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AN INSIGHT OF CURRENT FRAME AND SEQUENCE BASED NON-UNIFORMITY CORRECTION METHODS RELATED TO DIFFERENT APPLICATION SCENARIOS

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ABSTRACT

This paper gives an insight into frame and sequence based non-uniformity correction (NUC) methods for fixed pattern noise (FPN) reduction. The presented methods derive comprehensive literature studies of primarily adaptive sequence based techniques and are contrasted with frame based methods. Thereby different application scenarios, e.g. static scene and camera motion, static camera and scene changes, are considered. The performance of NUC methods can be evaluated by different metrics. Subsequently, an excerpt of performance metrics published in the literature are introduced.

***Index Terms*—** focal plane arrays, infrared image, fixed pattern noise, non-uniformity correction, performance metrics

1. INTRODUCTION

The spatial and temporal non-uniformities in infrared focal plane arrays (IR-FPA) are still not satisfactorily resolved problem on thermal imaging due to different sensitivities of the detectors. The resulting temporally non stationary fixed pattern noise yields in degrading spatial resolution, radiometric accuracy and temperature resolvability. Due to the temporal drift a single initial calibration does not provide a permanent solution. Other calibration methods which need to interrupt the thermal camera's normal operation periodically are also less suitable. However, scene based non-uniformity correction methods operate on single images or image sequences including camera motion and changes in scene respectively, allow a continuous imaging process. Frame based methods e.g. Geometric Filter [1] and Anisotropic Diffusion Filter [2] derived from other noise reduction and edge preserving filter applications are just as suitable as in cases of FPN reduction. Among others, methods processing on image sequences are Constant Statistic/Range [3],[4] and Kalman filter [5],[6] based approaches, as well as least mean square (LMS) [1],[7] and recursive least square [8] algorithms.

This paper is organised as follows. In Section 2 two approaches for sequence based NUC methods, and three approaches for frame based NUC methods are reviewed. Performance metrics for evaluation of NUC methods are described in Section 3. In Section 4 the problems of the methods related to different application scenarios are discussed. The conclusions of the paper are summarised in Section 5.

2. NON UNIFORMITY CORRECTION METHODS

2.1. Frame Based Methods

2.1.1. Morphologic NUC

This method proposed by Rico Nestler, ZBS Ilmenau e.V. realises the reduction of temporal fixed pattern noise with the help of a masked morphological operation. The impact of the fixed pattern noise is determined with the weighted difference between the receptor point and the median result (antimedian). The ranking operation contains sorting and indexing of elements in a defined neighbourhood of a current selected receptor point. Afterwards the median is assigned to this receptor point, if a change condition is fullfilled.

With the aid of a mask the number of included neighbours and thus the filtering results can be controlled according to acertain task and camera. So the type of median and mask should be adapted on the specific fixed pattern noise characteristic.

2.1.2. Geometric Filter

In [1] a geometric filter for speckle suppression is proposed. The filter assumes a simple model of noise instead of a specific noise statistics. It is based on the interpretation of several speckle spots as hills and valleys within the undisturbed signal. In consideration of their convex hull, these valleys and hills should be stepwise filled and removed. The filter process is an iterative process where the value of the current central pixel will be interrelated with its neighbourhood by a fixed policy. A modified version of Geometric Filtering was developed at ZBS Ilmenau e.V., these includes a varying step size and an adapted policy.

2.1.3. *Anisotropic Diffusion Filter*

This technique [2] is derived from the physical process of diffusion (compensation of a substance concentration) in an anisotropic medium.

$$\frac{\partial u(x,y,t)}{\partial t} = \frac{\partial c(x,y)\cdot u_x(x,y,t)}{\partial x} + \frac{\partial c(x,y)\cdot u_y(x,y,t)}{\partial y} \quad (1)$$

Using of this principle for adaptive image filtering, the substance compensation parameter at location $u(x,y)$ corresponds to the pixel value at location $u(i,j)$. The control parameter $c(x,y)$ corresponds to $c(i,j)$ based on the actual state of current image position. The filter works without reducing details e.g. lines or edges that are important for the interpretation of the image.

For the fixed pattern noise reduction an adaptation of the algorithm is realised. The pixel value calculation takes pixels at varying distances into account, instead of its direct neighbours.

