 10.0    | 10.0    | 10.0    | 10.0       | 10.1     | 10.0       |
| Cielab| 33.36         | 35.03         | 34.3    | 34.9     | 34.0    | 33.4     | 30.0    | 34.2    | 34.0    | 33.4       | 33.6     | 33.7       |
| HV S  | 4.885         | 4.870         | 4.87    | 4.86     | 4.88    | 4.80     | 4.90    | 4.87    | 4.87    | 4.80       | 4.88     | 4.76       |
| HV Sm | 4.922         | 4.915         | 4.92    | 4.90     | 4.92    | 4.84     | 4.94    | 4.91    | 4.91    | 4.94       | 4.92     | 4.90       |
| Img 4  | 10.02         | 10.13         | 10.1    | 10.1     | 10.1    | 10.0     | 10.1    | 10.1    | 10.1    | 10.0       | 10.1     | 10.0       |
| Cielab| 23.49         | 24.04         | 24.0    | 23.9     | 23.7    | 23.4     | 21.9    | 24.1    | 23.7    | 23.4       | 23.7     | 21.9       |
| HV S  | 5.401         | 5.476         | 5.47    | 5.47     | 5.50    | 5.35     | 5.34    | 5.49    | 5.51    | 5.35       | 5.46     | 5.30       |
| Img 5 | 11.90 | 0.15 | 0.40 | 0.70 | 0.40 | 0.80 | 0.40 | 0.80 | 0.15 | 0.15 | 0.40 | 0.70 | 0.40 | 0.15 | 0.80 | 0.40 |
|-------|-------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| Ciel ab | 24.32 | 24.67 | 24.6 | 24.6 | 24.5 | 24.4 | 24.1 | 24.6 | 24.5 | 24.4 | 24.5 | 24.8 | 23.1 | 0.19 | 0.01 |
| HV | 5.955 | 5.946 | 5.94 | 5.95 | 5.85 | 5.94 | 5.95 | 5.86 | 5.95 | 5.95 | 5.96 | 5.96 | 5.96 | 5.96 | 5.96 |
| Sm | 5.989 | 5.988 | 5.98 | 5.99 | 5.89 | 5.98 | 5.99 | 5.90 | 5.99 | 5.99 | 5.99 | 5.99 | 5.99 | 5.99 | 5.99 |
| Img 6 | 10.14 | 10.09 | 10.1 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 |
| Ciel ab | 43.31 | 48.49 | 43.8 | 46.8 | 45.6 | 42.4 | 35.4 | 43.7 | 45.7 | 42.4 | 43.7 | 39.5 | 35.4 | 0.11 | 0.11 |
| HV | 5.739 | 5.719 | 5.79 | 5.70 | 5.74 | 5.68 | 5.81 | 5.78 | 5.73 | 5.68 | 5.74 | 5.78 | 5.81 | 5.81 | 5.81 |
| Sm | 5.802 | 5.790 | 5.86 | 5.77 | 5.82 | 5.74 | 5.86 | 5.85 | 5.81 | 5.74 | 5.81 | 5.84 | 5.86 | 5.84 | 5.86 |
| Img 7 | 10.02 | 9.976 | 9.98 | 9.96 | 9.98 | 9.89 | 10.0 | 9.98 | 9.98 | 9.89 | 9.89 | 9.90 | 9.99 | 9.99 | 10.0 |
| Ciel ab | 32.93 | 34.44 | 33.9 | 34.2 | 33.5 | 33.2 | 29.2 | 33.8 | 33.5 | 33.2 | 33.3 | 32.1 | 29.2 | 0.06 | 0.06 |
| HV | 5.666 | 5.649 | 5.65 | 5.64 | 5.65 | 5.55 | 5.72 | 5.64 | 5.65 | 5.55 | 5.66 | 5.69 | 5.72 | 5.72 | 5.72 |
