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Research on Ground Compensation Method for Abnormal Response of Aerial Camera Pixels

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Abstract**:** The poor quality of production in aerial cameras can result in a variety of pixel-related issues that may be difficult to recover. One such issue is bad pixels, which can produce bright or dark stripes that are significantly different from the image's background. Additionally, abnormal spectrum responses can lead to pronounced blurring or color distortions in multispectral images, while pixel pollution can result in clear gray stripes in the image. These problems cannot be resolved by the camera itself, but instead require ground compensation methods to improve image quality. In this paper, we implement three different statistical methods for ground compensation to address the issue of low pixel production and enhance overall image quality.

Key Words: bad pixels, image quality improvement, ground compensation statistical methods.

1. Introduce

The distortion caused by radiation in aerial cameras has a significant impact on the usability of images. Researchers have focused on addressing poor radiation quality resulting from inconsistencies between pixel responses and visible light sensor imaging differences, and proposed solutions accordingly [1]. For instance, conventional stripe noise can be eliminated using methods such as wavelet analysis [2,3] and L1 norm regularization [4,5]. Correlation techniques have also been employed to remove independent column stripe noise [6,7]. However, the rapid advancement of high-altitude sensors has revealed additional imaging issues in detector performance [8], such as invalid, dead, overheated, polluted, and abnormally filtered pixels. These problems give rise to further image quality issues beyond stripe and noise, including excessively light or dark lines, color deviation, and gray stripes in the image, which complicate image interpretation [9,10,11]. Therefore, a new approach is needed to address these issues individually, and to restore or compensate for abnormal images.

The innovation of this paper are as follows:

(1) The first step is to collect various problems and their causes that occur

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during the imaging process of the detector. Including invalid pixels, dead pixels, overheated pixels, abnormal filter response, pixel pollution, these issues can lead to the appearance of light and dark stripes and color deviation in the image

(2) The weighted averages method was proposed to remove bright or dark stripes in the image.

(3) To address the issue of abnormal filter response and resulting color deviation in multispectral images, a new multispectral least squares method was proposed.

(4) To mitigate the impact of pixel pollution and improve the radiation quality of aerial airborne camera images, a new histogram matching method has been proposed.

2 Method

2.1 Weighted averages method

To address the issues caused by invalid, dead, and overheated pixels resulting in overly bright or dark lines in the image, various techniques can be employed to recover the missing information. These may include the use of inpainting technology, texture synthesis technology, spatial statistical methods [12], and partial differential equations [13]. These approaches can help establish a model for reconstructing the missing information within the image [14,15,16]. Additionally, the weighted averages method, which is a fundamental algorithm for interpolation, can serve as a simple and effective solution to this problem. The formula of weighted averages method is as follows:

$$Y(s_i^{bad}) = mean(Y(s_i^{left}) + Y(s_i^{right})) \quad (1)$$

Where $Y(s_i^{bad})$ is new DN of too bright or too dark lines, $Y(s_i^{left})$ is DN of pixel to left of s_i^{bad}, $Y(s_i^{right})$ is DN of pixel to right of s_i^{bad}.

In Figure 1, the line running lengthwise through the image is generated by bad pixels. To address this issue, a simple yet effective method can be employed. The DN (Digital Number) of the stripe caused by the bad pixels can be replaced by the DN of the surrounding image using a formula, denoted as Formula 1. This approach allows for the seamless integration of the surrounding image information, effectively removing the line caused by the bad pixels. The simplicity and effectiveness of this

method make it a practical solution for addressing such issues.



Figure 1 Bad pixel image

2.2 Improved histogram matching method

During aerial camera imaging, it is common to encounter environmental interference such as dust and other objects that may fall on the camera lens or probe. These objects often do not detach with the camera's rotation, leading to the presence of gray or white stripes in the captured image, as shown in Figure 2. To address this issue, various methods can be employed. These may include using image processing techniques like filtering or inpainting to remove or minimize the appearance of these stripes in the image, resulting in improved image quality [17,18].



