Radiometrically accurate scene-based nonuniformity correction for array sensors

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A novel radiometrically accurate scene-based nonuniformity correction (NUC) algorithm is described. The technique combines absolute calibration with a recently reported algebraic scene-based NUC algorithm. The technique is based on the following principle: First, detectors that are along the perimeter of the focal-plane array are absolutely calibrated; then the calibration is transported to the remaining uncalibrated interior detectors through the application of the algebraic scene-based algorithm, which utilizes pairs of image frames exhibiting arbitrary global motion. The key advantage of this technique is that it can obtain radiometric accuracy during NUC without disrupting camera operation. Accurate estimates of the bias nonuniformity can be achieved with relatively few frames, which can be fewer than ten frame pairs. Advantages of this technique are discussed, and a thorough performance analysis is presented with use of simulated and real infrared imagery. © 2003 Optical Society of America

1. INTRODUCTION

Focal-plane array (FPA) sensors have become the most prominent detector used in infrared (IR) and visible-light imaging systems in recent years. The wide use of FPAs is primarily attributable to the advances in solid-state detector technology, which have led to compactness, cost-effectiveness, and high performance.1 One of the primary applications of long-wave and midwave IR-sensor arrays is broadband thermal imaging, where maximizing broadband spatial resolution and intensity signal-to-noise ratio is of paramount importance. A few applications include night-vision systems, airborne and space-based reconnaissance and surveillance systems, astronomical imaging, and forest-fire early detection systems.

Though FPA detectors have been put into high use, they are still plagued by spatial noise, or nonuniformity. Even in state-of-the-art high-performance sensors, nonuniformity remains a serious problem.2 Nonuniformity arises mostly as a result of variation in detector-to-detector photoresponse,3 but it may also be caused by nonuniformity in an array’s readout characteristics. Nonuniformity severely degrades image quality and affects radiometric accuracy in IR imaging applications. Moreover, the nonuniformity problem is further complicated by the fact that it drifts temporally, rendering a one-time factory calibration ineffective. Hence nonuniformity correction (NUC) remains an important problem in the IR imaging realm.

Traditionally, NUC techniques fall into two categories consisting of calibration-based and scene-based techniques. Calibration-based techniques utilize a spatially constant temperature source that is placed in the camera’s field of view. In a two-point calibration (TPC), which is the most commonly used calibration technique, the calibration target is imaged at two different, known temperatures, and the nonuniformity is approximated for each detector in a linear fashion by using these target images.4 Calibration-based techniques have the benefit of providing radiometrically accurate imagery, although at the cost of periodically obstructing camera operation (in addition to requiring special optomechanical hardware). Scene-based techniques, in contrast, are algorithmic in nature. They are able to remove nonuniformity without interrupting camera operation but compromise the radiometric accuracy of the imagery, as they often are statistical in nature. Many different scene-based NUC algorithms have been proposed in the literature. Statistical algorithms have been reported by Narendra and Foss,5,6 Harris and Chiang,7,8 and Chiang and Harris.9 These algorithms typically rely on the constant-statistics assumption, which states that scene statistics (i.e., mean and variance) become constant over time. A statistical algorithm developed by Hayat et al.10 relaxes the constant-statistics assumption to that of a constant-range assumption and instead requires only that all detectors be exposed to the same high- and low-irradiance values. A Kalman-filtering approach was recently presented by Torres and Hayat11 that adopts the constant-range assumption and is able to capture stochastic drift in the nonuniformity parameters. Motion-based algorithms have been proposed by O’Neil12,13 and Hardie et al.,14 whose techniques use the idea that each detector should have an identical response when observing the same scene point over time. Recently, an algebraic-based algorithm was proposed by Ratliff et al.15,16 This technique utilizes global one-dimensional (1D) motion to algebraically compute estimates of the bias nonuniformity. This latter technique does not use or require any statistical assumptions about the scene.

In this paper, we propose a novel technique that bridges the algebraic scene-based algorithm with
correction. Hence this new radiometrically accurate scene-based algorithm (RASBA) is able to provide the key advantages of both scene-based and calibration-based methods. Moreover, the RASBA is able to maintain radiometric accuracy without disrupting sensor operation. These techniques are combined by performing a limited absolute calibration to a fraction of the FPA detectors and then relying on the algebraic scene-based algorithm to effectively transport this calibration to remaining uncalibrated photodetectors. We have previously developed a technique that combines limited calibration with the 1D algebraic scene-based algorithm.17 The technique, however, was developed under the restrictive assumption of subpixel 1D motion. Here we present a major generalization of it that facilitates the integration of limited calibration with scene-based correction while utilizing image frames exhibiting global motion of arbitrary magnitude and direction [i.e., arbitrary 1D or two-dimensional (2D) motion].

