“De-Ghosting” Artifact in Scene-Based Nonuniformity Correction of Infrared Image Sequences

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Abstract. In this paper we present a new technique to improve the convergence and to reduce the ghosting artifacts based on constant statistics (CS) method. We propose to reduce ghosting artifacts and to speed up the convergence by using enhanced constant statistics method with the motion threshold. The key advantage of the method is based in its capacity for estimate detectors parameters, and then compensate for fixed-pattern noise in a frame by frame basics. The ability of the method to compensate for nonuniformity and reducing ghosting artifacts is demonstrated by employing video sequences of simulated and several infrared video sequences obtained using two infrared cameras.

Keywords: Infrared detectors, focal-plane array, non-uniformity correction, fixed-pattern noise, ghosting artifact.

1 Introduction

Infrared imaging systems are employed in several applications such as defense, astronomy and medical science. In general, those systems are based on the infrared focal-plane array IRFPA technology. An IRFPA is a die composed of a group of photodetectors placed in a focal plane forming a matrix of $X \times Y$ pixels, which gives the sensor the ability to collect the IR information.

It is well known that nonuniformity noise in IR imaging sensors, which is due to pixel-to-pixel variation in the detectors responses, can considerably degrade the quality of IR images since it results in a fixed-pattern-noise (FPN) that is superimposed on the true image. Even more, what makes matter worse is that the nonuniformity slowly varies over time, and depending on the technology used, this drift can take from minutes to hours. In order to solve this problem, several scene-based nonuniformity correction (NUC) techniques have been developed [1-6]. Scene-based techniques perform the NUC using only the video sequences that are being imaged, not requiring any kind of laboratory calibration technique.

Our group has been given special attention to NUC methods based on estimation theory [7]. Seeking for more effectiveness in the reduction of NUC, we

propose to improve the previously published Minimizing the Ghosting Artifact to RLS Filter scene-based NUC method [8]. Now, we proposed NUC method based in constant statistics CS. This algorithm exhibits the advantages of desirable for simplicity and low mathematical operations [9, 10]. However, the method has shown the following weakness: the supposition that the input scene is constantly moving, in general, is not valid and ghosting artifacts are generated; the assumption that the best target for the unknown input infrared irradiance is an average over its neighboring pixels is scene dependent generating a poor correction in pixels, which are part of objects boundaries. Then, for improving the performance of the CS-NUC algorithm, we propose to reduce ghosting artifacts adding the effects of to speed up the convergence of the algorithm and motion threshold. Both, mixed effects, are tested with simulated and real IR data.

This paper is organized as follows. In Section 2 the IR-FPA model and the CS-NUC method with the proposed enhancement are presented. In Section 3 the proposed method is tested with video sequences of simulated and real raw IR data captured using two infrared cameras. In Section 4 the conclusions of the paper are summarized.

2 The CS Algorithm for Infrared Video Sequences

In this section, the previously published scene-based NUC method [8] is presented for completeness. We begin reviewing the most common model used for the nonuniformity presented IR-FPA technology, and we finish developing the techniques with the ability of being used to reduce ghosting artifacts and to speed up convergence of such method.

2.1 CS Method

First, we assume that each infrared detector is characterized by a linear model. Then, for the ij th detector in the focal-plane array, the measured readout signal $Y_{ij}(n)$ at a given time n can be expressed as

$$Y_{ij}(n) = a_{ij}(n) \cdot X_{ij}(n) + b_{ij}(n) \quad (1)$$

Where $a_{ij}(n)$ and $b_{ij}(n)$ are the gain and the offset of the ij th detector, and $X_{ij}(n)$ is the real incident infrared photon flux collected by the respective detector. Each corrupted data pixel $Y_{ij}(n)$ is the input to one of the linear regressors. Equation (1) is reordered for obtain the inverse model given by:

$$X_{ij}(n) = \frac{Y_{ij}(n) - m_{ij}(n)}{s_{ij}(n)} \quad (2)$$

Mean and mean deviation of $Y_{ij}(n)$ can be calculated by the following recursive equations:

$$m_{ij}(n) = \frac{Y_{ij}(n) + (n-1) \cdot m_{ij}(n-1)}{n} \quad (3)$$

$$s_{ij}(n) = \frac{|Y_{ij}(n) - m_{ij}(n)| + (n-1) \cdot s_{ij}(n-1)}{n} \quad (4)$$

2.2 Performance of the CS-NUC Method

The main problems detected on the performance of the CS-NUC method are originated by two basic constraints used in the development of the method. The first is related to the supposition that the scene is constantly moving with respect to the detector. Then, the problem is that when the scene is not moving for a few frames, this is not valid, and the ghosting effect appears. This consists in a ghost present in the next frames.

