A New Reference-free Infrared Image Quality Metric for Nonuniformity Correction

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ABSTRACT

Infrared imaging suffer from an undesired fixed-pattern noise mainly due to the response disparity of the individual detectors in a focal-plane array. Even though this nonuniformity noise can be removed after a blackbody calibration procedure, it tends to reappear due to the intrinsic nature of infrared sensing. Online nonuniformity correction techniques have been employed for denoising and tracking the drift, also avoiding to halt normal camera operations. In this paper, a new reference-free infrared imaging quality metric is presented. The main purpose of the proposed metric is to evaluate the quality of the denoised infrared images in real-time, exchanging the typical need of calibration sources by the knowledge of the fixed-pattern noise statistics. We compare the performance of the proposed metric against standard reference-based and reference-free metrics, using a variety of real-time nonuniformity correction techniques. Results show that the new metric is able to track the nonuniformity correction performance, constantly evaluating the quality of the denoised infrared image sequences.

Keywords: Image Quality Index, Nonuniformity Correction, Infrared Focal Plane Arrays, Image Enhancement, Infrared Imaging Systems.

1. INTRODUCTION

Fixed-pattern noise (FPN) is a serious and undesired problem found in infrared focal-plane array (IRFPA) cameras, despite of the advances in fabrication techniques. The FPN is caused by the differences of the photoresponse between detectors in the FPA, even when they measure an uniform radiation level. The main problem with the FPN is that it degrades the quality, accuracy and resolving power of the captured data. This affect their applicability in several situations, such as in pattern recognition. Moreover, the FPN tends to drift slowly in time, thus a single calibration procedure may not suffice.

In order to remove the FPN, several nonuniformity correction (NUC) techniques have been developed throughout the years. The typical mathematical model for the IRFPA is presented as follows: for the $(ij)^{th}$ detector in the array we have that

$$Y_{ij}(n) = A_{ij}(n)X_{ij}(n) + B_{ij}(n) + V_{ij}(n) , \quad (1)$$

where $Y_{ij}(n)$ is the readout data and $X_{ij}(n)$ is the true input irradiance captured during the n-th frame. $A_{ij}(n)$ is associated to the gain of the detector, mainly due to the responsivity, and $B_{ij}(n)$ is associated to the offset of the detector, mostly related to the dark current. Finally, $V_{ij}(n)$ represents the temporal noise, typically introduced at the readout electronics stage.

Considering the affine model given in Eq. (1), if we take a pair of images for two different but constant temperatures, namely T_1 and T_2, we can compute the parameters associated to each $(ij)^{th}$ detector, and thus compensate for them. This NUC correction procedure is known as two-point calibration (TPC), where the nonuniform gain and bias parameters can be obtained by

$$A_{ij} = \frac{Y_{ij}^{T_2} - Y_{ij}^{T_1}}{X_{ij}^{T_2} - X_{ij}^{T_1}} \qquad B_{ij} = Y_{ij}^{T_2} - A_{ij} \ X_{ij}^{T_2} . \quad (2)$$

The TPC technique is the most effective option to compensate for the FPN, in despite of being a reference-based method that needs to halt the normal camera operation and make use of expensive black-body radiators.

As an alternative to the reference-based NUC methods such as TPC, exist the scene-based NUC algorithms. Such algorithms estimate the nonuniformity parameters, i.e. gain and offset, by using the information and statistics provided by the readout video sequence. This estimation is made using block of frames or in a frame-by-frame basis. Special interest has been received by frame-by-frame methods that allow to perform the estimation of the nonunifmormity parameters and the compensation for the FPN in real time. Within these methods, Harris *et. al* in [1] developed a recursive version of the constant statistics NUC technique that was presented before by Narendra *et. al* in [2]. The parameters are estimated as follows:

$$
\begin{aligned}
B_{ij}(n+1) &= \hat{\mu}_{Y_{ij}}(n+1) \quad (3) \\
&= \frac{Y_{ij}(n+1) + n\hat{\mu}_{Y_{ij}}(n)}{n+1} \\
A_{ij}(n+1) &= \hat{\sigma}_{Y_{ij}}(n+1) \\
&= \frac{|Y_{ij}(n+1) - \hat{\mu}_{Y_{ij}}(n+1)| + n\hat{\sigma}_{Y_{ij}}(n)}{n+1}
\end{aligned}
$$

