Noise-cancellation-based nonuniformity correction algorithm for infrared focal-plane arrays

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The spatial fixed-pattern noise (FPN) inherently generated in infrared (IR) imaging systems compromises severely the quality of the acquired imagery, even making such images inappropriate for some applications. The FPN refers to the inability of the photodetectors in the focal-plane array to render a uniform output image when a uniform-intensity scene is being imaged. We present a noise-cancellation-based algorithm that compensates for the additive component of the FPN. The proposed method relies on the assumption that a source of noise correlated to the additive FPN is available to the IR camera. An important feature of the algorithm is that all the calculations are reduced to a simple equation, which allows for the bias compensation of the raw imagery. The algorithm performance is tested using real IR image sequences and is compared to some classical methodologies.

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1. Introduction

The most popular infrared (IR) detector packed in modern IR cameras is the focal-plane array (FPA). In spite of the large number of advances in this technology, FPA detectors still face a serious and undesirable problem, which is referred to in the literature as fixed-pattern noise (FPN) or nonuniformity (NU) noise. The NU noise is mainly attributable to the different photo response of each detector in the array even though they receive the same IR input irradiance and are fabricated using the same materials and fabrication techniques. Moreover, the NU severely degrades the quality of the acquired images because it results in an additive and multiplicative pattern of noise that is superimposed over the real image. In addition, the NU noise tends to drift slowly in time; therefore, frequent compensations for NU are required during the operation of the camera. In the literature, the additive and multiplicative components of the FPN are also called bias and gain NU, respectively.

Nonuniformity correction (NUC) has been performed using calibration techniques. The calibration is performed by placing in the field of view of the camera a uniform-intensity calibration device. Although calibration is the most basic, accurate, and effective NUC method, it is undesirable in some applications because it interrupts the normal operation of the imaging system. Moreover, calibration requires the use of a blackbody radiator source, which is expensive, heavy, and requires its own electrical and mechanical hardware [1]. As an alternative approach, a large number of signal-processing-based techniques have been developed to compensate for the FPN. The main advantage of such techniques is that they allow the continuous operation of the camera and do not demand calibration sources. However, these methods rely on both the diversity in the irradiance seen by each photodetector and the motion in the scene that is being imaged [1–3].

Here we propose a new signal-processing technique for NUC. This technique is derived by using a

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noise-cancellation (NC) system, a well-known solution used to recover signals that are corrupted by additive noise in audio applications. As in any NC-based algorithm, the main assumption is that there is available an external source of noise, which is correlated to the additive FPN that corrupts the IR imagery [4]. In practical implementation of NC systems, the external correlated source of noise is obtained directly from the process, which in our case involves the use of a blackbodylike source of noise. In contrast, in the proposed algorithm we simulate the random process correlated with the bias NU in order to synthesize the required source of external noise. The simulation of this source of noise was made considering both the quasi-stationarity of the FPN and some assumptions about its statistics. So, the NC-based NUC technique exploits such a synthetic source of noise to generate a replica of the additive FPN, which is subtracted to the raw IR imagery. As in most NC systems, a finite impulse response (FIR) filter must be designed in order to produce the replica of the additive noise. An interesting and important feature of our NC-based algorithm is that all the calculations are finally reduced to a simple equation that allows for the bias compensation of the raw imagery. Based on this result, the proposed methodology can be described as a generalization of the Harris constant-statistics (CS) algorithm. Nevertheless, the simple assumptions that we have made are not as restrictive as a zero-mean and unity-variance input irradiance, which is an advantage of our solution. Moreover, theoretically, the proposed algorithm does not require any kind of motion for the information that is being imaged.

The remainder of this paper is organized as follows. In Section 2 we discuss the mathematical model of the FPA and all the assumptions made in order to simplify such a model. The design method of the aforementioned FIR filter is described in Section 3, where some implementation issues are also given. The performance of the proposed methodology is evaluated in Section 4 by using the root mean square error (RMSE) as the main comparison metric. Finally, in Section 5 we apply our algorithm to real IR sequences and compare it with some well-known algorithms. The conclusions are summarized in Section 6.

