Infrared Physics & Technology 76 (2016) 691–697

Contents lists available at ScienceDirect

Infrared Physics & Technology

journal homepage: www.elsevier.com/locate/infrared

Regular article

Guided filter and adaptive learning rate based non-uniformity correction algorithm for infrared focal plane array

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ARTICLE INFO

Article history:
Received 26 August 2015
Accepted 28 April 2016
Available online 3 May 2016

Keywords:
Infrared focal plane array
Non-uniformity correction
Neural network
Guided filter
Adaptive learning rate

ABSTRACT

Imaging non-uniformity of infrared focal plane array (IRFPA) behaves as fixed-pattern noise superimposed on the image, which affects the imaging quality of infrared system seriously. In scene-based non-uniformity correction methods, the drawbacks of ghosting artifacts and image blurring affect the sensitivity of the IRFPA imaging system seriously and decrease the image quality visibly. This paper proposes an improved neural network non-uniformity correction method with adaptive learning rate. On the one hand, using guided filter, the proposed algorithm decreases the effect of ghosting artifacts. On the other hand, due to the inappropriate learning rate is the main reason of image blurring, the proposed algorithm utilizes an adaptive learning rate with a temporal domain factor to eliminate the effect of image blurring. In short, the proposed algorithm combines the merits of the guided filter and the adaptive learning rate. Several real and simulated infrared image sequences are utilized to verify the performance of the proposed algorithm. The experiment results indicate that the proposed algorithm can not only reduce the non-uniformity with less ghosting artifacts but also overcome the problems of image blurring in static areas.

1. Introduction

Infrared focal plane arrays (IRFRA) imaging system has tremendous value on both military and civilian applications. However, at present due to the immature manufacturing process, the response under the same infrared irradiance varies between the different detection element within an IRFPA. This phenomenon will impose the fixed pattern noise (FPN) in the infrared image which is called non-uniformity of IRFRA [1], and the non-uniformity has a serious impact on the sensitivity and the quality of IRFPA imaging system. Thus it is very essential to develop an effective non-uniformity correction (NUC) algorithm to achieve higher quality infrared images.

The NUC algorithm aims to eliminate the unwanted FPN and recovery the real infrared image. It is generally identified into two main categories, the reference-based non-uniformity correction (RBNUC) and the scene-based non-uniformity correction (SBNUC). RBNUC methods mainly contains two-point correction and multi-point correction methods [2], and etc. These methods employ uniform blackbody as reference irradiance sources to calculate the correction parameter. The advantages of these methods lie in its simplicity and low computational complexity. However, its correction process must be repeated because of the temporal drift of the response characteristic parameter of IRFPA. This procedure may also reduce the reliability of the infrared system and increase its maintenance costs.

On the other hand, the correction parameter of SBNUC usually depends on the information of the imaging scene, which has highly application value. Moreover, the non-uniformity is corrected during the normal operation of the imaging system, which would reduce the operation complexity and avoid imaging interruption. Some SBNUC methods have been proposed over the years, and these methods can be broadly classified into four categories which are the statistics based method, the temporal filtering based method, the registration based method and the optimal estimation based method. Several typical methods of SBNUC are introduced as follow.

(1). The Constant statistics (CS) based method [3] assumes that the temporal mean and variance of each pixel are identical, however it heavily relies on the scene moving and have to spend much time to converge.

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http://dx.doi.org/10.1016/j.infrared.2016.04.037
1350-4495/

(2). The temporal high-pass filtering (THP) based method [4] sets a high-pass filtering in the temporal domain and the FPN will be removed due to its low-frequency characteristic. However, The THP method will remove the static object and cause serious ghosting artifact. Although the spatial low-pass and the temporal high-pass NUC methods [5] apply a solution to solve this problem, the gain of FPN still cannot been removed. Besides, the cut-off frequency of the spatial filter and the temporal filter are difficult to determine as well.

(3). The registration-based method [6,7] considers that different infrared detection elements should have identical response when observing the same scene position and the difference response between them is mainly caused by the FPN. However the accuracy of registration affects the NUC performance seriously. Thus it is hard to employ this approach to correct the imaging scene with a weak infrared radiation or less image detail feature.

(4). The optimal estimation based method mainly contains Neural network based (NN–NUC) [8], Kalman filter based [9,10] and particle filter based [11], and etc. the NN–NUC based methods are widely used because of its better adaptively and noise immunity. However, the traditional NN–NUC would result in ghosting artifact to the moving object and image blurring to static scene, which restrict its application.

Considering the drawbacks of the traditional NN–NUC methods, this paper proposes a novel NUC method based on the combination of an edge-preserve filter and the adaptive learning rate with temporal factor. Several real and simulated infrared sequences are adopted to test its performance, and experimental results indicate that this method can correct the non-uniformity effectively with few FPN residues left. Furthermore, the correction result of this method could be much closer to the real image.