This paper is structured as follows. Section 2 presents the detector models and the motion assumptions made by the new technique. In Section 3, development of the new RASBA is presented, and the limited calibration procedure is discussed. Section 4 contains a thorough performance analysis of the new technique. The conclusions are stated in Section 5.

2. SENSOR AND MOTION MODELS
Consider an image sequence \( y_k \) generated by an \( M \times N \) FPA, where \( k = 1, 2, 3,... \) represents the image frame number. A commonly used linear model for the \( ij \)th FPA-sensor output at time \( k \) is given by

\[
y_k(i, j) = a(i, j)z_k(i, j) + b(i, j),
\]

where \( z_k(i, j) \) is the number of photons collected by the \( ij \)th detector during the camera integration time and \( a(i, j) \) and \( b(i, j) \) are the detector gain and bias, respectively, for \( i = 1, 2,...,M \) and \( j = 1, 2,...,N \). The standard TPC technique makes use of this model, accounting for both gain and bias nonuniformity.

In some applications, bias nonuniformity dominates gain nonuniformity; therefore, as a way to simplify the model of Eq. (1), the gain is assumed uniform across all detectors with a value of unity. Thus the detector model becomes

\[
y_k(i, j) = z_k(i, j) + b(i, j). \tag{2}
\]

The algebraic algorithm uses the above simplified model, and hence it is a bias NUC algorithm.

Throughout this paper, we make the assumption that the temperature of objects does not change during the time between image frames. Thus, for two image frames exhibiting 2D motion between them, we may approximate the irradiance at a given pixel in the second frame as a linear interpolation of four corresponding pixels from the first frame. This 2-D motion, or shift, is decomposed into a vertical and a horizontal component, denoted by \( \alpha \) and \( \beta \), respectively. Each shift is written as its whole-integer and fractional parts, i.e., \( \alpha = \lfloor \alpha \rfloor + \Delta \alpha \) and \( \beta = \lfloor \beta \rfloor + \Delta \beta \), where \( \lfloor \cdot \rfloor \) indicates the integer part of the shift toward zero (e.g., \( [2.5] = 2 \) and \( [-1.5] = -1 \)). Thus, for a pair of image frames exhibiting downward-\( \alpha \) and rightward-\( \beta \) shifts (we adopt the convention that downward vertical motion and rightward horizontal motion are positive), we may linearly interpolate four irradiance values from the \( k \)th frame to model the irradiance value in a corresponding pixel in the shifted \( (k + 1) \)th frame. Hence we model each \( (k + 1) \)th detector response as

\[
y_{k+1}(i, j) = |\Delta \beta|[(\alpha + \Delta \alpha)z_k(i - \alpha - 1, j - \beta - 1) + (1 - |\Delta \alpha|)z_k(i - \alpha, j - \beta - 1)]
\]

\[
+ (1 - |\Delta \beta|)(\alpha + \Delta \beta)z_k(i - \alpha - 1, j - \beta) + (1 - |\Delta \alpha|)z_k(i - \alpha, j - \beta)]
\]

\[
+ b(i, j), \tag{3}
\]

where \( i = 2 + \lfloor \alpha \rfloor), 3 + \lfloor \alpha \rfloor,...,M \) and \( j = 2 + \lfloor \beta \rfloor, 3 + \lfloor \beta \rfloor,...,N \). If Eq. (3) is expanded, four multiplicative combinations of the fractional shift terms result. We define these constants as \( \gamma_1 = |\Delta \alpha| |\Delta \beta|, \gamma_2 = (1 - |\Delta \alpha|)|\Delta \beta|, \gamma_3 = |\Delta \alpha|(1 - |\Delta \beta|), \gamma_4 = (1 - |\Delta \alpha|)(1 - |\Delta \beta|) \). Upon substitution of these terms, Eq. (3) becomes

\[
y_{k+1}(i, j) = \gamma_1 z_k(i - \lfloor \alpha \rfloor - 1, j - \lfloor \beta \rfloor - 1) + \gamma_2 z_k(i - \lfloor \alpha \rfloor, j - \lfloor \beta \rfloor - 1)
\]

\[
+ \gamma_3 z_k(i - \lfloor \alpha \rfloor - 1, j - \lfloor \beta \rfloor) + \gamma_4 z_k(i - \lfloor \alpha \rfloor, j - \lfloor \beta \rfloor)] + b(i, j). \tag{4}
\]

A graphical representation of this linear interpolation model is depicted in Fig. 1(a).