Figure 2 Dirty pixel images

The presence of gray stripes in images captured during aerial camera imaging can be addressed using the relative radiation correction method [19]. In this context, an improved Histogram matching method has been implemented to achieve relative radiation correction of the image. The formula is as follows:

$$R_{mean}^{j} = \sum_{j=1}^{d} (M_{i,j} + \varepsilon_{i,j}) \tag{2}$$

$$\varepsilon_{i,j} = \lambda \sqrt{\frac{\sum_{i=1}^{m} (x_{i,j} - \overline{x_{i,j}})^2}{i-1}} \tag{3}$$

$$M_j = \frac{\sum_{j=1}^{d} x_{i,j}}{m}, i = 1, 2, ..., m \tag{4}$$

where $x_{i,j}$ represents the number of probe i whose DN value is j. Specifically, the i-th probe DN value within a period of time is the occurrence times of j, also known as statistical value. d is total number of aerial camera probes. M_j is the probability density of the grayscale value j in the reference image. R_{mean}^{j} is the cumulative probability density of the grayscale value j in the reference influence.

For the grayscale value k on the i-th probe of the image to be corrected, if the cumulative probability density of k is between R_{mean}^{j-1} and R_{mean}^{j}, then k becomes j-1, otherwise it becomes j. Although Eq. 6-8 are not complex, the correction results are very good.

2.3 Multispectral least square method

The abnormal response of a filter can cause spectral discontinuity, resulting in blurred or color-deviated images. To address this issue, extracting complementary information from other complete spectral segments can be beneficial [20]. As shown in Figure 3, abnormal responses are observed in the blue spectrum. In column 1000 of (a), the blue spectral segment exhibits blurred spots, while (b) represents the color deviation in the image.



(a) blurred screen of image (b) color deviation

Figure 3 Blue spectrum responds to abnormal image

The proposed method for addressing color deviation caused by abnormal filter response involves using the DN (Digital Number) values around the missing spectral segments to fit other non-missing spectral segments. For instance, if a portion of the blue spectrum is missing, the DN values of the surrounding areas can be utilized to linearly fit the distribution of DN values in the red and green bands. This process allows for the estimation of the linear fitting coefficients for the blue spectrum, ultimately enabling the computation of the missing DN values in the blue spectral segment. The calculation formula is as follows:

$$Y(s_i^{true}) = a \times Y(s_i^{red}) + b \times Y(s_i^{green}) + c \ , i \in 1,2,...,k \tag{5}$$

$$a = \frac{(x_1^r - \bar{x})(y_1^r - \bar{y}) + (x_2^r - \bar{x})(y_2^r - \bar{y}) + ... + (x_n^r - \bar{x})(y_n^r - \bar{y})}{(x_1^r - \bar{x})^2 + (x_2^r - \bar{x})^2 + ... + (x_n^r - \bar{x})^2} \tag{6}$$

$$b = \frac{(x_1^g - \bar{x})(y_1^g - \bar{y}) + (x_2^g - \bar{x})(y_2^g - \bar{y}) + ... + (x_n^g - \bar{x})(y_n^g - \bar{y})}{(x_1^g - \bar{x})^2 + (x_2^g - \bar{x})^2 + ... + (x_n^g - \bar{x})^2} \tag{7}$$

$$c = \overline{Y(s_i^{true})} - a \times \overline{Y(s_i^{red})} - b \times \overline{Y(s_i^{green})} \tag{8}$$

Where $Y(s_i^{true})$ is blue spectrum normally. $\bar{x}$ is the mean of the red/green spectrum, and $\bar{y}$ is the mean of the blue spectrum that responds normally.

In order to obtain the logical relationship between the red, green, and blue segments, the value of *a b c* can be calculated using equations 5-8 as described in the above. The calculation of *a b c* helps to determine the correct DN values that should be replaced in response to abnormal DN in the blue spectrum.

$$Y(s_i^{lose}) = a \times Y(s_i^{red}) + b \times Y(s_i^{green}) + c \ , i \in k, k+1, k+2, ..., n \tag{9}$$

Where $Y(s_i^{lose})$ is new DN of abnormal bule spectrum.

2.4 Schematic

The schematic of the proposed model, as depicted in Figure 4, outlines the steps involved in the image processing pipeline. The first step involves inputting the problem image, followed by a series of image correction methods.

