A New Solution for Correcting Nonuniformity of Scanning-type Infrared Sensors

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Abstract:

The scanning-type infrared line sensors are widely used for high-quality general imaging and spectroscopic imaging applications. And the striping fixed pattern noise produced by IRLS can hardly be removed cleanly by many scene-based non-uniformity correction methods, though which can work effectively for staring focal plane arrays. A novel nonuniformity correction algorithm for IRLS combining constant-statistics approach with neural networks is proposed, correcting the aggregate nonuniformity in separate stages. First, the nonuniformity is pre-corrected by use of knowledge on local constant statistics constraint, producing the channel-correction result, which is filtered by a median filter to act as the ideal output of the neural network in the next stage. Second, a linear neural network added some optimization strategies is adopted, making the correction parameters of line sensors update column by column and generating final corrected result at one frame. By applying the technique to both simulated and real infrared image sequences, it is demonstrated that the scene-based algorithm has advantages of low complexity and can achieve a higher correction level in tens of frames, removing striping noise effectively. Its potential to realize real-time hardware-based applications is huge.

Keywords: Nonuniformity correction; Infrared line scanner; Focal plane arrays; Scanning type; Constant Statistics; Neural networks;

1. Introduction

Focal plane array (FPA) sensors have become the most prominent detector used for space and satellite applications. And the one-dimensional FPA, also called infrared line scanner (IRLS) are widely used to obtain infrared images of target on high resolution in some military cases and aerospace applications. For IRLS, the final images are generated by horizontal sweeping on the line sensors. Hence, it suffers from a common problem called the fixed pattern noise (FPN), which usually manifests as horizontal stripes. The striping FPN severely limits the system performance and decreases the temperature resolution, so modern image processing techniques are required to realize nonuniformity correction (NUC).

A considerable amount of research has been focused on developing adaptive scene-based NUC techniques that in essence identify the true IR image from the FPN by exploiting motion-related features in image sequences. The frequently referred scene-based techniques include those based on constant-statistics (CS) [1,2] assumption, the Kalman-filtering approach [3], a neural-network (NNT) implementation based on least mean square error (LMSE)[4,5,6], and the registration-based NUC methods[7]etc.

Although the above mentioned algorithms can have, to some degree, a preferable effect in correcting staring-type FPA, but they are not readily applied to the case of scanning type FPN. Specifically, the constant statistics method and the NNT approach may introduce disturbing traces remained after correction, the so-called ghosting effect; the registration-based methods cannot effectively suppress striping noises because the interference of the horizontal stripes severely decreased the accuracy of relative motion (mostly horizontal) estimate between frames. In addition, Kalman-filter approaches need thousands of frames to achieve accepted corrected results, and the computation is very complicated.

Motivated by this, we proposed an improved NUC algorithm for IRLS. The novelty of our method is modification and integration of the existing NUC methods, local constant-statistics (LCS) and neural networks. First, every row of pixels is treated as one channel and then normalize these channel outputs so that each channel has the first- and second-order statistics that are equal to the mean of its neighboring statistic items, thus we get the channel-correction-based result of nonuniformity[8].

This is followed by the nonuniformity correction using linear neural network. The preceding corrected result is filtered by a vertical one-dimensional median filter in order to obtain a preliminary estimate of the true scene as ideal output of the neural network. Then the individual detector gain and bias parameters are estimated column by column recursively at the least mean squares (LMS) sense, and the final result of gain and bias are taken as the average of their estimated values along rows.

2. Development of NUC Algorithm

2.1 Preliminary Correction Based on LCS

Infrared line scanners generate one field image by push-brooming the line array sensors, so the nonuniformity demonstrates as stripe patterns. For IRLS of size $M\times N$, there are M detectors need correcting. Pixels belong to each row of a frame are characterized by a linear model. The input–output relationship for each row can be expressed as

$$z_k(i, j) = b_k(i)\cdot y_k(i, j) + c_k(i) \tag{1}$$

Where $b_k(i)$ and $c_k(i)$ are the gain and bias parameters for the i^{th} row, i= 1, 2…M. k=1,2… is the frame number. $y_k(i,j)$ is detector output of FPA and $z_k(i,j)$ is the channel-correction output of the k^{th} frame.