2. Mathematical Model of an IR FPA

In an IR FPA, each detector converts the incident IR energy into electrical energy, such as current or voltage. This response can be modeled as a function of the input irradiance. Unfortunately, the input–output characteristics of the detectors vary from detector to detector, even though extreme care is taken to manufacture detectors having similar properties. This implies that the mathematical model must be formulated in terms of a pixel-by-pixel characteristic, i.e., spatially. In addition, such a model must include the effects of both the FPN and the temporal noise. The temporal noise refers to the noise that varies from frame to frame and it is due to the random nonideal photodetection process. The FPN refers to any spatial pattern that does not change significantly from frame to frame. The FPN results in a multiplicative component and an additive component that are superimposed over the real image. The multiplicative component of the FPN is due to variations in detector responsivity (or gain), detector size, spectral response, and the thickness of the coating of each detector. The additive component of the FPN is mainly due to the detectors' dark current.

We have adopted here the commonly used affine model for each photodetector [5]. Thus, the readout data at the (i,j)th detector in the FPA at the kth time sample is given by

$$Y_{i,j}[k] = A_{i,j}[k]X_{i,j}[k] + B_{i,j}[k] + V_{i,j}[k], \qquad (1)$$

where $A_{i,j}[k]$ and $B_{i,j}[k]$ are the multiplicative and additive components of the FPN, respectively. The term $V_{i,j}[k]$ is the additive temporal noise and $X_{i,j}[k]$ represents the true input irradiance collected by the (i,j)th detector during the integration time. The time dependence of Eq. (1) is included for generality, but it will be dropped later (Assumption A2).

To achieve a fairly good estimate of the true incident irradiance, let us make the following assumptions:

A1

In many operational conditions, the additive FPN dominates the multiplicative FPN [1]. This means that compensating for the additive FPN from the read-out data will highly improve the image quality, generating a good approximation of the true incident radiation. Under this scenario, we are focused solely on the additive FPN compensation. So, let us define the true input irradiance approximation $S_{i,j}[k] \triangleq A_{i,j}[k]X_{i,j}[k]$.

A2

We are interested in solving the NUC problem within a short time interval, namely, within a block of frames no longer than a couple of minutes. Therefore, the bias temporal variations in each pixel can be considered negligible in our model. Thus, the term $B_{i,j}[k]$ is assumed to be a deterministic constant, in symbols, $B_{i,j}$ [1]. In addition, we assume that $B_{i,j}$ can take any value in the range $[B_{\min}, B_{\max}] \cap \mathbb{Z}$, with $\mathbb{Z}$ the set of integer numbers, which is common to all the photodetectors in the FPA. The rationale for this assumption is given in Section 3.

A3

As in several approaches, the temporal noise $V_{i,j}[k]$ included in the aforementioned model will be assumed to be a white zero-mean random sequence with known variance σ_v^2 common to all the photodetectors [1,5].

In light of these simplifying assumptions, Eq. (1) reduces to

$$Y_{i,j}[k] = S_{i,j}[k] + B_{i,j} + V_{i,j}[k]. \quad (2)$$

For the sake of simplicity in the notation, from now on the pixel subscripts i, j are dropped with the understanding that all operations are performed on a pixel-by-pixel basis.

3. Algorithm Design

Let us refer to the block diagram of the algorithm shown in Fig. 1. The first input to the NC system is the detectors' read-out data $Y[k]$, which correspond to the sum of the approximated irradiance, the additive FPN, and the temporal noise. The second input, $\beta[k]$, is an additive noise signal, which is given by some source of noise statistically correlated with the additive component of the FPN. According to the Fig. 1, by properly designing the filter $H(z)$, the signal $\hat{B}[k]$ will be a good estimate of B and, consequently, the system output will be a good estimate of the irradiance approximation $S[k]$.