(1) Removing Stripes with Weighted Averages Method: This step

focuses on eliminating any stripes or artifacts present in the image using the Weighted Averages method. This technique likely involves analyzing the pixel values in the vicinity of the stripes and applying a weighted average to smoothen out the irregularities.

(2) Correcting Image with Dirty Pixels using Improved Histogram Matching Method: The next stage involves addressing dirty pixels within the image using an Improved Histogram Matching method. This method likely aims to adjust the dirty pixel values to better match the overall histogram distribution, thereby reducing the impact of dirty or defective pixels on the image quality.

(3) Removing Blurred Screen or Color Deviation with Multispectral Least Square Method: The final step in the process focuses on removing blurred screen or color deviation from the image using the Multispectral Least Square method. This likely involves leveraging multispectral information and applying a least squares optimization approach to correct for any blurring or color inconsistencies in the image.

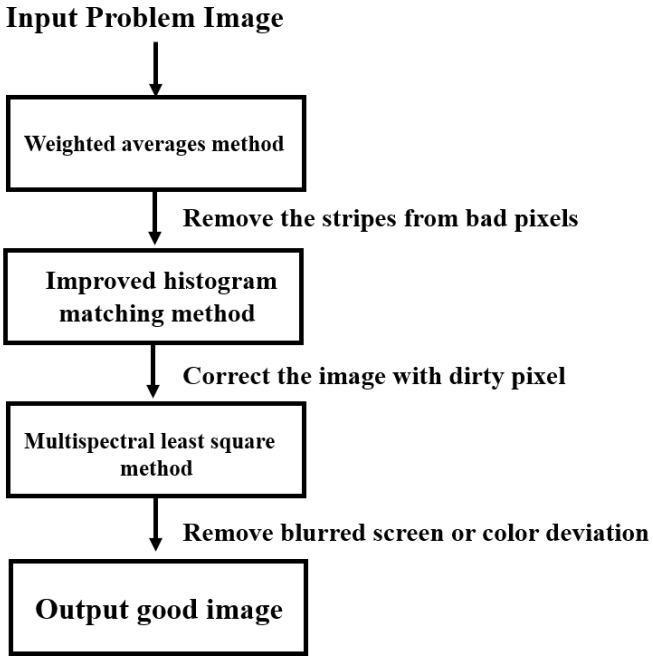


Figure 4 A schematic of remove the stripes, blurred screen and color deviation.

4 Numerical Experiments

4.1 Sensors and Dataset

4.1.1 Sensors

The experimental dataset was captured by a high-altitude camera with a spectral range of 0.45~0.89 μm and a spatial resolution of approximately 16 meters. The high-altitude camera was manufactured in China.

4.1.2 Dataset

The test dataset (Set1) consists of 20 images. The test images exhibit several types of imperfections and distortions, including a stubborn gray stripe at columns 300-350, a bright line at column 1072, and an abnormal response in the blue segment at the 9000th pixel. These types of imperfections can impact the overall quality and fidelity of the images, making it challenging to interpret or extract meaningful information from them.



(a) bad pixel image



(b) blue response abnormally image



(c) "dirty"pixel image



(d) blurred screen of image

Figure 5 Three types of typical problem images

4.2 Evaluation

The proposed striping evaluation method involves using three indices: visual, generalized noise (GN), and white balance, to evaluate the quality of the images [21,22].

The visual index likely refers to the subjective assessment of the image quality by human evaluators. This index may involve looking at the overall image appearance, color uniformity, and the presence of any visible stripes or artifacts.

GN is a quantitative measure of the image noise, which can be computed using various methods, such as the standard deviation of pixel values, the signal-to-noise ratio (SNR) [23], or the peak signal-to-noise ratio (PSNR) [24]. This index provides a measure of the overall noise level in the image. GN is used to evaluate the repair images of bright lines caused by bad pixels and gray lines caused by “dirty” pixels.

The white balance index is a measure of the color balance in the image. This index assesses whether the colors in the image are accurate and balanced, or whether there are any color casts or deviations from the true colors. This index can be computed using various color models, such as RGB, HSL[25], or LAB [26]. White balance is being used to evaluate the repair images, which is affected by blurred screen or color deviation caused by abnormal response of blue spectrum filters.