2.2. Sequence Based Methods

The methods described in the following subsections are based on a statistical linear model for the detector response.

$$Y_n = T_n A_n + B_n + N_n \quad (2)$$

where Y_n is the read-out signal, A_n and B_n are the gain and the offset and T_n is the irradiance at time n collected by the detector during the detection integration time. The term N_n represents the additive read-out noise. Its estimation in this paper is not taken into account. Note that the model and all following operations are performed on a pixel-by-pixel basis.

2.2.1. *Constant Range*

The key assumption in the Constant-Range NUC method is that within each sequence of frames, all detectors are exposed to approximately the same range $[T_{min}, T_{max}]$ of irradiance. It is assumed that the irradiance is an uniformly distributed random variable, so the mean and variance of the irradiance can be estimated.

In the following a modified Constant Range method [1],[3],[4] is selected to demonstrate the estimation of the parameter Gain and Offset, without considering the temporal noise.

$$A_n = \sqrt{\frac{\sigma_Y^2}{\sigma_T^2}} \quad (3)$$

$$B_n = \mu_{Y,n} - A_n \mu_{T,n} \quad (4)$$

The algorithm subsequently computes the mean and variance of read-out data. The adaptation is based on a comparison between the per-pixel-difference of the current and the previous read-out data and a threshold value. If the difference is greater than the threshold, the algorithm employs an exponential windowing estimation:

$$\mu_{Y,n} = E[Y_n] = (1-\alpha)\cdot Y_n + \alpha \cdot E[Y_{n-1}] \quad (5)$$

$$\sigma_{Y,n} = (1-\alpha)\cdot |Y_n - E[Y_n]| + \alpha \cdot \sigma_{Y,n} \quad (6)$$

where $\alpha, 0 < \alpha < 1$ is the time constant. If no significant change is observed the algorithm uses:

$$\mu_{Y,n} = E[Y_n] = \frac{Y_n + (n-1)\cdot E[Y_{n-1}]}{n} \quad (7)$$

$$\sigma_{Y,n} = \frac{|Y_n - E[Y_n]| + (n-1)\cdot \sigma_{Y,n-1}}{n} \quad (8)$$

2.2.2. *Kalman filter*

The Kalman filter‘s theory [5] [6] uses a state-space representation, and therefor equation (2) must be rewritten as

$$Y_n = H_n X_n + N_n \quad (9)$$

where $H_n = [T_n \; 1]$ is a observation vector with T_n containing the unknown irradiance value of detector and can be estimated in different ways (e.g. constant range assumption [6] or lowpass filter [5]). $X_n = [A_n \; B_n]^T$ is the state vector containing the gain and the bias at frame n.

The state equation is modeled by a gaussian markov model (GMM) and describes the drift of gain and bias between frame $n-1$ and n:

$$X_n = \Phi X_{n-1} + W_{n-1} \quad (10)$$

where Φ is a 2×2 transition diagonal matrix between the frames. The diagonal elements are the drift parameters α and β. They are assumed to be constants close to one. W_n is the GMM‘s driving noise.

Based on this theory the state vector X_n is estimated by the following Kalman filter algorithm. The first part is the a priori estimation of the state vector $\hat{X}_n^-$ and the error covariance matrix P_n^-, where M and Q are the covariance matrices of driving and additive noise, respectively.

$$\hat{X}_n^- = \Phi \hat{X}_{n-1} + M \quad (11)$$

$$P_n^- = \Phi P_{n-1} \Phi^T + Q \quad (12)$$

The second part is the a posteriori estimation. This includes estimation of Kalman Gain K_n:

$$K_n = P_n^- H_n^T (H_n P_n^- H_n^T + R)^{-1} \quad (13)$$

and

$$\hat{X}_n = \hat{X}_n^- + K_n(Y_n - H_n \hat{X}_n^-) \quad (14)$$

$$P_n = (I - K_n H_n) P_n^- \quad (15)$$

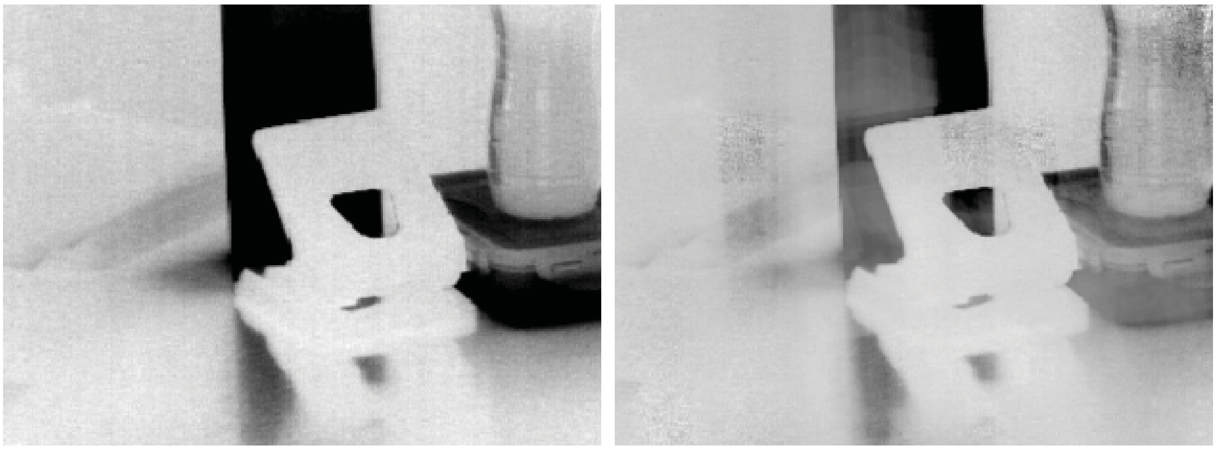

Fig. 1. Constant Range Method, Original Image(left), Corrected Image (right)

where $\hat{X}_n$ and P_n are the estimated states and error covariance matrix at time n. R is the covariance matrix of the additive noise and I represents the identity matrix.

3. PERFORMANCE METRICS

In order to evaluate the performance of NUC methods different metrics are presented in the literature [7], [9], [10], [11], [12]. The metrics are cabable of evaluating the performance of a single NUC algorithm; however, they are not able to compare different NUC methods.

3.1. Root Mean Square Error (RMSE)

This metric [10] is only applicable to real non-uniformity infrared data, if existing related reference data T_{ij} (an IR sequence calibrated with black bodies) to corrected $\hat{T}_{ij}$ frames. The same applies to the calculation of the PSNR, based on calculation RMSE:

$$RMSE = \frac{1}{N \cdot M} \sqrt{\sum_{i=1}^{N} \sum_{j=1}^{M} \left(T_{ij} - \hat{T}_{ij} \right)^2} \tag{16}$$

$$PSNR = 20 \cdot \log_{10} \left(\frac{2^b}{RMSE} \right) \tag{17}$$

3.2. Universal Image Quality Index Q

The index Q [11] requires reference images respectively and models any image distortion with help of three factors; loss of correlation, luminance distortion, and contrast distortion. It is defined as:

$$\begin{aligned} Q &= \frac{4\sigma_{xy}\bar{x}\bar{y}}{(\sigma_x^2 + \sigma_y^2)(\bar{x}^2 + \bar{y}^2)} \\ &= \frac{\sigma_{xy}}{\sigma_x \sigma_y} \cdot \frac{2\bar{x}\bar{y}}{\bar{x}^2 + \bar{y}^2} \cdot \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2} \end{aligned} \tag{18}$$

The dynamic range of Q is $[-1\ 1]$, where $+1$ represents the best performance. It can be achieved if the reference image x and the corrected IR image y are identical.

3.3. Roughness Index ρ

This performance metric [7] is commonly used in scenarios where no reference images are available. It measures the pixel-to-pixel roughness of an image in horizontal and vertical direction and is defined by

$$\rho(F) = \frac{\|h \otimes F\| + \left\|h^T \otimes F\right\|}{\|F\|} \tag{19}$$

where h is the spatial mask $[-1\ 1]$, the asterisk denotes discrete convolution, F is the image and $\|F\|$ is its L1 norm. The closer the index to 0, the better is the performance of the corrected image.

Effective-Roughness Index ERo

An optimisation of the performance index ρ [12] is achieved by a pre-processing step to amplify the high spatial frequencies. That means filtering of the image F with a Laplacian or Sobel operator g.

$$ERo(F) = \rho(g \otimes F) \tag{20}$$

3.4. Hysteresis - Mean Absolute Difference (MAD)

This method described in [9] is based on the calculation of the mean absolute error (MAE). If the reference images are not known for the infrared data the central frame is estimated in two different ways. It is only possible for image sequences. One estimate is formed using the previous frames, while the other estimate is formed using the following frames in reverse order. In the best case both estimates would be identical and equal to the true central image. Differences between both estimates represents a type of hysteresis or inconsistency for the NUC algorithm.