Consider that the NC system synthesizes $\hat{B}[k]$ using a FIR filter with N coefficients, which we have denoted as h_k, $k = 0, 1, \ldots, N-1$. Following the least-squares FIR filter design method, we calculate the mean-squared error (MSE) of the output as follows:

$$\mathrm{MSE} = \mathsf{E}\{e[k]^2\} = R_{YY}[0] - 2\sum_{i=0}^{N-1} h_i R_{\beta Y}[i] + \sum_{i=0}^{N-1}\sum_{j=0}^{N-1} h_i h_j R_{\beta\beta}[i-j], \quad (3)$$

where $R_{YY}[n]$ and $R_{\beta\beta}[n]$ are the discrete autocorrelation sequences, at the nth lag, of the signals $Y[k]$ and $\beta[k]$, respectively. The term $R_{\beta Y}[n]$ is the discrete cross-correlation sequence at the nth lag, between $\beta[k]$ and $Y[k]$. The optimal filter for synthesizing $\hat{B}[k]$ is given as the solution of the so-called normal equations. In symbols:

$$\begin{bmatrix} h_0 \\ h_1 \\ \vdots \\ h_{N-1} \end{bmatrix} = \begin{bmatrix} R_{\beta\beta}[0] & R_{\beta\beta}[1] & \cdots & R_{\beta\beta}[N-1] \\ R_{\beta\beta}[1] & R_{\beta\beta}[0] & \cdots & R_{\beta\beta}[N-2] \\ \vdots & \vdots & \ddots & \vdots \\ R_{\beta\beta}[N-1] & R_{\beta\beta}[N-2] & \cdots & R_{\beta\beta}[0] \end{bmatrix}^{-1} \times \begin{bmatrix} R_{\beta Y}[0] \\ R_{\beta Y}[1] \\ \vdots \\ R_{\beta Y}[N-1] \end{bmatrix}. \quad (4)$$

Discussion. Theoretically speaking, the only condition that an NC-based estimator imposes on the estimation problem is that the external noise source, $\beta[k]$ in this case, must be highly correlated with the additive FPN and uncorrelated, or weakly correlated, with the approximated incident radiation. Notably, this requirement does not imply any restriction over the camera movement because the incident radiation and the additive FPN are not correlated: the FPA input depends on the scene that is being imaged and the additive FPN depends on the noise associated with the optoelectronic processes. Therefore, the performance of the NC-based method mainly depends on the source of correlated noise, $\beta[k]$, and how we generate this noise.

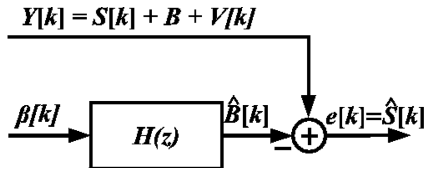


Fig. 1. Block diagram of the NC-based algorithm.

In light of the assumption that the FPN is constant in a short period of time, i.e., among a finite number of frames, a simple and efficient way to obtain such an external signal, $\beta[k]$, is to approximate the raw IR of a blackbody radiator by using a (software) simulated blackbody radiator. To this end, the spatially uniform part of the radiator is modeled by a constant number for all the pixels, while the FPN is simulated by determining an appropriate spatial distribution for the noise. To complete the specification of the simulated source of noise, it suffices to specify the spatial distribution of the FPN.

Let us mention some sources of noise that generate the FPN. The additive component of the FPN is mainly due to the detectors' dark current, which is kept almost constant and does not vary from frame to frame. Moreover, the FPN is also due to differences in detector sizes, doping density, and foreign matter that gets trapped during fabrication, all of which give rise to both temperature dependence, showing fluctuations that create pattern noise, and offset voltages due to the on- and off-chip amplifiers used on the FPA.

With this background, we can see that we do not have control or knowledge of several factors and sources that give rise to the FPN. Therefore, its statistical model cannot be obtained in an accurate way. This is mainly due to the multiple sources of noise that generate the FPN, their complex interaction, and the detector-dependent characteristic of the FPN. In addition, the pattern of the noise depends strongly on the design and manufacture of the FPA. In light of these difficulties, in this work we have assumed that the simulated additive FPN that corrupts the uniform data, at each pixel, is an unknown, discrete, deterministic, and constant parameter within the time window of a block of frames (Assumption A2). Moreover, it has been assumed that the simulated FPN lacks spatial correlation between pixels. So, a simple yet effective manner to simulate the additive FPN is to consider a matrix of random variables spatially uncorrelated and following a uniform distribution with known common range: $[\beta_{\min}, \beta_{\max}] \cap \mathbb{Z}$. It must be noted that in [6] we employed such a model for the FPN, obtaining good results. As a practical matter, our experience with the problem shows that the range $[\beta_{\min}, \beta_{\max}]$ can be selected from the dynamic range of the camera under analysis.