The second is related with large uniform areas in the scene. Even when the scene is in constantly moving with respect to the detector, the moving camera ensures no variation of photons on the sensor because may come from uniform areas. This also consists of being ghosts in the next frames.

In the next section, we propose enhanced method CS-NUC to be included in the algorithm to reduce the ghosting.

2.3 Nonuniformity and Proposed Ghosting Correction Algorithm

All scene nonuniformity correction algorithms require that the objects in the image do not remain stationary for too long. This can be accomplished by either periodically moving the camera or else requiring objects in the scene to move. If an object in the image violates this assumption and remains stationary for a large number of iteration, the object will blend into the background. If this stationary object eventually moves from the field of view, it will leave a reverse ghost image in the scene. The de-ghosting technique detects the changes of each pixel and compare them with threshold value. This technique slows down the performance of the algorithm. This effect is minimizing if CS method is modifying the Mean and Mean Deviation as follows:

$$m_{ij}(n) = \frac{Y_{ij}(n) + \dots + Y_{ij}(n-k) + (n-k-1) \cdot m_{ij}(n-1)}{n} \quad (5)$$

$$s_{ij}(n) = \frac{|Y_{ij}(n) + m_{ij}(n)| + \dots + |Y_{ij}(n-k) + m_{ij}(n-k)| + (n-k-1) \cdot s_{ij}(n-1)}{n} \quad (6)$$

k can be chosen by trial and error, so that there is a compromise between speed of convergence with an acceptable number of mathematical operations. Note that with k=0 is normal CS-NUC (Eq. (3,4)).

3 Evaluation of the Proposed Methods Upgrades

The main goal of this section is to test the ability of the proposed method to reduce nonuniformity on simulated and real infrared video data. The algorithm is tested with simulated infrared image sequences. As a quantitative measure of performance, we use the Root Mean Square Error (RMSE), which measures the difference between the true infrared image with the corrected image using the proposed method. The RMSE is calculated by:

$$RMSE(n) = \left\{ \frac{1}{pm} \sum_{i=1}^p \sum_{j=1}^m (\hat{x}_{ij}(n) - x_{ij}(n))^2 \right\}^{1/2} \quad (7)$$

where $p \times m$ is the number of detectors in the FPA. A low value of RMSE means a better correction of the frame data. The evaluation procedure for each set of data is detailed in the following sections. Also, as a quantitative measure of performance, we use the performance parameter ρ , which measures the roughness in an image. More precisely, for any digital image f , we define

$$\rho = \frac{\|h_1 * f\|_1 + \|h_2 * f\|_1}{\|f\|_1} \quad (8)$$

where h_1 is a horizontal mask, $[1, -1]$, $h_2 = h_1^T$ is a vertical mask, the asterisk denotes discrete convolution, and, for any image f , $\|f\|_1$ is its L_1 norm (the L_1 norm is simply the sum of the magnitudes of all pixels). The two terms in the numerator of Eq. (8) measure the pixel-to-pixel roughness in the horizontal and the vertical directions, respectively. Normalization by f_1 in Eq. (8) makes ρ invariant under scaling. Clearly, ρ is zero for a constant image, and it increases with the pixel-to-pixel variation in the image.

Fig. 1. Results on simulated data with emphasis in ghost artifacts reduction after 700 frame, a) frame with simulated nonuniformity, b) The corresponding frame corrected by the previous CS method [10] and c) The corresponding frame corrected by the enhanced SC method

3.1 Results with Simulated IR Video

The video has been generated using simulated images, where the intensity or gray level indicates the bodies temperature. FPN is added to each image generating the corrupted sequence. As an example, Fig. 1a shows a corrupted data frame.

