A New Scene-Based Non-Uniformity Correction Algorithm for Infrared Focal Plane Array

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Abstract. Non-uniformity exists in all IRFPA detectors. A new scene-based algorithm is developed to compensate for bias non-uniformity in focal-plane arrays. The technique is based on use of estimates of interframe sub-pixel shifts in an image sequence, in conjunction with a linear interpolation model for the motion, to exact information on the bias non-uniformity algebraically. Through a serial of experiment on real IRFPA images, we find the algorithm is effective and is more promising in comparison with the statistical approaches.

1. Introduction
Focal-plane array (FPA) sensors have become the most prominent detectors used in recent years. With several thousands or even millions of detectors synthesized together into an array, the detector-to-detector variability in the FPA fabrication process is inevitable. Hence, infrared FPA sensors all suffer from a common problem, known as fixed-pattern noise (FPN) or spatial non-uniformity, which decreases the resolution severely, and leads to image degradation [1]. To get good images, a solution using modern image processing technique is required to continuously compensate for the FPN, that is, non-uniformity correction (NUC). NUC techniques fall into two main categories, namely, calibration-based and scene-based techniques. Calibration-based methods have the desirable property and can provide radiometrically accurate corrected imagery. Their main disadvantage is that the FPA must be recalibrated periodically. Thus, the camera is “blind” during these periods [2]. The alternative approaches are scene-based NUC techniques, which can overcome the above disadvantage.

In essence, scene-based techniques identify the true IR image form the FPN by exploiting motion-related features in image sequences. Scene-based techniques are generally classified by two main approaches, namely, statistical and registration based. In detail, registration based techniques comprise the dithered-scanning method [3], motion compensated average approach [4], the panoramic view compensation [5] and the algebraic scene-based algorithm [6].

This paper presents a scene-based algebraic algorithm for NUC. Through a serial of experiments with this method, we proved the algorithm’s validity.

2. Principles
We make the assumption that the primary source of FPN is due to the detector biases, and then a commonly used linear model for the FPA-sensor output can be simplified; besides that, we assume the radiation emanating from the scene does not change significantly during the time between image frames. Thus, when two image frames exhibit an arbitrary translational motion between them, we can
approximate the irradiance at a given pixel in the \((k+1)\)th frame as a linear interpolation of the corresponding adjacent pixels irradiance from the \(k\)th frame.

2.1. FPA detector response models
Basing on the first assumption, we assume gain is equal to 1. Thus, the uniform-gain detector model for the \((i,j)\)th FPA-sensor output at time \(k\) is given by

\[
V_n(i, j) = \phi_n(i, j) + \theta(i, j)
\]

Where \(V_n(i,j)\) is output response, \(n\) is proportional to the number of photos collected by the \((i,j)\)th detector during the camera integration time, \(\phi_n(i,j)\) here terms irradiance, \(\theta(i,j)\) is bias.

For convenience, we define a bias non-uniform matrix for an image sequence \(V_n\) generated by an \(M \times N\) FPA as follow

\[
P = \begin{bmatrix}
\theta(1,1) & \theta(1,2) & \cdots & \theta(1,N) \\
\theta(2,1) & \theta(2,2) & \cdots & \theta(2,N) \\
\vdots & \vdots & \ddots & \vdots \\
\theta(M,1) & \theta(M,2) & \cdots & \theta(M,N)
\end{bmatrix}
\]

Considering with two consecutive frames, we may decompose the 2D motion between them into a vertical component \(\alpha\), and a horizontal component \(\beta\). Supposing in case of \(\alpha>0\) and \(\beta>0\), the shift is in the down-rightward direction, we obtain a bilinearly-interpolated approximation for the \((k+1)\)th detector output in terms of the involved irradiances in the previous frame as Eq. (3) and (4).

\[
V_{k+1}(i+1, j) = \alpha \phi_k(i, j) + (1 - \alpha) \phi_k(i + 1, j) + \theta(i + 1, j) \quad 0 < \alpha \leq 1
\]

\[
V_{m+1}(i, j + 1) = \beta \phi_m(i, j) + (1 - \beta) \phi_m(i, j + 1) + \theta(i, j + 1) \quad 0 < \beta \leq 1
\]