In Subsection 3.A we exploit the fact that at each pixel $\beta[k]$ is constant within the time window recorded. Hence, we can evaluate the NC-based method in order to obtain an explicit expression for the sequences of filtered images. This implies that all the calculations will be reduced to a simple formula, which is an important issue for future hardware implementation.

A. Algorithm Simplification

Let us assume that, during a sample time of K frames, the (software) simulated additive noise $\beta[k]$ takes a certain value, say β_0 with $\beta_0 \neq 0$. Then, using the definition of the autocorrelation and cross-correlation sequences, the required correlation functions at the nth lag are given by

$$R_{\beta\beta}[n] = \beta_0^2\left(1 - \frac{n}{K}\right), \qquad R_{\beta Y}[n] = \beta_0\left(1 - \frac{n}{K}\right)\bar{Y}_{K-n}, \tag{5}$$

where $\bar{Y}_{K-n}$ stands for the sample mean of the readout signal when the samples from $k = 0$ up to $k = K - 1 - n$ are considered, in symbols: $\bar{Y}_{K-n} = (K-n)^{-1}\sum_{k=0}^{K-1-n} Y[k]$. Plugging Eq. (4) into the expression for the error $e[k]$ and recalling that $e[k] = \hat{S}[k]$ we obtain, after some algebraic manipulation, a simple formula for the estimate of the approximate irradiance:

$$\hat{S}[k] = Y[k] - \frac{K\bar{Y}_K + [K - (N-1)]\bar{Y}_{K-N}}{2K - (N-1)}. \tag{6}$$

Notably, the estimator depends solely upon the observed data, the size of the block of frames, K, and the number of filter coefficients, N, of the filter $h[k]$.

In addition, note that the sequence of compensated images does not depend on the value β_0 and, moreover, for fixed K and N, the estimated additive NU is a constant number. This result is in agreement with the assumption that the additive NU is constant within the time window under study. Note that using one filter coefficient ($N = 1$), the proposed algorithm reduces to $\hat{S}[k] = Y[k] - \bar{Y}_K$, which means that the estimated bias is given by $\hat{B} = \bar{Y}_K$, recalling the well-known Harris CS NUC method. However, our method does not impose the requirement of zero mean and unit variance for the IR input irradiance, which are the most restrictive assumptions in Harris' algorithm [5].

Thus, the main advantage of our NC-based method is the reduction of all the required computations to an explicit equation that was obtained from the assumption on the statistical spatial distribution of the additive FPN. Furthermore, the simplicity of Eq. (6) produces an algorithm that is easy to implement in practice.

4. Performance Evaluation

According to Eq. (6), two parameters can be used as control knobs in our algorithm: K, the number of frames used to calculate the sample mean, and N, the number of filter coefficients in the FIR filter. We study now the impact of these two parameters on the noise compensation capability of our algorithm. To assess performance, the RMSE between the true and the estimated irradiance will be used as a quantitative metric of NUC. Mathematically, the RMSE at the kth frame is defined as

$$\mathrm{RMSE}[k] = \left[\frac{1}{PQ}\sum_{i=0}^{P-1}\sum_{j=0}^{Q-1}(S_{i,j}[k] - \hat{S}_{i,j}[k])^2\right]^{\frac{1}{2}}, \tag{7}$$

where P and Q are the number of detectors in the FPA. The term $S_{i,j}[k]$ (correspondingly, $\hat{S}_{i,j}[k]$) is the true approximated input irradiance (correspondingly, the estimate of the approximated irradiance) at the (i,j)th pixel. The true quantity $S_{i,j}[k]$ was obtained using a two-point calibration method with blackbody radiators. Note that the RMSE is actually an average RMSE over all pixels in a frame. Of