| Sm | 5.698 | 5.690 | 5.70 | 5.68 | 5.70 | 5.59 | 5.75 | 5.69 | 5.69 | 5.59 | 5.70 | 5.72 | 5.75 | 5.75 | 5.75 |
| Img 8 | 9.966 | 9.987 | 9.99 | 9.98 | 9.99 | 9.90 | 10.0 | 9.99 | 9.99 | 9.99 | 9.99 | 10.0 | 9.96 | 10.0 | 10.0 |
| Ciel ab | 28.77 | 29.59 | 29.3 | 29.5 | 29.1 | 28.8 | 26.5 | 29.3 | 29.1 | 28.8 | 29.0 | 29.2 | 26.5 | 19.9 | 0.11 |
| HV | 5.000 | 5.009 | 5.01 | 5.00 | 5.02 | 4.91 | 5.00 | 5.01 | 5.02 | 4.91 | 5.01 | 4.87 | 5.02 | 5.02 | 5.02 |
| Sm | 5.051 | 5.064 | 5.06 | 5.06 | 5.07 | 4.96 | 5.05 | 5.06 | 5.07 | 4.96 | 5.06 | 4.92 | 5.07 | 4.92 | 5.07 |
| Img 9 | 10.09 | 10.09 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 | 10.0 |
| Ciel ab | 16.98 | 17.07 | 17.0 | 17.1 | 17.4 | 16.8 | 16.4 | 17.1 | 17.4 | 16.8 | 17.0 | 18.1 | 16.4 | 17.0 | 18.4 |
| HV | 5.578 | 5.581 | 5.58 | 5.58 | 5.58 | 5.54 | 5.58 | 5.58 | 5.58 | 5.54 | 5.58 | 5.58 | 5.58 | 5.58 | 5.58 |
| Sm | 5.605 | 5.608 | 5.60 | 5.60 | 5.61 | 5.56 | 5.60 | 5.61 | 5.56 | 5.61 | 5.56 | 5.56 | 5.35 | 5.61 | 5.61 |
| Img 10 | 10.29 | 10.29 | 10.2 | 10.2 | 10.3 | 10.2 | 10.2 | 10.3 | 10.2 | 10.2 | 10.3 | 10.2 | 10.3 | 10.3 | 10.3 |
| Ciel ab | 26.00 | 26.43 | 26.3 | 26.4 | 26.2 | 25.9 | 24.6 | 26.4 | 26.2 | 26.0 | 26.1 | 26.3 | 26.4 | 26.3 | 26.4 |
| HV | 6.301 | 6.313 | 6.31 | 6.31 | 6.33 | 6.25 | 6.28 | 6.31 | 6.33 | 6.24 | 6.31 | 6.32 | 6.33 | 6.32 | 6.33 |
| Sm | 6.362 | 6.374 | 6.37 | 6.37 | 6.39 | 6.31 | 6.34 | 6.37 | 6.39 | 6.30 | 6.37 | 6.38 | 6.39 | 6.38 | 6.39 |
| Img 11 | 10.44 | 10.41 | 10.4 | 10.4 | 10.4 | 10.3 | 10.4 | 10.4 | 10.4 | 10.3 | 10.4 | 10.4 | 10.4 | 10.4 | 10.4 |
| Ciel ab | 28.61 | 29.43 | 29.2 | 29.4 | 29.0 | 28.7 | 26.5 | 29.2 | 29.0 | 28.7 | 28.8 | 29.5 | 26.5 | 28.8 | 26.5 |
| HV | 5.251 | 5.242 | 5.24 | 5.23 | 5.25 | 5.17 | 5.26 | 5.24 | 5.24 | 5.17 | 5.25 | 5.03 | 5.26 | 5.03 | 5.26 |
| Sm | 5.285 | 5.283 | 5.28 | 5.27 | 5.29 | 5.21 | 5.29 | 5.28 | 5.29 | 5.21 | 5.28 | 5.06 | 5.29 | 5.06 | 5.29 |
For the results obtained from different denoising filters, instead of showing big tables like Table 1 above, we extracted the best performing results from those big tables and create summarized tables. Table 2 summarizes the best BM3D filtering results for three denoising configurations. It can be seen that the combination of GFPCA and post-denoising has the best performance. The PSNR value has been improved from 10 dB to 17.9 dB.