We assume every row of pixels as one channel. The aim of our preliminary correction is to force pixels belonging to channel i to have the same first- and second-order statistics with mean of the corresponding statistics of the adjacent two channels i-1 and i+1. Consequently, the statistical difference between local channels is decreased and the striping noise is weakened. This is what we refer to as the local constant statistics (LCS) constraint.[2,9].

The channel-based correction can be performed interframely. Once the constraint of LCS is defined, it is possible to determine the gain and bias of each row by sample mean and the standard deviation estimates. The mean and standard deviation estimates for i^{th} channel of the k^{th} frame are given by

$$\mu_k(i) = \frac{1}{N}\sum_{j=1}^{N} y_k(i,j), \sigma_k(i) = \frac{1}{N}\sum_{j=1}^{N}(y_k(i,j) - \mu_k(i))^2 \quad (2)$$

where $i = 1,2,...,M$, μ and σ are column scalars which have N elements. The mean of first- and second-order statistics items for the neighboring channels of i^{th} channel are formed as

$$\begin{aligned} \mu m_k(i) &= [\mu_k(i-1) + \mu_k(i+1)]/2 \\ \sigma m_k(i) &= [\sigma_k(i-1) + \sigma_k(i+1)]/2 \end{aligned} \quad (3)$$

where i=2,3,…M-1, when i=1 or i=M we made the assumptions as Eq. (4), (5) shows,

$$\mu m_k(1) = \mu_k(1), \mu m_k(M) = \mu_k(M) \quad (4)$$

$$\sigma m_k(1) = \sigma_k(1), \sigma m_k(M) = \sigma_k(M) \quad (5)$$

The primary part of the LCS-based NUC involves estimating the group mean and standard deviations of the local channels. In order to increase the accuracy of the statistics estimates, we need to get a sufficient number of samples. So we take into account the data from the previous frames, deriving the following recursive formula, consequently, the process of implementation can be simplified because of recursive computation.

$$\begin{aligned} \overline{\mu}_k(i) &= (1-\lambda)\cdot\overline{\mu}_{k-1}(i) + \lambda\cdot\mu m_k(i) \\ \overline{\sigma}_k(i) &= (1-\lambda)\cdot\overline{\sigma}_{k-1}(i) + \lambda\cdot\sigma m_k(i) \end{aligned} \quad (6)$$

where λ is the forgetting factor, representing weight of the statistic items obtained from the current frame in the estimate of the whole past frames and $0 < \lambda < 1$. The value of λ can be determined by the shift rate of the fixed pattern noise, if the nonuniformity shifts a little faster, λ can be chosen from [0.5, 1].

For each channel to have first- and second-order statistics that are equal to the mean of its neighboring statistics, we apply the following correction to obtain the estimate of $z_k(i,j)$.

$$z_k(i,j) = [\frac{y_k(i,j) - \mu_k(i)}{\sigma_k(i)}]\overline{\sigma}_k(i) + \overline{\mu}_k(i) \quad (7)$$

For i =1, 2…M. The effective gain and bias estimates from Eq. (7) are given by

$$\hat{b}_k(i) = \frac{\overline{\sigma}_k(i)}{\sigma_k(i)}, \hat{c}_k(i) = \overline{\mu}_k(i) - \frac{\overline{\sigma}_k(i)}{\sigma_k(i)}\cdot\mu_k(i) \quad (8)$$

2.2 Further NUC Using Neural Networks

In the second phase of the proposed algorithm, a neural network is introduced to realize the detector-level NUC. We must note that though the first stage NUC requires a few frames, this NNT procedure based on the preceding correction needs only one frame, because each neuron can learn N-1 times along one row. Hence we omit the frame number index in the following derivation.