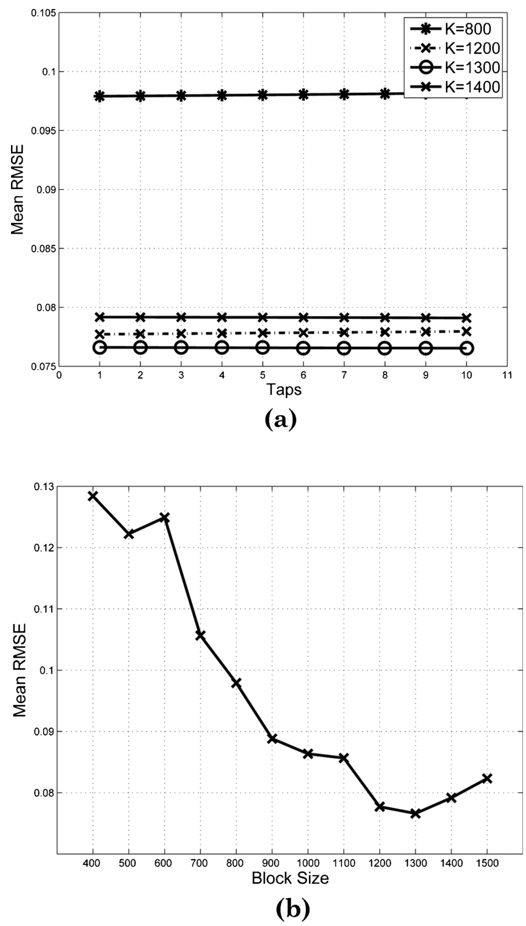


Fig. 2. Average RMSE per pixel as a function of (a) both the number of filter coefficients and the number of frames in each block and (b) the number of frames in each block.

course, the lower the value of RMSE, the better the NUC achieved.

For our tests we used outdoor midwave IR (3–5 μm) videos collected at 1 p.m. on a sunny day using an InSb-FPA-based cooled camera (AMBER Model AE-4128). Each video was collected at a sample rate of 30 frames per second (fps), and each frame has a size of 128 × 128 pixels, where each pixel is quantized in integer values using 16 unsigned bits. The NUC capability of the algorithm was evaluated using different block lengths, in particular, $K \in \{400, 500, \ldots, 1500\}$. In addition, we considered the following values for the number of filter coefficients: $N \in \{1, 2, \ldots, 10\}$. The RMSE, averaged one more time over the sample time, is shown in Fig. 2 as a function of both the number of filter coefficients and the length of the block. It can be seen that the RMSE for a fixed block length is almost insensitive to the number of coefficients. For this particular case, we will choose $N = 10$ as a good reference. According to these results, the parameters yielding the best performance are $K = 1300$ frames and $N = 10$ coefficients. Note that the raw IR data has an average RMSE of 0.1435, while, after the NUC, the average RMSE was reduced to 0.0765. Our results confirm the accuracy and robustness of the proposed method to estimate the additive FPN.

5. Applications to Real Infrared Image Sequences

The algorithm was tested using IR data captured with the AMBER camera and using the best set of parameters obtained in the previous section. A sample uncorrected frame taken from the video sequence as well as the FPN compensated versions of it using two-point calibration and the NC-based algorithm are shown in Figs. 3(a)–3(c).

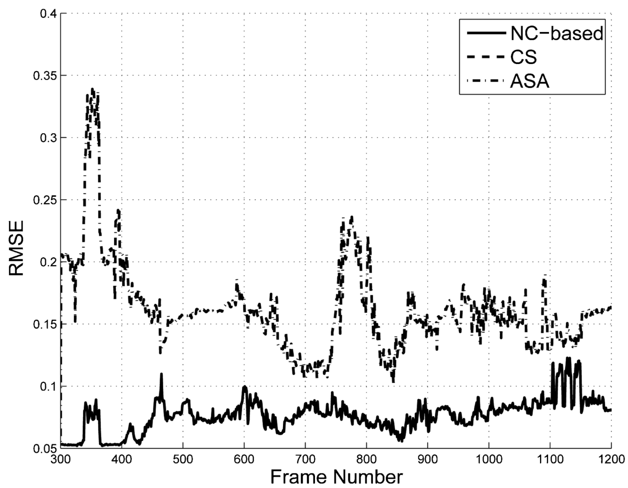
Using the RMSE as a metric, we have compared our algorithm with two classical NUC methodologies: the Harris CS algorithm [5] and the Hayat adaptive statistical algorithm (ASA) [7]. As a reference, we considered a laboratory two-point correction of the raw imagery. The main results of such a study are shown in Fig. 3(d). It can be seen that the NC-based algorithm has performance similar to that observed for the CS methodology, but the difference with CS is that our assumptions are weaker than the ones made in CS. Namely, we do not impose a zero-mean Gaussian distribution to the approximated irradiance.