2.2. Normalization of biases between two consecutive detectors
A vertical correction matrix is defined for the vertical component \(\alpha\) as Eq. (5).

\[
\tilde{V}(i, j) = \sqrt{\alpha} \left[ \alpha V_k(i - 1, j) + (1 - \alpha) V_k(i, j) - V_{k+1}(i, j) \right] = \theta(i - 1, j) - \theta(i, j)
\]

Where \(\tilde{V}(1,j)=0, i=2,3,\cdots, M, j=1,2,\cdots, N\). Further intuitionistic formulation is given by

\[
\tilde{V} = \begin{bmatrix}
0 & 0 & \cdots & 0 \\
\theta(1,1) - \theta(2,1) & \theta(1,2) - \theta(2,2) & \cdots & \theta(1,N) - \theta(2,N) \\
\vdots & \vdots & \ddots & \vdots \\
\theta(M-1,1) - \theta(M,1) & \theta(M-1,2) - \theta(M,2) & \cdots & \theta(M-1,N) - \theta(M,N)
\end{bmatrix}
\]

The algorithm we proposed is based on the use of information of interframe sub-pixel shifts. With the combination of the linear interpolation model (3) and the matrix (5), we can normalize biases of a certain column to a common value \(b(1,N)\) in row order. Further, if we repeat this process on, the biases can only exist in rows. From the above description, we observe that the biases between columns may be difference, but each column can only own a common bias. By this way, we normalize all rows progressively, and moreover, biases of an array can be normalized to a common value in the end.

2.3. Vertical and horizontal correction matrix
To get vertical correction matrix \(V_B\), local addition should be executed in every column in matrix \(\tilde{V}\). Then vertical correction matrix \(V_B\) may be described by

\[
V_B(i, j) = \sum_{r=2}^{i} \tilde{V}(r, j) = \theta(1, j) - \theta(i, j)
\]

Another form is given by Eq. (8).
As discussed above, biases in every column will finally be normalized to $b(1, N)$ after a certain frame being added up with $V_B$. Similarly, we can also get horizontal correction matrix $H_B$, which is described by

$$
V_B = \begin{bmatrix}
0 & 0 & \cdots & 0 \\
\theta(1,1) - \theta(2,1) & \theta(1,2) - \theta(2,2) & \cdots & \theta(1,N) - \theta(2,N) \\
\vdots & \vdots & \ddots & \vdots \\
\theta(1,1) - \theta(M,1) & \theta(1,2) - \theta(M,2) & \cdots & \theta(1,N) - \theta(M,N)
\end{bmatrix}
$$

(8)

As discussed above, biases in every column will finally be normalized to $b(1, N)$ after a certain frame being added up with $V_B$. Similarly, we can also get horizontal correction matrix $H_B$, which is described by

$$
H_B = \begin{bmatrix}
0 & \theta(1,1) - \theta(1,2) & \theta(1,1) - \theta(1,3) & \cdots & \theta(1,1) - \theta(1,N) \\
0 & \theta(2,1) - \theta(2,2) & \theta(2,1) - \theta(2,3) & \cdots & \theta(2,1) - \theta(2,N) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & \theta(M,1) - \theta(M,2) & \theta(M,1) - \theta(M,3) & \cdots & \theta(M,1) - \theta(M,N)
\end{bmatrix}
$$

(9)

2.4. Global correction matrix

It is assumed that the vertical correction matrix $V_B$ of a random vertical component $a$ has been got. We get the corrected horizontal component $\tilde{\beta}^C$, which is transformed by vertical correction matrix $V_B$, by adding $V_B$ up to the relevant $\beta$. Next we calculate the horizontal correction matrix $H_B^c$ of component $\beta^C$, which is shown in Eq. (10).

$$
H_B^c = \begin{bmatrix}
0 & \theta(1,1) - \theta(1,2) & \theta(1,1) - \theta(1,3) & \cdots & \theta(1,1) - \theta(1,N) \\
0 & \theta(1,1) - \theta(2,1) & \theta(1,1) - \theta(2,3) & \cdots & \theta(1,1) - \theta(2,N) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
0 & \theta(1,1) - \theta(M,1) & \theta(1,1) - \theta(M,3) & \cdots & \theta(1,1) - \theta(M,N)
\end{bmatrix}
$$