Table 3 summarizes the best wavelet denoising results for three denoising configurations. We can see that hybrid denoising has slight edge over the other configurations. The PSNR value has been improved from 10 dB to 17 dB. Table 4 summarizes the best diffusion denoising results for the three denoising configurations. It can be seen that the results are worse than other denoising algorithms. Table 5 to Table 7 summarize the median filtering results. We can observe that the 7x7 option achieved the best among the three median filters. Actually, the best performing method is the hybrid denoising using 7x7 median filter with GFPCA and the PSNR value has reached 22 dB from 10 dB. This is quite remarkable. Table 8 summarizes the FFDNET results. The performance is better than BM3D, wavelet, and diffusion, but worse than those median filters.

We also include some denoised images for the pre-denoising case in Figure 7. The post-denoising and hybrid denoising results can be found in Fig. A1 and Fig. A2 of the Appendix. It can be seen that the median filter with 7x7 size has the closest intensity to the ground truth. BM3D, wavelet, and FFDNET all have smooth results, but somehow their images look darker than the ground truth.

Table 2. Best performing BM3D denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Img | PSNR (dB) | CIELAB | HVS (dB) | HVSm (dB) |
|-----|----------|--------|----------|-----------|
| 12  | 10.14    | 10.13  | 10.1    | 10.1      |
|     | 2        | 4      | 37      | 26        |
|     | 62       | 40     | 39      | 47        |
|     | 62       | 40     | 39      | 47        |
|     | 62       | 40     | 39      | 47        |
|     | 62       | 40     | 39      | 47        |

Table 3. Best performing wavelet denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics | Hybrid Denoising/ Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|---------|----------------------------------|---------------------------------|-------------------------------|
| PSNR (dB) | 17.565/GFPCA | 17.901/GFPCA | 15.768/GFPCA |
| CIELAB | 10.414/GFPCA | 10.209/GFPCA | 12.975/GFPCA |
| HVS (dB) | 12.847/GFPCA | 13.228/GFPCA | 11.058/GFPCA |
| HVSm (dB) | 13.038/GFPCA | 13.436/GFPCA | 11.203/GFPCA |
Table 3. Best performing wavelet denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics   | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|-----------|----------------------------------|----------------------------------|--------------------------------|
| PSNR (dB) | 17.012/Baseline                  | 15.331/Standard                  | 16.612/GFPCA                   |
| CIELAB    | 11.997/GFPCA                     | 12.860/GFPCA                     | 11.887/GFPCA                   |
| HVS (dB)  | 11.955/Baseline                  | 10.511/GFPCA                     | 11.599/GFPCA                   |
| HVSm (dB) | 12.177/Baseline                  | 10.641/GFPCA                     | 11.775/GFPCA                   |

Table 4: Best performing diffusion filter denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics   | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|-----------|----------------------------------|----------------------------------|--------------------------------|
| PSNR (dB) | 16.393/Baseline                  | 15.353/Standard                  | 14.822/GFPCA                   |
| CIELAB    | 13.374/GFPCA                     | 13.353/GFPCA                     | 14.490/GFPCA                   |
| HVS (dB)  | 11.318/Baseline                  | 10.466/Standard                  | 9.851/GFPCA                    |
| HVSm (dB) | 11.524/Baseline                  | 10.652/Standard                  | 9.969/GFPCA                    |

Table 5: Best performing median filter (3x3) denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics   | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|-----------|----------------------------------|----------------------------------|--------------------------------|
| PSNR (dB) | 19.362/GFPCA                     | 19.467/GFPCA                     | 18.841/GFPCA                   |
| CIELAB    | 8.905/GFPCA                      | 8.475/GFPCA                      | 9.438/GFPCA                    |
| HVS (dB)  | 14.444/GFPCA                     | 14.804/GFPCA                     | 13.963/GFPCA                   |
| HVSm (dB) | 14.777/GFPCA                     | 15.138/GFPCA                     | 14.288/GFPCA                   |

Table 6: Best performing median filter (5x5) denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics   | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|-----------|----------------------------------|----------------------------------|--------------------------------|
| PSNR (dB) | 21.647/GFPCA                     | 21.218/GFPCA                     | 21.405/GFPCA                   |
| CIELAB    | 7.312/GFPCA                      | 7.376/GFPCA                      | 7.550/GFPCA                    |
| HVS (dB)  | 16.791/GFPCA                     | 16.531/GFPCA                     | 16.632/GFPCA                   |
| HVSm (dB) | 17.399/GFPCA                     | 17.069/GFPCA                     | 17.266/GFPCA                   |