A linear neuron model in Eq. (9) can be considered as the simplest neural network structure. Where $x(i,j)$ is the irradiance actually received by each sensor, also acts as the neuron output; the pre-correction result $z(i,j)$ is the neuron input, namely

$$x(i,j) = g_i \cdot z(i,j) + o_i \quad (9)$$

Where g and o are weight and offset of the neuron respectively, i=1,2…M and j=1,2…N.

Traditional NNT algorithms must renew g and o frame by frame and can't remove the horizontal stripes effectively when applied to image sequences produced by the IRLS. Because the network expected output is mean of the four nearest neighboring pixels of estimated outputs, and the mean value is not a satisfactory estimate for wiping off horizontal stripe noises.

Therefore, a median filter is used to provide a robust estimate of the true irradiance for neurons, but it also reduces the spatial signal resolution. Note that after channel correction, the fluctuation of striping noise is weakened. So it is possible to use a small median window to achieve a high correction level and to reduce the computation load at the same time. Furthermore, the steepest descent regression is used to identify $\hat{g}_i$ and $\hat{o}_i$ based on $z(i,j)$, and the reduced spatial resolution can be restored by the self-learning of correction parameters in NNT.

g_i and o_i must be updated using linear regression to obtain a good estimation for the real infrared data by minimizing some error function $E(i,j)$, which is defined as the difference between the estimated output $\hat{x}(i,j)$ and the target scene estimate $T(i,j)$,obtained with the median filter, as shown in Eq.(10)

$$E(i,j) = \hat{x}(i,j) - T(i,j) \quad (10)$$

In order to minimize the error $E(i,j)$ in the mean square error sense, the parameters are recursively and smoothly updated with a portion of each respective error gradient column by column. However, the learning process is not robust enough and some optimization strategies[6] are added to prevent the production of ghosting artifacts, which is a problem present in most scene-based NUC techniques. The three adopted optimizations, including momentum, regularization and adaptive learning rate, have their own respective advantages. Specifically, the regularization factor r is only added to the gain updating, forcing all the gain values in the same column to have a unitary mean, and accelerating the convergence rate. The use of momentum can improve the stability of the algorithm by preventing the local minima problem and suppressing the production of ghosting. In addition, the adaptive learning rate $\eta(i,j)$ can speed up the convergence greatly and control the production of artifacts. It is defined to be inversely proportional to $\sigma^2_{z(i,j)}$ which is the local spatial square variance of the input pixel $z(i,j)$ and can be computed previously as a priori. Hence the improved parameter learning process are described as

$$\begin{aligned} \hat{g}_i(j+1) &= \hat{g}_i(j) - \eta(i,j)\cdot E(i,j)\cdot y(i,j) \\ &+ \alpha\cdot[\hat{g}_i(j) - \hat{g}_i(j-1)] + r_j \end{aligned} \quad (11)$$

$$\hat{o}_i(j+1) = \hat{o}_i(j) - \eta(i,j)\cdot E(i,j) + \alpha\cdot[\hat{o}_i(j) - \hat{o}_i(j-1)] \quad (12)$$

$$r_j = \gamma\cdot\left[1 - \frac{1}{M}\sum_{i=1}^{M}\hat{g}_i(j)\right] \quad \eta(i,j) = K\cdot\frac{1}{1+\sigma^2_{z(i,j)}} \quad (13)$$

where γ , and K (the maximum learning rate allowed) are all constants, j=1,2,…,N-1. The initial values for parameters estimation are g_i=1 and o_i = 0.

In practice, we may take further simplifications to facilitate real-time realization. Suppose the primary source of generated FPN is due to the sensor bias, which is consistent to the actual conditions. Therefore in NNT procedure, all the gains of sensors may be assumed to be 1. Correspondingly, the learning process of NNT may be simplified as

$$\hat{o}_i(j+1) = \hat{o}_i(j) - \eta(i,j)\cdot E(i,j) + \alpha\cdot[\hat{o}_i(j) - \hat{o}_i(j-1)] \quad (14)$$

$$\eta(i,j) = K/(1+\sigma^2_{z(i,j)}) \quad (15)$$

After evaluating the parameters, we get N estimates for each $\hat{g}_i$ and $\hat{o}_i$. These estimates are averaged to result in a final compensator to correct the IRLS outputs along rows, namely

$$g_i = \frac{1}{N}\sum_{j=1}^{N}\hat{g}_i(j), o_i = \frac{1}{N}\sum_{j=1}^{N}\hat{o}_i(j) \qquad i = 1,2,...,N \tag{16}$$

Indeed, the performance of NUC technique after simplification is equivalent, or even better.