(10)

Having obtained the above matrix $H_B^c$ and $V_B$, we define the global correction matrix $D$ as the sum of both matrixes, and it can be described by

$$
D = V_B + H_B^c = \begin{bmatrix}
0 & \theta(1,1) - \theta(1,2) & \theta(1,1) - \theta(1,3) & \cdots & \theta(1,1) - \theta(1,N) \\
\theta(1,1) - \theta(2,1) & \theta(1,1) - \theta(2,2) & \theta(1,1) - \theta(2,3) & \cdots & \theta(1,1) - \theta(2,N) \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\theta(1,1) - \theta(M,1) & \theta(1,1) - \theta(M,2) & \theta(1,1) - \theta(M,3) & \cdots & \theta(1,1) - \theta(M,N)
\end{bmatrix}
$$

(11)

For now, the matrix $D$ can be integrated with random frame, and as expected, all biases on frame finally be normalized to $\theta(1,1)$.

2.5. Error correction

Some studies have shown that estimation error in the motion parameters, $a$ and $\beta$, can have a significant effect on the performance of the 2D algebraic technique [7]. This also holds for the linear interpolation model (3) and (4). To decrease the error, $D_a$ is defined, which is made up of several vertical components $a$; by the same way, we define $D_\beta$. For every component $a$ or $\beta$ in $D_a$ or $D_\beta$, the matrixes $V_B^c$ and $H_B^c$ should be calculated first, and further, the vertical and horizontal mean correction matrixes $\tilde{V}_B^c$ and $\tilde{H}_B^c$ may be got by the algebraic average of $V_B$ and $H_B$. Because each row in matrix (10) is the same, we can get a second horizontal mean row vector $\tilde{H}_B^c$ along every column in $\tilde{H}_B^c$. Repeated $M$ times, a $M \times N$ horizontal mean correction matrix $\tilde{H}_B^c$ can be developed, and the global correction matrix $D$ is simply the sum of $\tilde{V}_B^c$ and $\tilde{H}_B^c$. The schematic diagram of the proposed technique is showed in Figure 1.
3. Experimental analysis

3.1. Estimated accuracy of motion

The camera we used is a 320×256 array, and the data sequences are 200 frames, which were generated by randomly moving the camera by hand at an outdoor scene. As is shown in Figure 2, X-axis and Y-axis are standard deviation of bias non-uniformity and absolute average error of motion estimation respectively. We see that the accuracy is rather acceptable when the non-uniformity is comparatively low, but with the increase of non-uniformity, the accuracy rises rapidly. Researching the curve, we find the cut-off value appears at 7.

As is widely known, smooth filter can effectively improve spatial non-uniformity. Thus, before motion estimation, we can practice smooth filter to increase estimated accuracy. The tendency of variation is obtained as shown in Figure 3, from which we can find that the estimated accuracy varies with respect to the dimension of shuttering. To decrease error in bad spatial non-uniformity situation, shuttering must include enough information on spatial diversity, besides that a suitable dimension of shuttering should be employed to ensure satisfying estimated accuracy.

(a=5×5; b=15×15; c=20×20)
3.2. Applications for real IR data
The validity of this algebraic algorithm was studied using real IR image sequences. The data were collected by a 320×256 FPA camera designed to use in 2.5-4.8 μm. The data sequences are 200 frames respectively, which were smooth filtered by a 5×5 shuttering before being experimented. The raw IR image is displayed in Figure 4 (a), and the corrected image is showed as Figure 4 (b). We see that the non-uniformity has been effectively removed; furthermore, we only used about 50 frames in the correction process to get this ideal image.

![Uncorrected image of the 100th frame](image1.png) ![Corrected result by this technique](image2.png)

Figure 4. Application to real infrared imagery.

4. Conclusion
An approach which uses a new scene-based algebraic algorithm to correct bias non-uniformity of FPA is proposed in this paper. The advantages of this technique are its simplicity and validity; it requires relatively few frames to generate an effective correction matrix, which is usually as long as thousands of frames by statistical algorithm, thereby permitting the execution of frequent on-the-fly non-uniformity correction as drift occurs. The technique was applied to real infrared data obtained from an IRFPA camera and the experimental results appeared promising.

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