Table 7: Best performing median filter (7x7) denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics   | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|-----------|----------------------------------|----------------------------------|--------------------------------|
| PSNR (dB) | 22.102/GFPCA                     | 21.552/GFPCA                     | 21.927/GFPCA                   |
| CIELAB    | 7.035/GFPCA                      | 7.140/GFPCA                      | 7.257/GFPCA                    |
| HVS (dB)  | 17.194/GFPCA                     | 16.708/GFPCA                     | 17.073/GFPCA                   |
| HVSm (dB) | 17.857/GFPCA                     | 17.295/GFPCA                     | 17.757/GFPCA                   |
Table 8. Best performing FFDNET denoising results for 10 dB noisy images. Bold numbers indicate the best in each row.

| Metrics   | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|-----------|-----------------------------------|---------------------------------|--------------------------------|
| PSNR (dB) | 17.761/GFPCA                      | 18.131/GFPCA                   | 17.020/HPM                     |
| CIELAB    | 10.686/GFPCA                      | 9.896/GFPCA                    | 11.655/GFPCA                   |
| HVS (dB)  | 13.123/GFPCA                      | 13.572/GFPCA                   | 12.309/HPM                     |
| HVSm (dB) | 13.342/GFPCA                      | 13.797/GFPCA                   | 12.506/HPM                     |

Figure 7. Demosaicing results using various pre-denoising approaches for 10 dB noisy images. For each image, a/b means the “a” is the denoising method and “b” is the pansharpening method.
We first present the demosaicing results without denoising in Table 9. This will help the comparison among those demosaicing results later. We observe that the averaged metrics in PSNR of all methods are all less than 20 dB, meaning that denoising alone cannot enhance the image quality.

