Minimum mean square error method for stripe nonuniformity correction

Weixian Qian (钱惟贤)*, Qian Chen (陈 钱), and Guohua Gu (顾国华)

 $440\ \text{Institute of Optic-Electronics, Nanjing University of Science and Technology, Nanjing 210094, China}$

*Corresponding author: Developer_plus@163.com

Received September 27, 2010; accepted January 6, 2011; posted online April 22, 2011

Stripe nonuniformity is very typical in line infrared focal plane (IRFPA) and uncooled starring IRFPA. We develop the minimum mean square error (MMSE) method for stripe nonuniformity correction (NUC). The goal of the MMSE method is to determine the optimal NUC parameters for making the corrected image the closest to the ideal image. Moreover, this method can be achieved in one frame, making it more competitive than other scene-based NUC algorithms. We also demonstrate the calibration results of our algorithm using real and virtual infrared image sequences. The experiments verify the positive effect of our algorithm.

OCIS codes: 100.2000, 110.3080. doi: 10.3788/COL201109.051003.

Stripe nonuniformity is a special kind of nonuniformity very popular in line infrared focal plane (IRFPA) and uncooled staring IRFPA. The most common nonuniformity is pixel nonuniformity, which supposes that different pixels have different nonuniformity parameters. Stripe nonuniformity is defined as all pixels in one stripe having the same nonuniformity parameters and different stripes having different nonuniformity parameters. These differences decide which stripe nonuniformity correction (NUC) should be considered as a special case^[1,2].

NUC techniques have been developed and implemented to perform the necessary calibration for all infrared (IR) imaging applications. These correction techniques can be divided into two primary categories: 1) reference-based correction using calibrated images on startup, and 2) scene-based techniques that continually recalibrate the sensor for parameter drifts^[3,4].

The most popular reference-based correction methods are the so-called one-point correction method and two-point correction method. The drawbacks of reference-based methods have been well-documented in literature^[5]. Hence, researchers have turned to scenebased NUC algorithms. Scribner *et al.* discussed least mean square (LMS)-based nonuniformity correction algorithm^[3], but it blurred the image. Harris *et al.* introduced the constant-statistics (CS) constraint NUC algorithm^[6]. However, their method required numerous image sequences for parameter estimation. Moreover, their algorithm produced ghosting artifacts which blurred the image.

In addition to scene-based NUC algorithms, destriping algorithms are often used in stripe NUC. The simplest destriping algorithm processes image data with a low-pass filter using discrete Fourier transform^[7]. The method is simple, but it often does not remove all stripes and leads to significant blurring within the image. Some researchers have removed the stripes using wavelet analysis, which takes advantage of scaling and directional properties to detect and eliminate striping patterns^[8]. Chen *et al.* proposed a power filtering method to distinguish striping-induced frequency components using the power spectrum, and then removed the stripes using a power finite-impulse response filter^[9]. Moreover, some destriping algorithms examine the distribution of digital numbers for each sensor, and adjust this distribution to some reference distribution, such as histogram matching and moment matching^[9,10]. The common problem of these destriping algorithms is that they do not regard the stripe as the nonuniformity. Hence, they only eliminate the offset of the stripe nonuniformity and not the gain. Therefore, these algorithms are not suitable for the stripe NUC.

The purpose of this study is to solve the stripe nonuniformity problem. In this letter, we develop the minimum mean square error (MMSE) method for stripe NUC. The goal of the MMSE method is to determine the optimal NUC parameters that make the corrected image the closest to the ideal image. However, because the effects of the destriping algorithms are not satisfactory, we compare our algorithm with the scene-based NUC algorithm.

The goal of our stripe NUC algorithm is to determine the optimal correction parameters which can minimize the difference between original image (image with nonuniformity) and ideal image (image without nonuniformity). We call this algorithm the MMSE NUC algorithm. In this letter, the mean square error (MSE) is constructed as

$$MSE_{i,j} = E\left\{ \left[d_{i,j}(n) - y_{i,j}(n) \right]^2 \right\} \\ = E\left\{ \left[d_{i,j}(n) - G_j x_{i,j}(n) - O_j \right]^2 \right\}, \quad (1)$$

where $y_{i,j}(n)$ is the input observation data at pixel (i, j)in the frame $n, x_{i,j}(n)$ is the real scene data without nonuniformity, G_j is the stripe nonuniformity gain parameter at column j, and O_j is the stripe nonuniformity offset parameter at column j, $\text{MSE}_{i,j}$ is the MSE at time domain of the pixel (i, j), E is the temporal mean till frame n, and $d_{i,j}(n)$ is the ideal image at frame n. The image column number is M and the image row number is N. Minimizing MSE, we have $\partial \text{MSE}_{i,j}/\partial G_j = 0$ and $\partial \text{MSE}_{i,j}/\partial O_j = 0$. Set

$$W_j = \begin{bmatrix} G_j \\ O_j \end{bmatrix}, X_{i,j}(n) = \begin{bmatrix} x_{i,j}(n) \\ 1 \end{bmatrix}.$$
 (2)