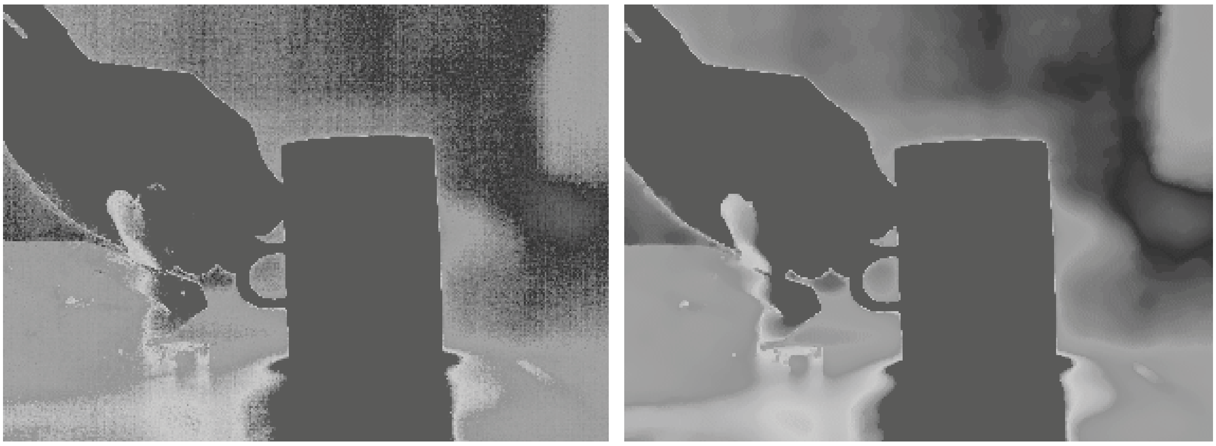

Fig. 2. Morphologic Filter, Original Image(left), Corrected image with 3 steps (right)

4. DISCUSSION

Frame based methods process single images whereas sequence based methods process image sequences. With respect to the implementation in an infrared camera system, this implies sequence based methods need a certain amount of time at the beginning to operate correctly. This is caused by the necessity of estimating of the initial parameters with the aid of a initial frame sequence. The length of the required starting time depends on the d method. The initial condition for correcting image sequences expect an initial gain and bias estimation. For example this can be achieved by the assumption of constant range $[T_{max}, T_{min}]$and the calculation of the mean of $[Y_{max}, Y_{min}]$ about an initial frame sequence [7]. In contrast from frame based methods operate correctly with the first frame.

Sequence based methods are mainly efficient in application scenarios where motion occurs, e.g. static scene and camera motion, static camera and scene changes. Therefore they sufer from typical problems like ghosting artifacts. These artifacts generally results due to non uniformly motion, that means temporally slowing or stopping across the image. Figure 1 shows an example to illustrate problems that appear in sequence based algorithms. Ghosting artifacts are visible on the black object in the middle and the box in the right. It is also noticeable that additive noise is not reduced. An approach for removing ghosting can be found in [4].

For the frame based approaches camera motion or scene changes are irrelevant. The result of a morphological filtering is shown in Figure 2, the results of an anisotropic diffusion filtering and a geometric filtering are depicted in Figure 3. These approaches provide a good reduction of FPN. However, a compromise between preserving lines and edges in the image and a satisfactory result for FPN reduction must be found. An advantage is the simultaneous correction of additive noise.

Another point that should be noted is the real-time capability of the algorithms, especially in the case of implementation in an infrared camera system where memory and computation power are limited. At this time, no reliable statement about real-time capabilities of the methods can be made besides theoretical derivable space and computation boundaries. Therefore, all algorithms have to be implemented and tested on the same camera system. Generally it can be assumed, that methods that converge very slow and require many iterations to reduce the noise, e.g. [2], [6] are not able to operate in real-time.

The performance metrics presented in this paper are usable as evaluation of a single NUC algorithm, e.g. the comparison of different parameters within the algorithm. The comparison of different NUC method by using the metrics is not significant. Therefore should be the visual impressions. Within a single NUC method, the results of the performance metrics can differ from visual impressions. Examples and more information can be found in [4], [9].

5. CONCLUSION

In this paper a selection of adaptive frame based and sequence based NUC methods are presented and the approaches are compared in an informal way. Problems that can occur in different application scenarios using different methods are introduced. In addition performance metrics for evaluating the methods are summerised.

6. ACKNOWLEDGMENTS

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Fig. 3. Anisotropic Diffusion (AD) and Geometrical Filter (GF) , Original Image(above), Corrected image AD with 10 iterations(bottom left), Corrected image GF with 4 iterations(bottom right)

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