| Image | Results | Standard | GSA | PRACS | LCS-CD | Best Score |
|-------|---------|----------|------|--------|---------|-------------|
| Ingo1 | PSNR    | 19.977   | 20.037 | 20.058 | 20.051 | 19.935      |
|       | Calib   | 19.721   | 19.767 | 19.771 | 19.741 | 19.777      |
|       | HVSm    | 19.429   | 20.549 | 19.601 | 18.634 | 19.470      |
|       | Ingo2   | PSNR    | 18.515   | 18.977 | 18.997 | 18.904 | 18.791   |
|       | Calib   | 15.701   | 16.019 | 16.065 | 15.760 | 15.713      |
|       | HVSm    | 14.108   | 14.365 | 14.377 | 14.506 | 14.461      |
| Ingo3 | PSNR    | 20.181   | 20.501 | 20.502 | 20.271 | 20.160      |
|       | Calib   | 7.956    | 7.904  | 7.848  | 8.013  | 7.797       |
|       | HVSm    | 15.101   | 15.217 | 15.177 | 15.221 | 15.081      |
|       | Ingo4   | PSNR    | 19.011   | 19.443 | 19.430 | 19.420 | 19.903   |
|       | Calib   | 8.009    | 7.417  | 7.440  | 7.429  | 7.284       |
|       | HVSm    | 14.118   | 14.942 | 14.957 | 15.050 | 14.468      |
|       | Ingo5   | PSNR    | 20.048   | 20.211 | 20.209 | 20.196 | 20.200   |
|       | Calib   | 6.604    | 6.565  | 6.546  | 6.593  | 6.571       |
|       | HVSm    | 15.873   | 16.000 | 15.997 | 15.970 | 15.966      |
|       | Ingo6   | PSNR    | 20.041   | 20.433 | 20.402 | 20.423 | 20.237   |
|       | Calib   | 8.710    | 8.604  | 8.620  | 8.756  | 8.645       |
|       | HVSm    | 15.852   | 15.065 | 15.080 | 15.105 | 15.073      |
|       | Ingo7   | PSNR    | 19.090   | 20.154 | 20.141 | 20.138 | 20.082   |
|       | Calib   | 7.741    | 7.601  | 7.640  | 7.781  | 7.637       |
|       | HVSm    | 15.702   | 15.874 | 15.879 | 15.986 | 15.731      |
|       | Ingo8   | PSNR    | 19.518   | 20.122 | 20.120 | 20.060 | 20.103   |
|       | Calib   | 5.998    | 5.987  | 5.997  | 6.006  | 5.991       |
|       | HVSm    | 15.114   | 15.473 | 15.463 | 15.440 | 15.311      |
|       | Ingo9   | PSNR    | 19.518   | 20.122 | 20.120 | 20.060 | 20.103   |
|       | Calib   | 7.622    | 7.473  | 7.419  | 7.580  | 7.666       |
|       | HVSm    | 14.990   | 15.205 | 15.210 | 15.191 | 15.165      |
|       | Ingo10  | PSNR    | 15.181   | 15.473 | 15.463 | 15.440 | 15.311   |
|       | Calib   | 7.507    | 7.421  | 7.415  | 7.477  | 7.468       |
|       | HVSm    | 15.378   | 16.043 | 16.024 | 16.075 | 16.110      |
|       | Ingo11  | PSNR    | 19.518   | 20.122 | 20.120 | 20.060 | 20.103   |
|       | Calib   | 8.286    | 8.227  | 8.187  | 8.254  | 8.092       |
|       | HVSm    | 11.504   | 11.503 | 11.502 | 11.520 | 11.486      |
|       | Ingo12  | PSNR    | 19.580   | 20.242 | 20.241 | 20.215 | 20.187   |
|       | Calib   | 7.799    | 7.710  | 7.703  | 7.815  | 7.705       |
|       | HVSm    | 15.785   | 16.187 | 16.187 | 16.187 | 16.187      |
|       | Ingo13  | PSNR    | 19.495   | 20.056 | 20.054 | 20.045 | 20.018   |
|       | Calib   | 7.571    | 7.473  | 7.407  | 7.458  | 7.467       |
|       | HVSm    | 15.389   | 15.536 | 15.556 | 15.657 | 15.671      |
|       | Ingo14  | PSNR    | 19.510   | 20.091 | 20.092 | 20.093 | 20.094   |
|       | Calib   | 7.512    | 7.416  | 7.405  | 7.463  | 7.464       |
|       | HVSm    | 15.704   | 15.844 | 15.844 | 15.844 | 15.844      |
|       | Aver.   | PSNR    | 19.250   | 19.554 | 19.535 | 19.611 | 19.461   |
|       | Calib   | 7.773    | 7.666  | 7.640  | 7.737  | 7.745       |
|       | HVSm    | 14.814   | 15.047 | 15.047 | 15.047 | 15.047      |

Table 9. Demosaicing results without denoising for 20 dB Poisson noisy images.
Table 10 summarizes the best BM3D filtering results for three denoising configurations. It can be seen that pre-denoising has the best performance. The PSNR value has been improved from 20 dB to 27.128 dB. Table 11 summarizes the best wavelet denoising results for three denoising configurations. We can see that hybrid denoising has slight edge over the other configurations. The PSNR value has been improved from 20 dB to 27 dB. Table 12 summarizes the best diffusion denoising results for the three denoising configurations. It can be seen that the results are worse than other denoising algorithms. Table 13 to Table 15 summarize the median filtering results. We can observe that the 3x3 option achieved the best among the three median filters. However, the median filter results are worse than BM3D and wavelet approaches. Table 16 summarizes the FFDNET results. The performance is better than BM3D, wavelet, and diffusion, but worse than those median filters.

We include some denoised images for the pre-denoising case in Figure 8. The post-denoising and hybrid denoising results can be found in Fig. A3 and Fig. A4 of the Appendix. It can be seen that the BM3D and medial filters have close resemblance to the ground truth. The wavelet and diffusion filter look dark as compared to the ground truth. Finally, FFDNET has over smoothed results.