Since the spatial nonuniformity drifts slowly, we can divide the image sequences into groups that include a fixed number of frames. For practical applications, during each group, the striping noise can be corrected by two stages and the NUC parameters derived from the current group can be used to compensate for the next group.

3. Performance Analysis for Simulated Data

In order to test the algorithm performance, we apply it to one artificial corrupted image sequence, which is formed by moving a 256×256 window from a large visible 8-bit image horizontally and vertically. Every pixel value of the true image in the same row is multiplied by the same gain and is added to the same bias, thus, the noise in pattern of horizontal stripes is generated from the clear scene. The means of gains and biases are 1 and 0 respectively, and both are of Gaussian random distribution. Different simulated nonuniformity can be introduced to the clean sequences by varying the variance of the gains and biases.

The NUC performance is evaluated using the performance indexes Q-factor [10], computed between the true clean image and the corrected results. For the Q-factor, the dynamical range is $[-1, 1]$, where +1 represents the best.

The standard deviation of the artificial gain and bias is σ_{gain}=0.2, σ_{bias}=30. The Q-factors for the corrupted image sequences are about 0.72 ('RAW'). Figure 1 displays correction capability of the proposed NUC algorithms. The images corrupted by the above striping noise are tested and Q-factors of the corrected results using different approaches are plotted. 'RAW' denotes quality of the corrupted image sequences. 'LCS' indicates the channel-correction results using local constant statistics constraint. Here we chose $\lambda = 0.5$ in implementation and we can see Q increased to 0.95 by less than 10 frames. However, when correction on LCS acts as the preprocessing of NNT approach, best enhancement of the image quality can be achieved, as 'LCS+NNT' shown, Q-factors of the corrected result are more than 0.96, which is very close to the ideal value 1. Furthermore, 'NNT' means each frame is corrected by only use of

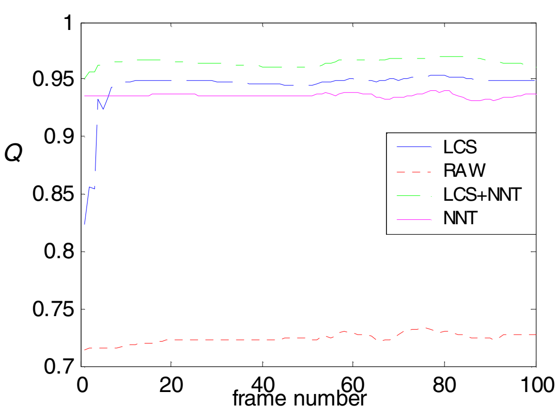
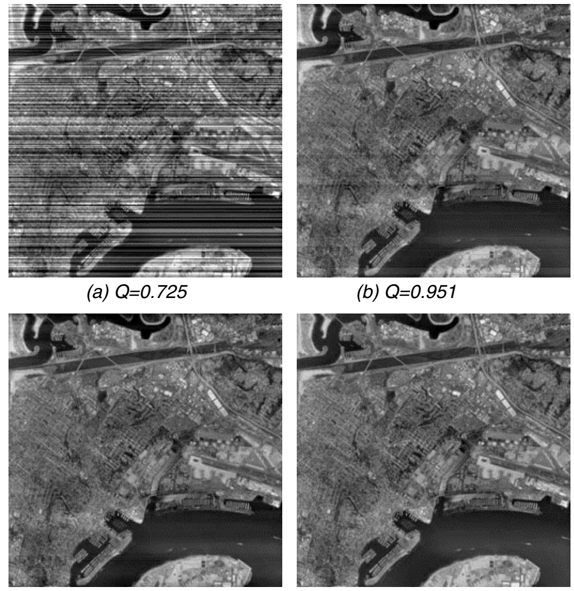