Hence, minimizing MSE means $\partial MSE_{i,j}/\partial W_j = 0$. Define

$$MSE_{j} = \left[\sum_{i} MSE_{i,j}\right] / N$$
$$= \left[\sum_{i} E\left\{ \left[d_{i,j}(n) - W_{j}^{T} \cdot X_{i,j}(n)\right]^{2} \right\} \right] / N$$
$$= E\left\{\sum_{i} \left\{ \left[d_{i,j}(n) - W_{j}^{T} \cdot X_{i,j}(n)\right]^{2} \right\} / N \right\}, (3)$$

define

$$\mathrm{MSE}'_{j} = \sum_{i} \left\{ \left[d_{i,j}(n) - W_{j}^{\mathrm{T}} \cdot X_{i,j}(n) \right]^{2} \right\} / N.$$
 (4)

Similarly, minimizing MSE means $\partial MSE_j/\partial W_j = 0$. According to $\partial MSE_j/\partial W_j = 0$, the NUC parameter W_j can be calculated. Next, we analyze whether we can use only one frame to obtain W_j and ignore the temporal mean E. Usually, sufficiently large frames cause $MSE_{i,j}$ to converge. Moreover, sufficiently large frames and a large N cause MSE_j to converge. In fact, if Nis large enough, one frame can cause MSE_j to converge. On the other hand, if N is large enough, the value of the MSE_j will not change through temporal mean, and $MSE'_j = MSE_j$.

The optimal W_j can be obtained according to $\partial \text{MSE}'_i / \partial W_i = 0.$

N

$$W_j^{\text{optimal}} = R_j^{-1} P_j, \qquad (5)$$

and

$$R_j = \sum_{i=1}^{N} \left[X_{i,j}(n) \cdot X_{i,j}(n)^{\mathrm{T}} \right] / N, \qquad (6)$$

$$P_{j} = \sum_{i=1}^{N} \left[d_{i,j}(n) \cdot X_{i,j}(n) \right] / N.$$
 (7)

To obtain the optimal solution in the stripe NUC, the desired signal $d_{i,i}(n)$ should be defined as

$$d_{i,j}(n) = \begin{cases} W_{j-1}^{\mathrm{T}} \cdot X_{i,j-1}(n) & j > 2\\ x_{i,1}(n) & j = 2 \end{cases}$$
 (8)

The core idea of the MMSE method is that the real scene in neighbor columns have high relativity, while the stripe nonuniformity in neighbor columns do not have relativity. The MMSE method can restrain the irrelevant signal and resume the relative signal. $W_{j-1}^{\mathrm{T}} \cdot X_{i,j-1}(n)$ is the nonuniformity corrected data in column j-1. The real scene in neighbor columns (j-1 and j) have high relativity. If the nonuniformity corrected data in column j-1 is taken as the desired signal $d_{i,j}(n)$, we can resume the relative real scene signal in column j. This is the reason that Eq. (8) is defined as the desired signal $d_{i,j}(n)$.

Our MMSE is an iterative method. The first column is set as the initial data. The second column stripe nonuniformity parameter W_2 is obtained through setting $d_{i,2}(n) = x_{i,1}(n)$. The third column stripe nonuniformity parameter W_3 is obtained by setting $d_{i,3}(n) = W_2^{\mathrm{T}} \cdot X_{i,2}(n)$, and so forth. Hence, we can calculate all the stripe nonuniformity parameters W^{optimal} . The edge area will destroy the high relativity of the neighbor columns. Hence, the MMSE only works on the non-edge area. Using the structure tensor edge-detection method, we can divide the image into an edge and a non-edge area^[4], defined as

$$T_{i,j}(n) = \begin{cases} 0 & (i,j) \text{ is edge} \\ 1 & \text{else} \end{cases} .$$
(9)

 R'_j and P'_j are changed to

$$R'_{j} = \sum_{i=1}^{N} T_{i,j}(n) \left[X_{i,j}(n) \cdot X_{i,j}(n)^{\mathrm{T}} \right] / \sum_{i=1}^{N} T_{i,j}(n), \quad (10)$$

$$P'_{j} = \sum_{i=1}^{j} T_{i,j}(n) \left[d_{i,j}(n) \cdot X_{i,j}(n) \right] \Big/ \sum_{i=1}^{j} T_{i,j}(n).$$
(11)

The final correction is

$$y_{i,j}(n) = W_j^{\text{optimal}'} \cdot X_{i,j}(n), \qquad (12)$$

and

$$W_j^{\text{optimal}'} = R_j'^{-1} \cdot P_j'. \tag{13}$$

To test the processing effect, we use real image sequences $S^1 = \{I_1^1, I_2^1, \ldots, I_k^1, \ldots, I_{500}^1\}$ acquired at the rate of 50 Hz by 320×240 (pixels) long-wavelength uncooled IRFPA to verify our algorithm.

