A Recursive Least Square Adaptive Filter for Nonuniformity Correction of Infrared Image Sequences *

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Abstract. In this paper, an adaptive scene-based nonuniformity correction methodology for infrared image sequences is developed. The method estimates detector parameters and carry out the non-uniformity correction based on the recursive least square filter approach, with adaptive supervision. 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 is demonstrated by employing several infrared video sequences obtained using two infrared cameras.

Keywords: Image Sequence Processing, Infrared Imaging, RLS.

Topic: Infrared Image and Video Processing, Infrared Sensor-Imaging.

1 Introduction

Infrared (IR) imaging systems employ an IR sensor to digitize the information, and due to its high performance, the most used integrated technology in IR sensors is the Focal Plane Array (FPA). An IR-FPA 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 work was partially supported by Proyecto DIUFRO EP N^o 120323 and Grant Milenio ICM P02-049. The authors wish to thank Ernest E. Armstrong (OptiMetrics Inc., USA) and Pierre Potet (CEDIP Infrared Systems, France) for collecting the data.

M. Lazo and A. Sanfeliu (Eds.): CIARP 2005, LNCS 3773, pp. 540–546, 2005.

this drift can take from minutes to hours. In order to solve this problem, several scene-based nonuniformity correction (NUC) techniques have been developed [1,2,3,4,5,6]. 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. Seeking for more effectiveness in the reduction of NUC, we propose an adaptive scene-based NUC method, based in a RLS (recursive least square) filter [7], to estimate detector parameters and to reduce the FPN in a fast and reliable frame by frame basis. Further, the NUC method based in a RLS algorithm exhibits the advantages of fast convergence rate and unbiased stationary error [8,9].

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

2 The NUC-RLS Algorithm for Infrared Video Sequences

The aim of this paper is to develop a scene-based NUC method for infrared video sequences using fundamental theory in parameters estimation. We begin reviewing the most common model used for IR-FPA technology, and then developing a RLS filter approach for NUC.

2.1 IR-FPA Model

In this paper, we adopt the commonly used linear model for the infrared detector. For the $(ij)^{\text{th}}$ detector in IR-FPA, the measured readout signal Y_{ij} at a given time n can be expressed as:

$$Y_{ij}(n) = g_{ij}(n) \cdot X_{ij}(n) + o_{ij}(n) \tag{1}$$

where $g_{ij}(n)$ and $o_{ij}(n)$ 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. Equation (1) is reordered for obtain the inverse model given by:

$$X_{ij}(n) = \frac{1}{g_{ij}(n)} \cdot Y_{ij}(n) - \frac{o_{ij}(n)}{g_{ij}(n)} \tag{2}$$

where this equation performs the NUC correction. The detector parameters have to be estimated using only the measured signal Y_{ij}, and the corrected image is obtained with the inverse model equation.

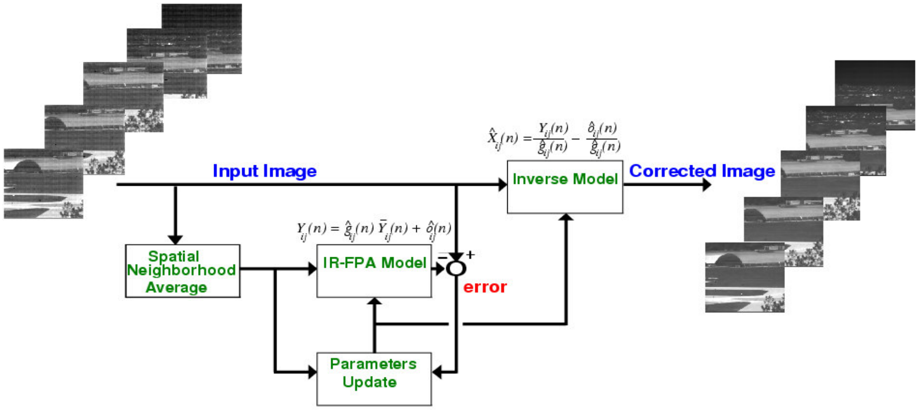

Fig. 1. Scheme of the proposed Scene-Based Non-Uniformity Correction Method

2.2 NUC-RLS Filter Method

We start re-writing equation (1) in a vectorial form:

$$Y_{ij}(n) = \Psi_{ij}^T(n)\Theta_{ij}(n) \tag{3}$$

where, $\Psi_{ij}(n) = [X_{ij}(n), 1]^T$ is the infrared data vector and $\Theta_{ij}(n) = [g_{ij}(n), o_{ij}(n)]^T$, is the detector parameter vector. Because the real incident IR is unknown, the key assumption of this paper is that X_{ij} can be initially estimated from the read-out data Y_{ij}. We propose to initially estimate the real X_{ij} applying a spatial lowpass filter over the corrupted image as follow:

$$\bar{Y}_{ij}(n) = \frac{1}{(2v+1)^2} \sum_{k=i-v}^{i+v} \sum_{l=j-v}^{j+v} Y_{kl}(n) \tag{4}$$

where $\bar{Y}$ is the smoothing version of Y, and only spatio correction is performed. If we supposes that the scene is constantly moving with respect to the detector, $\bar{Y}$ can be assumed as the corrected image and the equation (3) can be used for estimate the detector parameters with $\hat{\Psi}_{ij}(n) = \left[\bar{Y}_{ij}(n), 1\right]^T$, i.e., we suppose that the gain parameters have a spatial normal distribution with unit mean, and the bias have a spatial normal distribution with zero mean. Then, writing equation (2) as:

$$\hat{X}_{ij}(n) = Y_{ij}(n)/\hat{g}_{ij}(n) - \hat{o}_{ij}(n)/\hat{g}_{ij}(n) \tag{5}$$

we can remove the FPN of the corrupted image sequence making it a spatio-temporal NUC method. For a recursive update of the parameters, the RLS algorithm is used and all necessary equations to form the algorithm are:

$$\hat{\Theta}_{ij}(n+1) = \hat{\Theta}_{ij}(n) + \mathrm{K}_{ij}(n+1)\left[Y_{ij}(n+1) - \hat{\Psi}_{ij}^T(n+1)\hat{\Theta}_{ij}(n)\right]$$

$$\mathrm{K}_{ij}(n+1) = \mathrm{P}_{ij}(n)\hat{\Psi}_{ij}(n+1)\left[\lambda - \hat{\Psi}_{ij}^T(n+1)\mathrm{P}_{ij}(n)\hat{\Psi}_{ij}(n+1)\right]^{-1}$$

$$\mathrm{P}_{ij}(n+1) = \left[I - \mathrm{K}_{ij}(n+1)\hat{\Psi}_{ij}^{T}(n+1)\right]\mathrm{P}_{ij}(n)\cdot\frac{1}{\lambda} \qquad (6)$$

where, $\hat{\Theta}_{ij}(n) = [\hat{g}_{ij}(n), \hat{o}_{ij}(n)]^T$, is the estimated parameter vector, $\mathrm{K}_{ij}(n)$ is the correction vector, $\mathrm{P}_{ij}(n)$ is the covariance matrix, and λ is the forgetting factor. Varying λ within $0 < \lambda < 1$, we weight the influence of past error values.

The scheme of the proposed RLS-NUC method is shown in Fig. 1. The corrupted image is smoothed using a local spatial neighborhood average filter (4), and the IR-FPA model (3) is used for estimate the gain and offset of each detector with the RLS algorithm. The difference of the readout data and the output of the sensor model evaluated with the estimate real infrared data calculates the error signal. Then, the estimated parameters are introduced into equation (5) for computing the corrected image. On each step, the equation (6) is updated with a new infrared image.

Note that if the scene is not constantly moving with respect to the IR-FPA, on the output of the RLS-NUC method of Fig. 1, the smoothing version of Y is obtained. Therefore, the sensor parameter can not be update and a motion detection algorithm would be required, and it will be develop in future works.

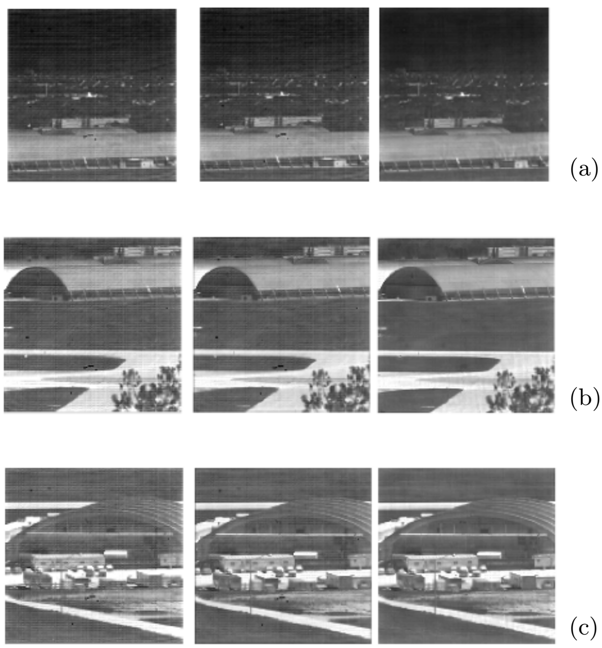

Fig. 2. Performance of the NUC-RLS method under real IR data. (a)(b) (c) The $200-th$ ($1600-th$) ($2630-th$) frames of the first set of IR data, at the left the raw corrupted frames, at the right the corresponding frames corrected first by the Scribners method and then by the proposed method.