In Section 3, we make use of the representations in Eqs. (2) and (4) in conjunction with pairs of image frames and a limited form of absolute calibration to develop the 2D RASBA.

3. DESCRIPTION OF THE TWO-DIMENSIONAL SCENE-BASED ALGEBRAIC ALGORITHM
We now present the development of the 2D RASBA. To achieve accurate estimates of the bias nonuniformity

![Figure 1](image-url)

**Fig. 1.** (a) Graphical depiction of the linear interpolation model for subpixel 2D motion. The shaded pixels represent the interpolated irradiance value at time \( k + 1 \). (b) Graphical representation of the recursive operation of the algorithm. The bold pixel partitions correspond to each \( G_1 \), representing the group of detectors whose biases are estimated iteratively in \( I \). The arrows indicate the direction of the algorithm iteration within each \( G_1 \).
across the entire array, we will need to introduce a limited (perimeter-only) calibration. The calibration of these perimeter detectors provides the necessary boundary conditions for the 2D RASBA to transport this calibration to interior, uncalibrated detectors.

The key idea behind the algebraic algorithm is to exploit the information contained in special groups of pixels from two image frames exhibiting global motion in order to extract the bias nonuniformity. Given the proper boundary conditions (achieved by calibrating the perimeter detectors), these bias terms may be manipulated in such a way as to explicitly solve for each true bias value. We begin by computing a bias differential for an \( ij \)th detector by linearly combining four detector outputs from a \( k \)th frame with one detector output from a \((k+1)\)th frame. More precisely, for two consecutive image frames exhibiting a down-rightward motion (the algorithm will be extended to all types of motion below), we compute a bias differential for the \( ij \)th detector by forming the linear combination

\[
\Delta(i,j) = \gamma_1 y_k(i-\lfloor \alpha \rfloor -1,j-\lfloor \beta \rfloor -1) \\
+ \gamma_2 y_k(i-\lfloor \alpha \rfloor ,j-\lfloor \beta \rfloor -1) \\
+ \gamma_3 y_k(i-\lfloor \alpha \rfloor -1,j-\lfloor \beta \rfloor) \\
+ \gamma_4 y_k(i-\lfloor \alpha \rfloor ,j-\lfloor \beta \rfloor) - y_{k+1}(i,j).
\] (5)

Now observe that if we substitute Eqs. (2) and (4) into Eq. (5), all the terms in Eq. (5) that involve \( z \)'s will vanish, leaving a linear combination of bias terms alone. Indeed,

\[
\Delta(i,j) = \gamma_1 b(i-\lfloor \alpha \rfloor -1,j-\lfloor \beta \rfloor -1) \\
+ \gamma_2 b(i-\lfloor \alpha \rfloor ,j-\lfloor \beta \rfloor -1) \\
+ \gamma_3 b(i-\lfloor \alpha \rfloor -1,j-\lfloor \beta \rfloor) \\
+ \gamma_4 b(i-\lfloor \alpha \rfloor ,j-\lfloor \beta \rfloor) - b(i,j),
\] (6)

where \( i = 2 + \lfloor \alpha \rfloor, \ 3 + \lfloor \alpha \rfloor, \ldots, \ M \) and \( j = 2 + \lfloor \beta \rfloor, \ 3 + \lfloor \beta \rfloor, \ldots, \ N \). Now suppose that we calibrate the topmost \( \lfloor \alpha \rfloor \) rows and leftmost \( \lfloor \beta \rfloor \) columns of detectors, causing the perimeter detectors to have unity gain and zero bias. With such imposed boundary conditions on the biases, we observe that for the top-leftmost uncalibrated detector (i.e., for \( i = \lfloor \alpha \rfloor + 1 \) and \( j = \lfloor \beta \rfloor + 1 \)), the differential bias \( \Delta(\lfloor \alpha \rfloor +1,\lfloor \beta \rfloor +1) \) is precisely equal to \(-b(i,j)\). Hence we define the first bias estimate of the uncalibrated detectors as \( \hat{b}(\lfloor \alpha \rfloor +1,\lfloor \beta \rfloor +1) = -\Delta(\lfloor \alpha \rfloor +1,\lfloor \beta \rfloor +1) \). Next we use Eq. (6) to progressively update each \( \hat{b}(i,j) \) beyond \( i = \lfloor \alpha \rfloor + 1 \) and \( j = \lfloor \beta \rfloor + 1 \) (recall that these bias differentials can be computed a priori for each pair of frames from the data and knowledge of the shift alone). The recursion in the algorithm starts (in the case of down-rightward motion) with the top-leftmost uncalibrated detector and proceeds in a downward and rightward manner, completing one row or column at a time. In this way, each bias value is progressively estimated until all array indices have been exhausted.