Qian *et al.* presented a scene-based NUC algorithm comprising a space low-pass and a temporal high-pass (SLTH) NUC algorithm^[2]. This algorithm is improved from the CS constraint NUC algorithm and can decrease the standard deviation of the input observation data. According to the central limit theorem, the decrease in standard deviation of the observation data will enhance the convergence effect. Hence, the SLTH NUC algorithm has a significant improvement over the CS constaint algorithm. In fact, the SLTH NUC algorithm can effectively eliminate stripe nonuniformity.

The comparison of the two algorithms is shown in Fig. 1 (the 1st frame, 5th frame, and 40th frame). Figure 1 shows that both the SLTH and MMSE can eliminate stripe nonuniformity. However, the SLTH can fully eliminate stripe uniformity after the 40th frame, whereas the MMSE can achieve stripe NUC in one frame.



Fig. 1. Comparison of the two algorithms. (a) Original image (1st frame), (b) original image (5th frame), (c) original image (40th frame), (d) SLTH (1st frame), (e) SLTH (5th frame), (f) SLTH (40th frame), (g) MMSE (1st frame), (h) MMSE (5th frame), and (i) SLTH (40th frame).



Fig. 2. Comparison of the two algorithms on the virtual nonuniformity (40th frame). (a) Original image without nonuniformity, (b) original image with added virtual nonuniformity, (c) SLTH processed image, and (d) MMSE processed image.



Fig. 3. Comparison of the two algorithms MSE.

We used a real image sequence $S^2 = \{I_1^2, I_2^2, \ldots, I_k^2, \ldots, I_{100}^2\}$ to analyze our algorithm. The image sequence we used is ground-scene images without nonuniformity. Stripe nonuniformity was added to these images. The stripe nonuniformity gain obeys Gaussian distribution with the mean equal to 1 and the standard deviation equal to 0.01. The stripe nonuniformity offset also obeys Gaussian distribution with the mean equal to 3.

We used MSE at space domain to compare the convergence speed of two algorithms, defined as

$$MSE = \frac{\sum_{i=1}^{N} \sum_{j=1}^{M} (I - P)^2}{M \times N},$$
 (14)

where I is the original image without nonuniformity (the ideal image), P is the NUC processed image. Figure 2 shows the processing results of the two algorithms in the 40th frame of S^2 . Figure 3 indicates the MSE of the two algorithms.

When there is lesser MSE, the NUC effect is much better. After 40 frames, the SLTH algorithm begins to converge, whereas the MMSE algorithm requires only one frame to converge. The MSE value of the MMSE algorithm is similar to that of the SLTH algorithm. The same MSE means the same stripe NUC effect. Our algorithm's best advantage is that one frame processing can achieve good stripe NUC effect.

In conclusion, a useful stripe NUC algorithm using MMSE is proposed. The experimental results show that our stripe NUC can eliminate stripe nonuniformity effectively. Furthermore, our method can obtain optimal NUC coefficients directly from the correlation matrix, thus, it only requires one frame. Moreover, our algorithm has no convergence problem while other scene-based algorithms have. Therefore, this proposed algorithm is much more effective.

This work was supported by the Nanjing University of Science and Technology Research Funding (Nos. 2010ZDJH12 and 2010GJPY014).

References

- W. Qian, Q. Chen, G. Gu, and Z. Guan, Appl. Opt. 49, 1764 (2010).
- 2. W. Qian, Q. Chen, and G. Gu, Opt. Rev. 17, 24 (2010).
- D. A. Scribner, K. A. Sarkady, J. T. Caulfield, M. R. Kruer, G. Katz, C. J. Gridley, and C. Herman, Proc. SPIE 1308, 224 (1990)
- W. Zhao and A. Pope, IEEE Signal Process. Lett. 14, 401 (2007).
- M. Schulz and L. Caldwell, Infrared. Phys. Technol. 36, 763 (1995).
- J. Harris and Y.-M. Chiang, IEEE Trans. Image Process. 8, 1148 (1999).
- H. Shen, T. Ai, and P. Li, Remote Sensing and Spatial Information Sciences XXXVII. Part B1, 63 (2008)
- Z. Yang, J. Li, W. P. Menzel, and R. A. Frey, Proc. SPIE 4895, 187 (2003)
- J. Chen, Y. Shao, H. Guo, W. Wang, and B. Zhu, IEEE Trans. Geoscience and Remote Sensing 41, 2119 (2003).
- B. K. P. Horn and R. J. Woodham, Computer Graphics and Image Process. 10, 69 (1979).