Table 10. Best performing BM3D denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics        | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|----------------|----------------------------------|--------------------------------|--------------------------------|
| PSNR (dB)      | 27.122 / Standard                | 24.963 / GFPCA                  | 27.128 / GSA                   |
| CIELAB         | 3.845 / GPCA                     | 4.326 / GFPCA                   | 3.680 / GFPCA                  |
| HVS (dB)       | **23.002** / Standard            | 20.623 / GFPCA                  | 23.071 / SFIM                  |
| HVSm (dB)      | 23.895 / Standard                | 21.394 / GFPCA                  | **23.992** / SFIM              |

Table 11. Best performing wavelet denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics        | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|----------------|----------------------------------|--------------------------------|--------------------------------|
| PSNR (dB)      | **26.830** / Standard            | 23.364 / GFPCA                  | **26.830** / Standard          |
| CIELAB         | 4.793 / GFPCA                    | 4.936 / GFPCA                   | **4.722** / GFPCA              |
| HVS (dB)       | **22.581** / GSA                  | 18.783 / GFPCA                  | **22.559** / SFIM              |
| HVSm (dB)      | **23.477** / SFIM                 | 21.394 / GFPCA                  | **23.469** / SFIM              |

Table 12. Best performing diffusion filter denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics        | Hybrid Denoising / Best Algorithm | Post-Denoising / Best Algorithm | Pre-Denoising / Best Algorithm |
|----------------|----------------------------------|--------------------------------|--------------------------------|
| PSNR (dB)      | **25.519** / GSA                  | 23.178 / GFPCA                  | **25.367** / Standard          |
| CIELAB         | 5.415 / GFPCA                     | **5.016** / GFPCA                | 5.242 / GFPCA                  |
| HVS (dB)       | **20.887** / GSA                   | 18.614 / GFPCA                  | **20.702** / GSA               |
| HVSm (dB)      | **21.511** / GSA                   | 19.047 / GFPCA                  | **21.298** / GSA               |
Table 13. Best performing median filter (3x3) denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics     | Hybrid Denoising/Best Algorithm | Post-Denoising/Best Algorithm | Pre-Denoising/Best Algorithm |
|-------------|---------------------------------|------------------------------|-----------------------------|
| PSNR (dB)   | 26.654/Standard                 | 25.282/GFPCA                 | 26.661/GSA                  |
| CIELAB      | 3.644/GFPCA                     | 3.929/GFPCA                  | 3.580/GFPCA                 |
| HVSm (dB)   | 23.094/HCM                      | 21.221/GFPCA                 | 23.169/Standard             |
| HVSm (dB)   | 24.419/Standard                 | 22.219/GFPCA                 | 24.505/SFIM                 |

Table 14. Best performing median filter (5x5) denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics     | Hybrid Denoising/Best Algorithm | Post-Denoising/Best Algorithm | Pre-Denoising/Best Algorithm |
|-------------|---------------------------------|------------------------------|-----------------------------|
| PSNR (dB)   | 24.962/Standard                 | 24.889/GFPCA                 | 25.001/GLP                  |
| CIELAB      | 3.994/GFPCA                     | 3.886/GFPCA                  | 3.907/GFPCA                 |
| HVSm (dB)   | 21.247/Standard                 | 20.735/GFPCA                 | 21.377/SFIM                 |
| HVSm (dB)   | 22.493/Standard                 | 21.889/GFPCA                 | 22.648/SFIM                 |

Table 15. Best performing median filter (7x7) denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics     | Hybrid Denoising/Best Algorithm | Post-Denoising/Best Algorithm | Pre-Denoising/Best Algorithm |
|-------------|---------------------------------|------------------------------|-----------------------------|
| PSNR (dB)   | 23.710/Standard                 | 24.346/Baseline              | 23.768/GLP                  |
| CIELAB      | 4.453/GFPCA                     | 4.057/GFPCA                  | 4.344/GFPCA                 |
| HVSm (dB)   | 19.445/Standard                 | 19.963/Baseline              | 19.550/GLP                  |
| HVSm (dB)   | 20.438/Standard                 | 21.027/Baseline              | 20.558/GLP                  |

Table 16. Best performing FFDNET denoising results for 20 dB noisy images. Bold numbers indicate the best in each row.