In Fig. 1b and 1c the corresponding corrected frame by the CS-NUC method and the enhance CS-NUC method with $k=1$ are presented, respectively. In Fig. 1b and Fig. 1c we have shown a zooming of the corrected image, specifically of the zones indicated by boxes. In them, using only the naked eye is clear that the non-uniformity is better in the proposed method (Fig. 1c) than in the previous published method (Fig. 1b).

Figure 2 shows the calculated RMSE (a) and roughness (b) for the corrupted data, for each frame corrected using CS NUC method [10], and the enhanced CS-NUC method. Further, the average RMSEs computed for the whole infrared sequence are equal to 0.075 and 0.068 for the CS-NUC algorithm and the enhanced CS-NUC algorithm, respectively. It can be seen in Fig. 2a that the RMSE value obtained for the enhanced CS-NUC method has a greater convergence speed, because, for the same number of frame, it reaches a lower RMSE value than other method. It can be seen in Fig. 2b that the roughness parameter associated with the images indicate a reduction of enhanced CS-NUC method in relation to CS-NUC method.

Fig. 2. The performance parameters associated with the images; (a) the evolution of the RMSE between original and the corrected frames; (b) the evolution of the roughness. In both chart, x line represents the corrupted data (Raw); dot line represents the RMSE computed for the CS-NUC method (CS); dashed line represents the RMSE computed for the proposed enhanced CS-NUC method (E-CS); and Solid line represents original frame (Original).

3.2 Results with Two Real Infrared Image Sequences

The first sequence has been collected using a 128×128 InSb FPA cooled camera (Amber Model AE-4128) operating in the $3\text{--}5\text{ }\mu\text{m}$ range. As an example, Fig. 3a shows a corrupted readout data frame. In Fig. 3b and 3c the corresponding corrected frame by the CS-NUC method and the enhance CS-NUC method are presented, respectively. In Fig. 3b and Fig. 3c we have shown a zooming of the corrected image, specifically of the zones indicated by boxes. In them, using only the naked eye is clear that the non-uniformity is better in the proposed CS-NUC method (Fig. 3c) than in the previous published method (Fig. 3b).

Fig. 3. Results on simulated data with emphasis in ghost artifacts reduction after 915 frame, a) frame with simulated nonuniformity, b) The corresponding frame corrected by the previous CS method [10] and c) The corresponding frame corrected by the enhanced SC method

Fig. 4. Performance of the enhanced CS-NUC method under real IR data (Jade model camera), a) The raw corrupted frame, b) The corresponding frame corrected by the CS method and c) The corresponding frame corrected by the proposed enhance method

The second sequence of infrared data has been recorded using a 320×240 HgCdTe FPA cooled camera (CEDIP Jade Model) operating in the $8\text{--}12\text{ }\mu\text{m}$ range. As an example, Fig. 4a shows the corrupted readout data. In Fig. 4b, and Fig. 4c the corresponding corrected frames by the previous published method CS and the NUC method proposed in this paper are shown, respectively. The non-uniformity, visually presented in the raw frame, has been notably reduced by the proposed method; in Fig. 4b and Fig. 4c this is specially noticed in the marked region. In Fig. 4b it is possible to appreciate the ghosting present. This ghost effect disappears when we used the enhance method with nonuniformity

and ghosting correction algorithm, as it is shown in Fig. 4c. Note that the star in the extended zone is better visually in the Fig. 4c. Thus, we have shown experimentally with real IR data that the proposed scene- based CS-NUC method with ghost correction has the ability of notably reduce both the non-uniformity noise presented in IRFPA sensors and the ghosting generated by lack of motion in the recorded IR data.

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4 Conclusions

In this paper an enhanced version of our previously published NUC method, based in a constant statistics method is presented. The new algorithm has the ability to improve the nonuniformity correction and to eliminate ghosting artifacts more efficiently than the previous method. This is obtained by means adding the effects of to speed up the convergence of the algorithm and motion threshold. Furthermore, the evaluation with simulated and real data has demonstrated that the proposed method reduces ghosting artifacts and improves the RMSE parameter when compared with the previous published method. Using read-out data taken from cameras of two different technologies we were able to observe that the method is capable to reduce nonuniformity, minimizing ghosting, with fast convergence and low RMSE.

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