Figure 1 *Correction capability of the proposed algorithms.*

neural network and the Q-factor can rise to 0.936 by a single frame, though is a little lower than other two methods. Fig 2 displays the 60th frame of the simulated image sequence and the Q factors are listed below each diaphragm. Where (a) is the corrupted 60th frame, and channel correction based on LCS can weaken striping noise greatly as shown in (b). (c) depicts the final result with Q=0.971, which is almost the same with (d), the true scene. So further process by use of NNT can remove most of the striping noise and enhance the image quality remarkably.



(a) Q=0.725 *(b) Q=0.951*

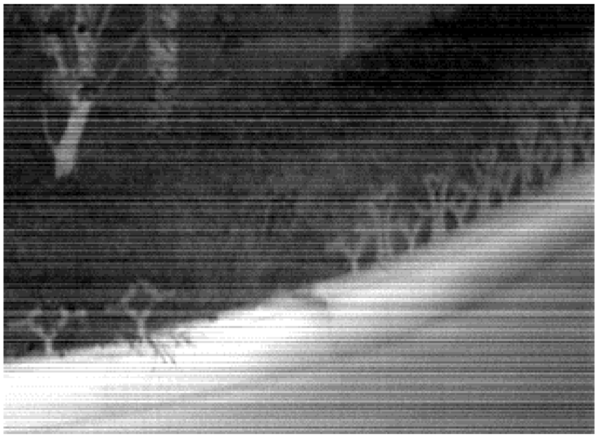
(c) Q=0.971 *(d) Q=1*

Figure 2 *The 60th frame of simulated image sequence.*
(a) The corrupted image; (b) Correction result with LCS;
(c)Correction result with 'LCS+NNT'; (d) True clean image

4. Experimental results of real IR data

In this section, the proposed algorithm will be applied to real infrared data captured with IRLS. We use a 288×4 uncooled scanning type IR FPA to capture a set of image sequence with 100 frames in length. The FPA is composed of indium antimonide (InSb) detectors with a response in the 3–5μm wavelength band. The size of each frame is 576 × 768. Each frame is a combination of two fields which are built up by sweeping line array sensors at one time. The NUC proceeded repeatedly as follows, we divided the image sequence into groups which each comprised 20 frames; For each frame group, the channel correction based on LCS was executed frame by frame, while the NUC using NNT was only applied to the last frame of the group. Then the obtained correction parameters were used to compensate the nonuniformity of the next group. The application results are shown in Fig. 3; (a) is the raw IR data of the 80th frame. In the recursive computation we made $\lambda = 0.5$. Note that the NNT correction requires as little as one frame for correction because each row contains a sufficient number of pixels. The final corrected frame is shown in Fig.3 (b), Note that most of striping artifacts are effectively removed and original resolution are remained.

Note that for a fixed IRLS, the mode of striation is almost fixed, so it is possible to remove the nonuniformity if the estimate of the desired neuron output were obtained with a larger median filter. But it



(a) Raw infrared data of 80th frame

(b) Corrected result by our proposed method

Figure 3 *The 80th frame of real infrared image sequence*

increases the computation load greatly and is time consuming to use a larger median filter. The intermediate stage of the LCS-based channel correction weaken the striping noise effectively, thus it helps to downsize the size of the median filter and to avoid computational complexity.

5. Conclusions

We have presented an improved NUC technique for infrared line scanners. It corrected the striping nonuniformity in two stages by different ways. From applications to simulative and real infrared data, we can conclude that the size of the median filter necessary to provide the preliminary scene estimate is dependent on the FPA and a higher correction level can be obtained by the proposed technique in tens of frames. The authors would like to acknowledge Xia Wang and Tingzhu Bai in the Key Lab of Infrared Technology of Beijing Institute of Technology for providing us the infrared cameras used here.

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