| Metrics     | Hybrid Denoising/Best Algorithm | Post-Denoising/Best Algorithm | Pre-Denoising/Best Algorithm |
|-------------|---------------------------------|------------------------------|-----------------------------|
| PSNR (dB)   | 26.674/Standard                 | 24.686/GFPCA                 | 26.676/GSA                  |
| CIELAB      | 3.916/GFPCA                     | 4.533/GFPCA                  | 3.914/GSA                   |
| HVSm (dB)   | 22.854/Standard                 | 20.444/GFPCA                 | 22.960/SFIM                 |
| HVSm (dB)   | 23.994/Standard                 | 21.161/GFPCA                 | 24.124/SFIM                 |
Figure 8. Demosaicing results using various pre-denoising approaches for 20 dB noisy images. For each image, a/b means the “a” is the denoising method and “b” is the pansharpening method.

3.3. Discussions

3.3.1. 10 dB case

From the results in Sections 3.1 and 3.2, we have following observations:

- All filters improved over the no filtering case.
- Median filter with 7x7 has the best performance in all four metrics. It has improved the PSNR by more than 10 dBs.
• Median filter with 5x5 is the second best.
• The worst filter is the diffusion filter.
• Pre-filtering is better than post-filtering in wavelet, and median filters with 5x5 and 7x7 sizes. However, other filters have opposite behavior.
• FFDNET did not yield better performance than conventional filters.
• Hybrid did not yield additional gains over either pre-filtering or post-filtering.

Figure 9. Comparison of different denoising methods for the 10 dB noisy images.
3.3.2. 20 dB case

For the 20 dB case, we have following observations:

- All filters improved over the no filtering case.
- BM3D filter has the best performance in all four metrics. It has improved the PSNR by more than 7 dBs.
- Wavelet, median filter with 3x3, and FFDNET have close performance.
- The worst filter is the median filter with 7x7. It appears that small filter size should be used for less noisy images.
- Pre-filtering is better than post-filtering in all cases except the median filter with 7x7 size.
- Hybrid did not yield any gains over either pre-filtering or post-filtering.

Figure 10. Comparison of different denoising methods for the 20 dB noisy images
4. CONCLUSIONS

Low light images have serious Poisson noise that affects the visual quality of images. In this paper, we present a thorough investigation of the various combination of denoising and demosaicing algorithms for low light images. Two noise levels (10 dB and 20 dB) were investigated using six conventional and one deep learning denoising algorithms. It was observed that, in serious low lighting conditions (10 dB), a conventional median filter can yield better performance than more advanced algorithms whereas in mild lighting conditions (20 dB), some modern algorithms such as BM3D and FFDNet start to have better results. One potential future direction is to look for some better deep learning based algorithms that can specifically deal with Poisson noise.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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Appendix

Fig. A1. Demosaicing results using various post-denoising approaches for 10 dB noisy images. For each image, a/b means the “a” is the denoising method and “b” is the pansharpening method.
Fig. A2. Demosaicing results using various hybrid-denoising approaches for 10 dB noisy images. For each image, a/b means the “a” is the denoising method and “b” is the pansharpening method.
Fig. A3. Demosaicking results using various post-denoising approaches for 20 dB noisy images. For each image, a/b means the “a” is the denoising method and “b” is the pansharpening method.
Fig. A4. Demosaicing results using various hybrid-denoising approaches for 20 dB noisy images. For each image, a/b means the “a” is the denoising method and “b” is the pansharpening method.

AUTHORS

Chiman Kwan received his Ph.D. degree in electrical engineering from the University of Texas at Arlington in 1993. He has one book, four book chapters, 15 patents, 65 invention disclosures, 375 technical papers in journals and conferences, and 550 technical reports. Over the past 25 years, he has been the PI/Program Manager of over 120 diverse projects with total funding exceeding 36 million dollars. He is also the founder and Chief Technology Officer of Signal Processing, Inc. and Applied Research LLC. He received numerous awards from IEEE, NASA, and some other agencies.

Jude Larkin received his B.S. in Computer Science from Franciscan University of Steubenville in 2015. He is a software engineer at ARLLC. He has been involved in diverse projects, including mission planning for UAVs, image fusion, image demosaicing, and remote sensing.