The recursion described above can be expressed more concisely as follows. Let \( D_{\text{cal},x}(D_{\text{cal},y}) \) be the calibration depth of the FPA in the \( x \) (\( y \)) direction (i.e., the number of perimeter rows and columns of the FPA that have been absolutely calibrated). To ease the description of the recursion, it is convenient to introduce the following partitioning of the pixels. For \( \ell \geq \min(D_{\text{cal},x}+1,D_{\text{cal},y}+1) \) and \( \ell \leq \min(M,N) \), define \( G_\ell \) to represent the group of pixels consisting of \( \{\ell,\ell+1,\ldots,M,N\}\), as depicted in Fig. 1(b). Note that such groups form a partition on all the uncalibrated detectors, i.e.,

\[
\bigcup_{\ell = \min(D_{\text{cal},x}+1,D_{\text{cal},y}+1)}^{\min(M,N)} G_\ell = \{(D_{\text{cal},x}+1,D_{\text{cal},y}+1),\ldots,(M,N)\}.
\] (7)

The entire algorithm can now be summarized in the following steps:

1. Initialization: For \( i = 1,\ldots,D_{\text{cal},x}, \ j = 1,\ldots,D_{\text{cal},y} \), set \( \hat{b}(i,j) = 0 \). (Recall that this follows from the perimeter calibration.)

2. Start the recursion: Put \( \ell = \min(D_{\text{cal},x}+1,D_{\text{cal},y}+1) \), and estimate the biases in \( G_\ell \) as follows: For \( (i,j) \in G_\ell \),

\[
\hat{b}(i,j) = -\Delta(i,j) + \gamma_1 \hat{b}(i-\lfloor \alpha \rfloor -1,j-\lfloor \beta \rfloor -1) \\
+ \gamma_2 \hat{b}(i-\lfloor \alpha \rfloor ,j-\lfloor \beta \rfloor -1) \\
+ \gamma_3 \hat{b}(i-\lfloor \alpha \rfloor -1,j-\lfloor \beta \rfloor) \\
+ \gamma_4 \hat{b}(i-\lfloor \alpha \rfloor ,j-\lfloor \beta \rfloor).
\] (8)

3. Calculate the biases in \( G_{\ell+1} \) according to the formula given by Eq. (8) for \( (i,j) \in G_{\ell+1} \).

4. Repeat the previous step and terminate the recursion when \( \ell = 1 + \min(M,N) \).

Note that when \( \lfloor \alpha \rfloor = \lfloor \beta \rfloor = 0 \), as in the case of subpixel 1D or 2D motion, Eq. (8) simplifies to

\[
\hat{b}(i,j) = \frac{1}{1-\gamma_4}[-\Delta(i,j) + \gamma_1 \hat{b}(i-1,j-1) \\
+ \gamma_2 \hat{b}(i,j-1) + \gamma_3 \hat{b}(i-1,j)].
\] (9)

To correct an arbitrary raw image frame, we simply subtract each radiometric bias estimate from its corresponding detector output, yielding an estimate of the true irradiance, \( \hat{z}_k(i,j) = y_k(i,j) - \hat{b}(i,j) \). Therefore, after correction, we are left with a radiometric image, with each corrected output ideally being of the form \( \hat{z}_k(i,j) = z_k(i,j) \).

In the above derivation, down-rightward motion was assumed. This assumption can be relaxed trivially by writing an analogous recursive relationship for each of the remaining three categories of motion. Moreover, to accommodate all possible motion categories, we require the calibration of detectors along the perimeter of the entire focal plane with an appropriate depth according to the maximum interframe shift to be used.