By using these three indices, the proposed striping evaluation method aims to provide a comprehensive evaluation of the image quality, taking into account both subjective and objective measures of image fidelity.

4.2.1 Generalized noise

GN is commonly used to evaluate the accuracy of image radiometric calibration. The smaller the generalized noise value, the more uniform the image quality.

Specifically, select a n×n uniform area image $f(i,j)$. Calculate the mean of each column of $f(i,j)$ and the mean (Ave) of $f(i,j)$, and then calculate the difference between the two (Err). Err is the GN, which is given by

$$Ave = \frac{\sum_{j=1}^{n}\sum_{i=1}^{n} f(i,j)}{n \times n} \tag{10}$$

$$GN = Err = \frac{\sum_{j=1}^{n} | (\sum_{i=1}^{n} f(i,j)/n) - Ave |}{n} \tag{11}$$

4.2.2 White balance

The white balance algorithm assumes that the average RGB of image is equivalent, i.e., ave (r)=ave(g)=ave(b). Statistical for a white area of an image, and then calculate the average values of all colors. Obtain the maximum average as the standard (MaxAve). AVE is divided by the average of each color to calculate the coefficient. The closer the sum of coefficients is to 1, the better. The formula is as follows:

$$\max R = \max(ave(r), ave(g), ave(b)) \tag{12}$$

$$R_r = \frac{\max R}{ave(r)}$$

$$R_g = \frac{\max R}{ave(g)}$$

$$R_b = \frac{\max R}{ave(b)} \tag{13}$$

$$WB = AVE(R_r + R_g + R_b) \tag{14}$$

WB is optimal as it approaches 1

4.3 Experiment

To verify that the three methods facilitate the restored of image, a series of numerical experiments to verify the effectiveness of the three proposed methods for restoring detector probe images. The schematic of the experiment involves three main steps:

For bad detector pixels: The Weighted Average Method (Eq. 1) is used to replace the stripes that run through the entire image caused by invalid pixels. This step likely involves applying the weighted averaging approach to the affected pixels to create a smoother transition and eliminate the stripes.

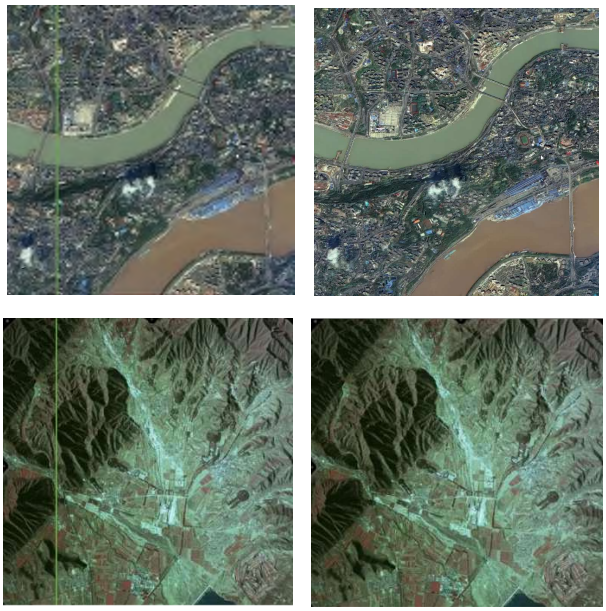
For gray stripes: The Improved Histogram Matching Method (Eq.2-4) is improved to remove gray fringes and improve image quality. This step likely involves analyzing the distribution of pixel values in the affected region and comparing it to a reference histogram to identify and correct the

abnormal values associated with polluted pixels. By optimizing the histogram matching process, this method aims to effectively remove the gray fringes and enhance the overall image quality.

For abnormal response to blue spectrum segment: The Least Square Method (Eq.5-8) is used to fill in the missing spectral data caused by abnormal responses of filters. This step likely involves using a least squares optimization approach to estimate the missing or distorted spectral information based on the available data. By effectively modeling the relationship between the observed and expected spectral responses, this method can help to recover the lost or distorted information and improve the accuracy of the overall spectral representation in the image.