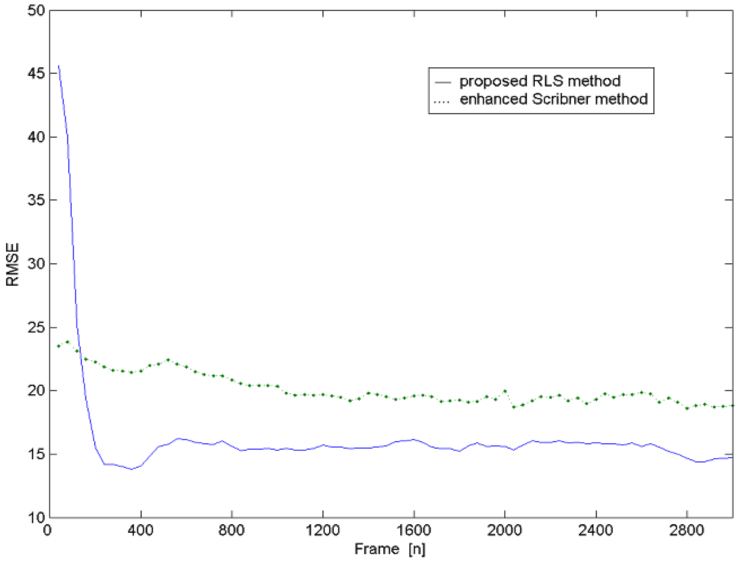

Fig. 3. The evolution of the RMSE between the reference (set 1 calibrated with black bodies) and the corrected frames of IR data set 1. Dashdot line represents the RMSE computed for the enhance Scribners NUC method, and solid line represents the RMSE computed for the proposed NUC-RLS method.

3 Performance Evaluation with Real Infrared Image Sequences

The main goal of this section is to test the ability of the proposed method for reduce nonuniformity on real video data. The algorithm is tested 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 $3 - 5\mu m$ range. As an example, figure 2 (a)(b)(c) shows from left to right a corrupted readout data frame, the corresponding corrected frame by enhance Scribner NUC method [6], and the corresponding corrected frame by the NUC method proposed in this paper. The NUC performance, in this case, is evaluated employing the index root mean square error (RMSE) computed between a reference (the real IR sequence calibrated with black bodies) and the corrected IR video sequence. Figure 3 shows the calculated RMSE for each frame corrected using enhance Scribner's NUC method and using the proposed method. Further, the average RMSEs computed for the whole infrared sequence are equal to 20.15 and 16.62 for the Scribner NUC method and the NUC-RLS algorithm proposed, respectively. Further, it can be seen in figure 2 using only the naked eye that the non-uniformity is notably reduced by the proposed NUC method.

The second sequence of infrared data has been recorded using a 320×240 HgCdTe FPA cooled camera (CEDIP Jade Model) operating in the $8 - 12\mu m$

(a)

(b)

(c)

Fig. 4. Performance of the NUC-RLS method under real IR data. (a)(b)(c) The $280-th$ $(500-th)$ $(1000-th)$ frames of the second set of IR data, at the left the raw corrupted frames, at the right the corresponding frames corrected first by the Scribners method and then by the proposed method.

range. As an example, figure 4 (a)(b)(c) shows from the left to right a corrupted readout data frame, the corresponding corrected frame by enhance Scribner NUC method, and the corresponding corrected frame by the NUC method proposed in this paper. Again, it can be seen by only using the naked eye, that the non-uniformity presented in the raw frame has been notably reduced by both NUC method. Thus, we have shown experimentally with real IR data that the proposed scene-based NUC-RLS method has the ability of notably reduces the non-uniformity noise presented in IR-FPA sensors and improve the enhance Scribner NUC method.

4 Conclusions

In this paper a NUC-RLS method is proposed. The main advantage of the method is based in its simplicity using only fundamental parameter estimation theory. The method has the ability of notably reducing the FPN after only processing around 300 frames. The key assumption of the method is that the real infrared data is obtained from the readout data applying an average spatial filter on each step time. It was shown experimentally using real IR data from two technologies that the method is able to reduce the non-uniformity with a faster convergence and low RMSE.

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