As is widely known, spatial nonuniformity tends to drift slowly in time. Traditionally, for radiometric imagery, the entire FPA must be frequently recalibrated to account for such drift. In the case of the RASBA, as drift occurs, only the perimeter of the FPA must be periodically recalibrated. This frequent perimeter calibration allows the RASBA to maintain radiometric accuracy within the
interior detectors throughout sensor operation. It is important to note that the RASBA uses many image pairs to estimate the bias nonuniformity. To decrease error and capture drift in these bias estimates, the algorithm employs a temporally local ensemble average of these estimates. Thus, so long as the perimeter remains calibrated, the algorithm is able to unobstructively maintain radiometric accuracy within the interior of the FPA. In all the results presented in this paper, the perimeter calibration is achieved by performing a one-time TPC to only the perimeter detectors. All data sequences were collected within a short time span after the TPC was performed, so that nonuniformity drift is considered negligible. Finally, we have designed an optical system that will perform such a perimeter calibration and are currently in the process of implementing it. The degree of radiometric accuracy attainable by the RASBA, along with other significant performance issues, is studied in Section 4.

4. PERFORMANCE ANALYSIS

In this section, simulated and real IR data are used to study the performance of the RASBA.

A. Degree of Radiometric Accuracy

The ability of the RASBA to maintain radiometric accuracy was studied by using real IR imagery. The data were collected from two different cameras. The first was a 12-bit 128 × 128 InSb FPA camera (Amber model AE-4128) operating in the midwave IR 3–5-μm range (the data were generated at the U.S. Air Force Research Laboratory, Wright-Patterson Air Force Base, Ohio). The second was a 12-bit 256 × 256 MgCdTe FPA camera (Amber Mini-Dewer) operating in the long-wave IR, 8.3–9.2-μm range (these data were collected at the U.S. Air Force Research Laboratory, Kirtland Air Force Base, N.M.).

Data set 1 was collected from the InSb IR camera. The data set contains 512 image frames and was generated by manually moving the camera by hand in a random fashion to create sufficient motion. Figure 2(a) shows the first image frame of data set 1. Note that the nonuniformity is clearly visible, having a strong crosshatch pattern. Before collecting this data set, the camera collected two sets of flat-field imagery at 291 and 303 K, respectively, so that a TPC could be performed. The two-point calibrated image frame 1 is displayed in Fig. 2(b). By using the nonuniformity parameters obtained from the TPC, we calibrated the entire perimeter of the image sequence.
with a calibration depth of 5 pixels. Since the algorithm assumes that each interior detector has unity gain, we divided all uncalibrated detectors by the mean gain value (calculated from the calibrated perimeter detectors) to enforce the validity of this assumption. This is done hereafter for all corrections performed on real IR data. These perimeter-calibrated data were then corrected by the RASBA. Image frame 1, which resulted from this correction, is shown in Fig. 2(c), scaled to the same dynamic range as that for the two-point image. It is important to note that in this correction, image pairs exhibiting shift parameters in the set $[-0.25, 0.25] \times [-0.25, 0.25]$, along with all 1D shifts, were omitted (the reason for this will be discussed later in Subsection 4.D). Hence, of the 511 image pairs, only 38 were used in the correction. The corrected outputs for frame 1, row 100 from the TPC and RASBA-corrected data set 1 are displayed in Fig. 2(d). Note the high degree of accuracy demonstrated by the RASBA, shown to be consistently within 0.5 K. In visually comparing the TPC image with the RASBA-corrected image, we see that in both images the nonuniformity has effectively been removed. Also note that dead pixels persist in the two-point image, whereas in the RASBA-corrected image they are largely suppressed.

To assess the degree of radiometric accuracy achieved by the RASBA, we first establish the TPC data as our benchmark. Since a significant number of problematic (i.e., dead and flickering) pixels persist after the TPC, and hence are not radiometric, we exclude these pixels from the comparison. We identify these problematic detectors by applying a median filter to each TPC image and then subtract it from its respective TPC image. If these differences are large (say above 10 K), then these detectors are identified as problematic. Now having identified these problematic detectors, we compute the error, denoted as $e(x,y)$, between the TPC and RASBA-corrected images, using only the interior, nonproblematic detectors. This same procedure is used in all subsequent IR data error computations.

In the computation of the error for data set 1, few detectors were identified as problematic (i.e., 0.008% of the entire array and 0.001% of the calibrated perimeter) and excluded. Figure 3 shows the empirically estimated probability density function of this error, indicating that nearly all error is within ±1 K. The statistics of the absolute error for this correction are summarized in Table 1. The mean absolute error $\mu_{\text{abs}}$ and the absolute error standard deviation $\sigma_{\text{abs}}$ are extremely low (i.e., 0.183 and 0.164 K, respectively), indicating that the RASBA has effectively obtained radiometric accuracy in the interior, uncalibrated detectors.