4.3.1 Weighted Averages Method Experiment

Remove bright lines caused by bad pixels using Eq.1, and replace the original gray values of the bright lines with the average gray values around the bright lines. The processing results are shown in Figure 6 (b). The radiance of the image has significantly improved compared to the original image. Additionally, the image quality is now more uniform and visually appealing. This indicates that the proposed method has been successful in addressing the issue of invalid pixels and enhancing the overall appearance of the image.





(a) bad pixel image (b) Processed image

Figure 6 Image processing before and after comparison

The comparison of radiometric correction accuracy (GN) before and after image processing for set1 is shown in Table 1.

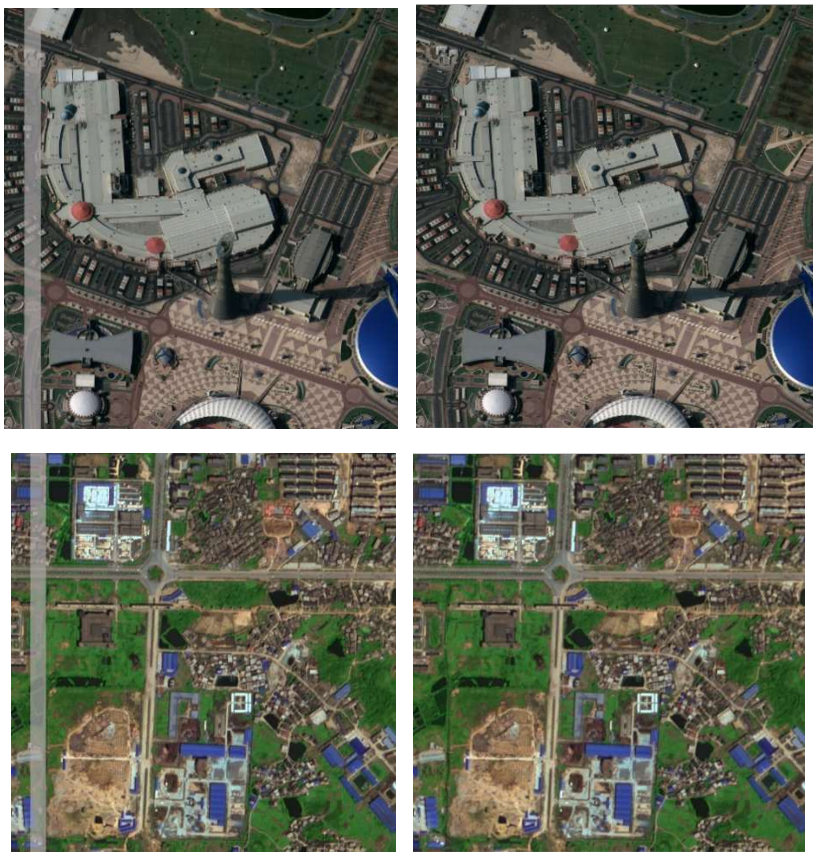
Table1 Comparison table of GN before and after images destriping

number	Original image GN	Processed image GN
1	0.012	0.005
2	0.023	0.018
3	3.821	2.855
4	3.514	2.871
5	2.474	2.291
6	6.352	5.324
7	2.677	2.045
8	4.125	3.215
9	4.658	4.048
10	0.161	0.152
11	6.012	4.215
12	0.125	0.111
13	3.385	2.136
14	2.354	2.012
15	3.785	2.025
16	4.521	3.954
17	0.524	0.174
18	0.652	0.245
19	6.581	6.154
20	3.256	2.357

Table 1 demonstrates an improvement in radiation correction accuracy for the processed image compared to the original image. This suggests that the proposed methods for removing light stripes have effectively enhanced the radiation correction in the image.

4.3.2 Improved Histogram Matching Experiment

Remove gray lines caused by “dirty” pixels using Eq 2-4. According to the lookup table, replace the DN value of the original image with a new DN value to obtain a new image with uniform image radiation. The processing results are shown in Figure 7 (b). Figure 7 only lists 2 image processing results, and the other 18 images are similar. The improved Histogram Matching has resulted in a significant improvement in radiance and image quality compared to the original image. This suggests that the proposed methods have effectively corrected for any variations in radiation intensity across the image and created a more uniform and visually appealing image.