The remainder is organized as follow. In Section 2, the mathematical model of non-uniformity and Scribner's NN–NUC algorithm are discussed. In Section 3, an improved method based on the guided filter to get desired image is proposed. In Section 4, an adaptive learning rate is introduced to protect static scene. In Section 5, the proposed algorithm is applied to several real and simulated infrared image sequences, and the conclusion is given in Section 6.

2. Related work

2.1. IRFPA and fixed pattern noise models

The response of each detection-element in an IRFPA can be approximated as a linear model, which is widely used and accepted. The linear model is defined as

$$x_{i,j}^n = a_{i,j}^n \cdot y_{i,j}^n + b_{i,j}^n \tag{1}$$

where n is the frame number, $x_{i,j}^n$ is the response of the detection-element (i, j), $y_{i,j}^n$ is the real infrared radiation received by the detection-element (i, j), $a_{i,j}^n$ and $b_{i,j}^n$ are the linear model parameters respectively. NUC algorithms aim to acquire the real value $y_{i,j}^n$ by estimating the correction coefficients from the raw value $x_{i,j}^n$.

$$\hat{y}_{i,j}^n = G_{i,j}^n \cdot x_{i,j}^n + O_{i,j}^n \tag{2}$$

where $\hat{y}_{i,j}^n$ is the estimated real radiation value, $G_{i,j}^n = 1/a_{i,j}^n$ and $O_{i,j}^n = -b_{(i,j)}^n / a_{(i,j)}^n$ are the NUC gain and offset correction coefficients respectively.

2.2. Neural network based NUC

In the NN–NUC method, every infrared pixel is treated as a neuron. Through a hidden layer, the pixel can be connected to its surround pixels. By this way, a desired output is estimated by the mean of the four nearest neighbor pixels and fed back to the upper layers of the network to calculate the correction coefficient. As the sense varies, the correction coefficient is updated by the steepest descent algorithm frame by frame in order to get the optimal correction result. The sketch map of the traditional NN–NUC method is indicated in Fig. 1.

In the traditional NN–NUC method, the desired output $f_{i,j}^n$ is estimated by the nearest 4 neighbor pixels.

$$f_{i,j}^n = \left(x_{i,j+1}^n + x_{i,j-1}^n + x_{i+1,j}^n + x_{i-1,j}^n \right)/4 \tag{3}$$

and the error function F is given by (the frame number and the pixel location are omitted)

$$F(G, O) = (G \cdot x + O - f)^2 \tag{4}$$

The steepest descent algorithm is applied to minimize the error function F and the iteration direction is given by the derivative of $F(G, O)$

$$\begin{cases} F_G = \frac{\partial F}{\partial G} = 2x \cdot (G \cdot x + O - f) = 2x \cdot (y - f) \\ F_O = \frac{\partial F}{\partial O} = 2(G \cdot x + O - f) = 2(y - f) \end{cases} \tag{5}$$

In the steepest descent algorithm, the parameters are updated recursively with a portion of each respective error gradient indicated as follows

$$\begin{cases} G_{n+1} = G_n - 2\alpha x(y - f) \\ O_{n+1} = O_n - 2\alpha(y - f) \end{cases} \tag{6}$$

where n is the frame number, α is a small positive parameter which controls the convergence step size.

3. The improved desired output

In summary, NN–NUC is a kind of iteration process which reduces the error function based on the feedback of the hidden layer frame by frame. An accurate desired image can keep the iteration process reducing the error in the right direction, while a rough would increase the correction errors. The traditional NN–NUC adopts the mean value of the four neighbor pixels as the desired output image. Although the mean filter is reasonable in certain smooth areas, it is not suitable for the infrared image with many details (i.e. edges). As the mean filter will cause gradient distortion and lose many detail features where the wrong correction coefficient would be generated. As the scene varies or the object moves in the image, the improper correction coefficient cannot be repaired immediately. As a result, the inappropriate correction coefficient will cause the ghosting artifact on the corrected image.

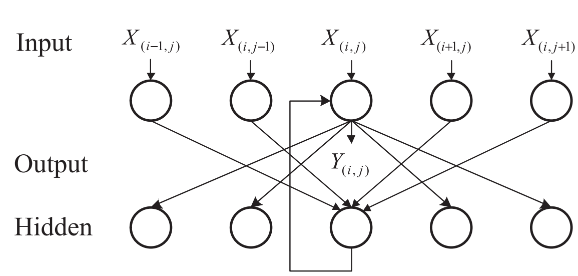

Fig. 1. Sketch map of the traditional NN–NUC method.