The algorithm was tested on a second data set, collected with the MgCdTe camera. This data set contains 64 image frames. In this image sequence, the camera was mounted to a stepper motor so that motion could be controlled. All motion is downward 1D subpixel motion. The imagery is of an optical breadboard with a 323-K flat-field source positioned underneath (this can be observed as the white circles in the image). Two flat-field image sequences were collected at 285 and 323 K, respectively, so that a TPC could be performed. Figure 4(a) shows the raw image frame 1 from data set 2. Note the significant number of dead and saturated pixels present. Figures 4(b) and 4(c) show the two-point calibrated and RASBA-corrected images, respectively, both scaled to the same dynamic range. Figure 4(d) shows plots of the outputs for raw image frame 1, row 181 for each corrected sequence. Observing the sharp spikes that are present in the TPC’s output. These spikes are dead or problematic pixels that persist in the TPC but have effectively been removed automatically by the RASBA. Note the four peaks in the output, which correspond to the 323-K temperature source, observed through the holes in the breadboard. Aside from problematic pixels, both techniques’ outputs are very close to the ideal temperature (within 1 K).

Examining the corrected images of data set 2, we note that there are still a high number of problematic pixels present in the TPC image. In the RASBA-corrected image, on the other hand, these dead pixels have been largely suppressed, although a slight striping pattern may be observed down a few of the columns. This striping results directly from error in the calibration of the perimeter detectors (i.e., problematic detectors in the calibrated perimeter). This phenomenon will be studied more precisely below. For this correction, 0.828% of the entire array and 1.372% of the calibrated perimeter were identified as problematic detectors. The empirical probability density function of the error for this correction is presented in Fig. 3. The mean absolute error statistics may be found in Table 1. Again, it is observed that the RASBA is maintaining a high degree of radiometric accuracy. It is important to note that the error in this correction, although small, is higher than that in the correction of data set 1. The reasons for this, as will be discussed in detail below, are that (1) a significant number of dead

| Data Set | $|e|_{\text{min}}$ (K) | $|e|_{\text{max}}$ (K) | $\mu_{\text{abs}}$ (K) | $\sigma_{\text{abs}}$ (K) |
|----------|----------------|----------------|----------------|----------------|
| 1        | 0.000          | 13.929         | 0.183          | 0.164          |
| 2        | 0.000          | 48.736         | 0.856          | 0.977          |
| 323-K flat field | 0.000 | 11.309 | 0.180 | 0.190 |

Fig. 3. Empirical probability density function of the mean error between the TPC and RASBA-corrected image sequences for data sets 1 and 2.
pixels are present in the calibration perimeter and (2) all image pairs exhibited 1D, constant-direction, subpixel motion.

A study was performed to investigate the number of frame pairs required by the algorithm to achieve radiometric accuracy. Data set 1 was corrected multiple times using an increasing number of frame pairs. After each correction, the RASBA-corrected image sequence was compared with the TPC image sequence. A plot of the mean absolute error versus the number of frame pairs is shown in Fig. 5. Note that once approximately ten or more frame pairs are used, the mean absolute error is no greater than 0.2 K. Hence a high level of radiometric accuracy can be maintained with a relatively low number of image pairs. This ability of the algorithm is ideal for hardware implementation, as it would require a relatively small number of on-chip frame buffers.

Since the 2D algebraic algorithm is a bias NUC algorithm, gain nonuniformity has an effect on algorithm performance. If gain nonuniformity is present, the algebraic algorithm essentially incorporates this gain nonuniformity into the bias estimate, making the bias estimate temperature dependent. Indeed, according to the linear response model and up to some degree, gain variation can be approximated by bias variation, which the algorithm can handle effectively. Data set 2 is known to have a significant amount of gain nonuniformity, but as was seen, the algorithm was able to effectively correct the data while maintaining a high degree of radiometric accuracy. However, we expect the effect of gain nonuniformity on the algorithm to become apparent when there are large
gradients in the irradiance observed by a detector. This is not extremely harmful, as the algorithm is able to quickly generate new estimates of the bias nonuniformity and incorporate them into the correction map. Future work will involve a comprehensive study of the temperature dependence of the bias estimates as well as exploring a gain-correction version of the algebraic algorithm.

A final, yet important, issue to note is that the accuracy of the calibration used in the perimeter detectors will directly affect the radiometric accuracy of the RASBA. Thus, worse performance would be expected if a one-point calibration instead of a two-point or multipoint calibration were used. In this paper a two-point calibration was used in all data corrections.