(a) “dirty”pixel image (b) Processed image

Figure 7 Image processing before and after comparison

The comparison of radiometric correction accuracy (GN) before and after image processing for set 1 is shown in Table 2.

Table2 Comparison table of GN before and after images

number	Original image GN	GN corrected by improved Histogram matching method	GN corrected by traditional Histogram Matching [13]
1	0.012	**0.005**	0.016
2	0.023	**0.018**	0.021
3	3.821	**2.855**	2.912
4	3.514	**2.871**	2.965
5	2.474	**2.291**	2.365
6	6.352	**5.324**	5.412
7	2.677	2.045	2.045
8	4.125	**3.215**	3.314
9	4.658	**4.048**	4.049
10	0.161	**0.152**	0.153
11	2.124	**2.001**	2.100
12	3.254	**3.125**	3.211
13	2.254	**2.147**	2.241
14	0.521	**0.498**	0.495
15	0.268	**0.201**	0.265

Table 2 demonstrates an improvement in radiation correction accuracy for the processed image compared to the original image. Moreover, it indicates that the improved Histogram matching method outperforms the traditional Histogram matching method in terms of radiation correction.

4.3.3 Multispectral Least Square Experiment

The proposed method using Eq 5-8 has effectively eliminated blurred screen of images or color deviation caused by abnormal response of the blue spectrum. Furthermore, it's excellent that the processing results shown in Figure 8(b) have demonstrated a significant improvement in radiance and image quality compared to the original image.

Figure 8 only lists two image processing results, but it's important to note that the other 18 images show similar results. This suggests that the proposed method is effective across a range of different images, indicating its potential for practical use in real-world scenarios.



(a)abnormal blue spectrum response image (b) Processed image

Figure 8 Comparison of images before and after blue spectrum compensation

The comparison of white balance (WB) before and after image processing for set 1 is shown in Table 2.

Table3 Comparison table of WB before and after images

Number	Without blue spectrum compensation	With blue spectrum compensation

1	0.876	0.948
2	0.905	0.94
3	0.86	0.91
4	0.80	0.85
5	0.75	0.83
6	0.84	0.91
7	0.88	0.94
8	0.93	0.96
9	0.81	0.90
10	0.78	0.79
11	0.76	0.80
12	0.85	0.88
13	0.73	0.81
14	0.85	0.89
15	0.74	0.79

Table 3 demonstrates improvements in white balance (WB) after blue spectrum compensation. A WB value closer to 1 indicates a more accurate representation of colors in the image, resulting in a more realistic and visually pleasing color reproduction.

5. Conclusions

This paper comprehensively presents for the first time the problems that often occur in detector probe imaging, including three types: The first is invalid pixels, dead pixels, or overheated pixels. The second is Spectral discontinuous response. The third is the Polluting pixel.

And proposed three new solutions to above three kinds of problems. For example, Weighted Average Method is proposed to remove bright or dark lines in images caused by invalid pixels. It likely involves assigning appropriate weights to neighboring pixels to average out the abnormal values and create a smoother transition across the affected area. This can help to effectively repair the image by mitigating the impact of the invalid pixels.

Multispectral Least Squares Method aims to handle spectral information loss caused by abnormal responses of filters. It likely involves

using a least squares optimization approach to estimate the missing or distorted spectral information based on the available data. By effectively modeling the relationship between the observed and expected spectral responses, this method can help to recover the lost or distorted information and improve the accuracy of the overall spectral representation in the image.

Histogram Matching Method is proposed to solve gray stripes caused by polluted pixels. It likely involves analyzing the distribution of pixel values in the image and comparing it to a reference histogram to identify and correct the abnormal values associated with the polluted pixels. By matching the histogram of the affected region to a desired target histogram, this method aims to improve the radiation quality and overall appearance of the image.

The effectiveness of these methods has been verified through a large number of experiments, indicating that they can successfully repair images and enhance the radiation quality of airborne camera images. It would be valuable to assess the performance of these methods on a diverse range of images and evaluate their applicability in different scenarios.

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