Additionally, we evaluated our algorithm and its NUC capabilities in another spectral window. We

(a)

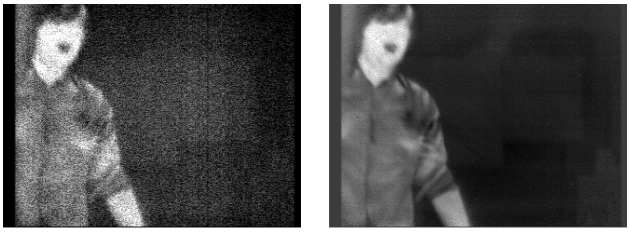
(b)

(c)



(d)

Fig. 3. (a) Sample raw image captured with the AMBER camera. The image in part (a) compensated for FPN using (b) two-point calibration and (c) the NC-based algorithm. (d) The RMSE at the k frame between the reference image and its corresponding corrected versions obtained using the NC-based algorithm, the CS algorithm, and the ASA algorithm.



(a) (b)

Fig. 4. NUC of real IR data captured with the FLIR camera. (a) A sample raw image and (b) the FPN compensated image obtained using the NC-based algorithm, with parameters $K = 1300$ and $N = 10$.

considered a second set of data corresponding to a 7–14 μm IR indoor imagery. For the correction, we kept the same parameters used for the AMBER camera case, i.e., $K = 1300$ and $N = 10$. This new set of data was captured at around 3 p.m. using an uncooled HgCdTe-FPA-based camera (FLIR Merlin) at a rate of 30 fps. The FPA size is 320×240 pixels and each pixel is quantized in integer values using 8 unsigned bits. The NUC capability of our algorithm for this IR imagery is depicted in Fig. 4. Note that the NU noise in the FLIR camera is much more severe than the NU noise in the AMBER camera. In spite of this, a simple naked-eye evaluation shows that the FPN has decreased significantly after the application of our filter; i.e., the image quality was improved to an acceptable level.

6. Conclusions

We have developed a scene-based NUC technique based on a NC system that compensates the additive component of the FPN. The main contribution of our solution is that it exploits a well-known solution for noise reduction in audio applications. In conjunction with some nonrestrictive assumptions, we developed a NUC algorithm where all the required computations are implemented in a single and simple equation. Based on both the excellent results obtained in two different technologies and that all the calculations are summarized in a single equation, we state that our algorithm could be a good solution for hardware implementation of the NUC problem.

The performance of our algorithm depends essentially on the number of frames used in the NUC and does not impose any further restriction on the IR data that is being imaged. Results obtained over mid- and long-wave IR data show the NUC ability of the algorithm where, according to a naked-eye evaluation, an excellent image quality is achieved. Although the effectiveness of our methodology to reduce the FPN and compensate for artifacts, such as dead pixels, was shown in the examples, our algorithm exhibits the presence of ghosting artifacts, as does almost every scene-based NUC algorithm available in the literature. Therefore, for future implementation some deghosting techniques, such as the one used in [8], could be included in the development.

Even though the NC-based method recalls the Harris CS algorithm, it does not require any assumption on the zero mean and unit variance of the input irradiance, which is the most restrictive assumption made by Harris. Moreover, it is easy to check that our method is actually a biased estimator of B, while CS is unbiased. The presence of bias in the estimate is not an issue related to the NC-based method; it is simply a consequence of the ill-posed nature of the NUC problem. Given that scene-based NUC methods employ no reference to perform the estimation, the resulting estimators suffer bias unless further assumptions are made, like in the case of CS where zero mean is assumed for the input irradiance.

In future work we will simulate a much more realistic version of the FPN by introducing some spatial correlation among the pixels of the simulated black body, the effect of the additive temporal noise, and the time variation in the FPN when a long time window is considered.

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