B. Robustness to Lack of Irradiance Diversity
A notable characteristic of the RASBA is its insensitivity to global scene irradiance diversity. Statistical scene-based algorithms typically require some assumption on the temporal and spatial irradiance diversity observed by each photodetector. For instance, the constant-statistics\(^{7,8}\) algorithm requires that each detector spend more or less an equal amount of time at a wide range of irradiance levels. This criterion fails when a portion of the focal plane observes a region of constant irradiance (e.g., the sky). No such assumptions are made by the RASBA. This phenomenon was studied in detail earlier in the context of the 1D scene-based version of the algebraic algorithm,\(^{16}\) and similar conclusions hold for the present 2D RASBA. This property of the RASBA allows it to correct flat-field image sequences. This is a special case that is unique to the algorithm. In the case of temporally constant flat-field imagery, motion becomes irrelevant (arbitrary) from frame to frame, and any shift value may be assumed by the algorithm. These image sequences are useful in that it is possible to examine the performance of the RASBA by correcting real imagery in the presence of no shift estimation error. These images are also useful when the true irradiance value of the flat-field target is known, because it is then possible to study algorithm performance with ideal perimeter calibration (i.e., the perimeter irradiance values can simply be replaced with the ideal, known irradiance values).

As a demonstration of the ability of the algorithm, the 323-K flat-field, 64-frame image sequence obtained by the MgCdTe camera was corrected by the RASBA (calibration depth of 2 pixels). The outputs from this correction for frame 1, row 128 are shown in Fig. 6. Arbitrary motion was assumed between each image frame for the RASBA-corrected image sequence (since motion is irrelevant in this special case). Note that in both plots the outputs are near the ideal value of 323 K, as expected. In the TPC, however, spikes are observed, indicating the remanence of problematic detectors, while there is small deviation in the RASBA-corrected output. For this correction, 0.383% and 0.644% of the entire array and perimeter detectors, respectively, were identified as problematic. The statistics of the absolute error for this correction are displayed in Table 1, indicating that a high degree of radiometric accuracy was achieved within the interior detectors.

C. Effect of Dead Pixels
The effect of dead pixels in the perimeter of the array on algorithm performance was studied. This preliminary study was conducted by generating a 128 × 128, 11-frame image sequence with random global motion. This sequence was created by downsampling a high-resolution 8-bit image (by a factor of 10—this allows us to generate subpixel shifts with 0.1-pixel resolution), and the motion between frames is random with a uniform distribution in the range \([-5, 5]\) \times \([-5, 5]\). Although the RASBA ideally expects shifts that are created according to a linear interpolation model, downsampling provides a more realistic shift mechanism and creates significant aliasing in the imagery, as occurs physically. All simulated image sequences for the remaining studies were created in this downsampling fashion. After the image sequence was created, bias nonuniformity was simulated as a normally distributed random image (zero mean). This nonuniformity was then added to the interior of each image frame, creating a calibration depth of 5 pixels. Dead pixels were simulated by randomly choosing pixels in the perimeter and setting them either to the maximum of the dynamic range (with probability of 0.5), simulating saturated pixels, or to the minimum of the dynamic range (with probability of 0.5), simulating dark pixels across all frames of motion. The dynamic range of this and all subsequent simulated image sequences was from 0 to 300 A.U., where A.U. indicates arbitrary units.

This simulation was performed as a function of the severity of the bias nonuniformity while increasing the percentage of the number of dead pixels in the calibration perimeter. The resulting surface plot of this study is shown in Fig. 7. Note that for each point in the surface, a new, random-bias map was generated. To reduce the random fluctuation in the surface, we performed the simulation ten times, and the resulting surfaces were averaged together. In examining the plot, we observe that the relationship is almost linear with regard to the percentage of perimeter dead pixels, independent of the severity of the bias nonuniformity.

The vertical striping observed in the corrected image of data set 2 [see Fig. 4(c)] is a direct result of error in the
calibrated perimeter detectors. This would include dead and saturated pixels as well as detectors with severe gain nonlinearities not resolvable by a linear TPC. One interesting observation is that dead pixels are more problematic for corrections containing 1D motion or corrections with motion in a constant direction. The reason for this is that the error due to the dead pixel is propagated along the direction of motion. In the 1D case, the dead-pixel error is always propagated along the same column or row, causing this error to always be included in each bias estimate. A similar phenomenon occurs for motion in a constant direction. When motion is not constant, this error is projected along many different motion angles and hence is more likely to be dispersed, especially in the case of 2D motion. To illustrate this projection error, Fig. 8 displays a flat-field 323-K RASBA-corrected image zoomed to a small dynamic range.

D. Sensitivity to Shift Estimation Error
In all corrections presented in this paper, shifts were estimated by using a gradient-based shift estimation algorithm.\textsuperscript{18,19} It is known, however, that when nonuniformity is present, error in the shift estimates increases dramatically.\textsuperscript{20} To improve the accuracy of the shift estimates in the presence of nonuniformity, we applied a smoothing filter to the image sequences before shift estimation.\textsuperscript{16} For all corrections in this paper, a mask size of 5 pixels was employed, yielding very reliable shift estimates in all the real data examples.

To understand the effect of any possible errors in the shift estimates on the RASBA’s performance, we performed a simulation study. This was done by first generating image sequences with constant motion (by means of downsampling) and adding to them normally distributed zero-mean bias nonuniformity with a standard deviation of 15. For each simulated sequence (of size 128 \times 128 by 11 frames), diagonal 2D motion is created. Since the true shifts of these image sequences are known, error is precisely induced into the shift estimates. These perturbed shift estimates are then used by the RASBA to correct the corrupted image sequence. A surface plot of the error in corrected frames is depicted in Fig. 9. As can be seen, the algorithm appears to be more sensitive to error in shifts that are subpixel. As these shifts get closer to zero, the error increases. In the case of subpixel 2D shifts, we multiply each bias estimate by the shift term $1/(1 - \gamma_4)$ [see Eq. (9)]. Thus, when the shifts are small, the term $1 - \gamma_4$ is small, and hence we divide each bias estimate by a small number. Note that when there is no error in the small shift estimates, the algorithm performs well, but as soon as a small amount of error is induced, the algorithm error increases significantly. Thus the RASBA is most sensitive to errors in small subpixel shifts. A similar study was performed for 1D shifts, and a nearly identical surface resulted.

In light of these results, another study was performed to investigate the accuracy of the RASBA as a function of the direction and the type (i.e., subpixel or superpixel) of motion used in correction. Identical image sequences were generated as in the shift sensitivity study (constant-motion 128 \times 128 by 11-frame sequences with bias nonuniformity standard deviation 15). In this study, the mo-
tion is precisely created, but the shift estimation algorithm is used to estimate the motion in the corrupted sequences. The resulting surface of this study is displayed in Fig. 10. The relative error in the shift estimates associated with this surface is displayed in Fig. 11.

Examining the surface in Fig. 10, we observe that indeed the RASBA is most sensitive to shifts, both 1D and 2D, near the origin. In fact, we see that algorithm accuracy is most affected in the subpixel region. Algorithm performance is best for the sequences exhibiting superpixel motion. Looking down the $\alpha$ and the $\beta$ axis (1D motion), we see that the error is lowest. The reason for this is that the RASBA is utilizing only one motion estimate, taking the other to be zero, and hence is seeing the effect of error in only one of the motion parameters. An important note to make here is that there is no error due to dead pixels, and as was observed above, the dead pixels affect the performance mostly in image pairs exhibiting 1D and constant-direction shifts. Recall that in the correction of data set 1 all 1D shifts and 2D shifts in the region $[-0.25, 0.25] \times [-0.25, 0.25]$ were omitted from the correction. The reason for this can now be understood in the context of Fig. 10 and the dead-pixel study of Subsection 4.C.

Finally, examining the shift error surface of Fig. 11, we observe that the relative error in the shifts is in fact smallest near the origin. This reinforces the fact that even a small error in the estimates of small shifts has an adverse affect on algorithm performance. Also, observe the peaks that occur on either side of the axes. This jump in shift estimate error occurs because when the motion is two dimensional, we are observing error due to both motion parameters, rather than error in a single parameter as in the 1D case. The shift estimation error is relatively flat in all other regions. Thus we realize that by omitting frame pairs exhibiting shifts in these problematic regions, algorithm performance can be dramatically improved.

5. CONCLUSION

We have presented a novel scene-based nonuniformity correction algorithm that, when coupled with limited absolute calibration, is able to maintain a high degree of radiometric accuracy without obstructing operation of the interior focal-plane array. The algorithm is able to do this by utilizing pairs of image frames exhibiting arbitrary one- and two-dimensional subpixel and superpixel motion in conjunction with a perimeter-only calibration technique. Initial performance of the technique demonstrates that it is able to consistently maintain radiometric accuracy to within $\pm 1$ K when compared with a standard two-point calibration. Future work will focus on a near-real-time implementation of the algorithm, including the construction of a perimeter-calibration system. An attempt to extend the algorithm to include rotational motion will also be made.

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