Using a different approach based on neural networks, Scrib-

ner *et. al* [3], [4] developed an adaptive retina-like approach for estimating the NU parameters while simultaneously correcting for the FPN. By using the inverse model of Eq. (1) for each detector, $\hat{X}_{ij}(n) = \hat{G}_{ij} Y_{ij}(n) + \hat{O}_{ij}$, the input irradiance $\hat{X}_{ij}(n)$ is constantly calculated while the parameters $\hat{G}_{ij}$ and $\hat{O}_{ij}$ are recursively updated using the steepest descent algorithm:

$$\hat{G}_{ij}(n+1) = \hat{G}_{ij}(n) - \eta\, E_{ij}(n) Y_{ij}(n) \qquad (4)$$
$$\hat{O}_{ij}(n+1) = \hat{O}_{ij}(n) - \eta\, E_{ij}(n) , \qquad (5)$$

where η is a fixed parameter known as the learning rate, and $E_{ij}(n)$ is the error calculated between the estimated input irradiance, $\hat{X}_{ij}(n)$ and a desired target, $T_{ij}(n)$. This target is typically set as a local spatial average of the estimated irradiance $\hat{X}(n)$. The parameters $\hat{G}_{ij}(n)$ and $\hat{O}_{ij}(n)$ are related to the desired gain and bias as follows: $\hat{A}_{ij}(n) = \hat{G}_{ij}(n)^{-1}$, and $\hat{B}_{ij}(n) = -\hat{O}_{ij}(n)\hat{G}_{ij}(n)^{-1}$.

A modification to this algorithm was later presented in [5], where an enhanced parameters balance is obtained by using an adaptive learning rate $\eta_{ij}(n)$ schedule that accelerates the convergence of the estimation process, defined as:

$$\eta_{ij}(n) = \frac{k}{1 + \sigma_{Y_{ij}}(n)} \qquad (6)$$

where $\sigma_{Y_{ij}}(n)$ is the local spatial standard deviation of the input image, and k is a constant.

Unfortunately, the performance of any scene-based NUC method can only be properly measured by comparing the denoised images, or the corresponding estimated NUC parameters, with the ones obtained by the TPC method, thus needing blackbody radiators. However, in order to avoid the use of calibration sources, as it is the aim of any scene-based NUC method, we need to employ some blind metric that allows to have a good perception of the quality of the denoised images. To the best of our knowledge, the used reference-free index is the roughness, which is based on a measure of the rugosity found on the denoised images. Even though it is a suitable and useful reference-free indicator for NUC purposes, it is not a categoric metric regarding the quality of the corrected images and its radiometric accuracy.

Based on this fact, we present a novel alternative to evaluate the NUC performance achieved in real-time by also only using the denoised images. The idea is based in measuring the distance between the expected distribution of the FPN and the real distribution estimated by the NUC method. In this way, instead of needing all the NU parameters, we only request the knowledge about their first and second order statistical moments, which can also be estimated from the data. In this way, the proposed NUC quality index allows to calibrate the parameters and compare the performance of any NUC algorithm by tracking its real-time evolution, without the requirement for calibration sources nor naked-eye evaluation.

This paper is organized as follows. In Section 2 we briefly review the image quality metrics and we expose some of they weakness in assessing the FPN. Next in Section 3 we introduce the new reference free index. The ability of the index to rank the results achieved by different NUC methods is demonstrated using IR video sequences in Section 4. Finally, in Section 5 we present the conclusions and some discussions of our work, and we indicate prospective paths for future work.

2. OBJECTIVE IMAGE QUALITY ASSESSMENT

Image quality measures are figures of merit used in the evaluation of imaging systems. The performance evaluation of a NUC method with or without a laboratory calibration data is a very complex task. In addition, a reference set of images is not always available for comparison purposes. For that reason, different metrics have been developed in order to evaluate the NUC performance. Such metrics point to several quality objectives such as pixel difference, correlation measure, edge quality, spectral distance, context measure, etc.

In general, the most effective way to address the NUC performance of a algorithm under study, is by means of quantitative measures. The MSE and the Improvement in Signal-to-Noise Ratio (ISNR) are widely used to asses image quality of any imaging system, and, of course, they are also used in NUC algorithm comparisons. Let us assume that an image $S = \{s_{ij}, i = 1, \ldots, p; j = 1, \ldots, m\}$ is corrupted in some way, generating the corrupted image $C = \{c_{ij}, i = 1, \ldots, p; j = 1, \ldots, m\}$. If we have an estimation of the non-corrupted image, $\hat{S} = \{\hat{s}_{ij}, i = 1, \ldots, p; j = 1, \ldots, m\}$, the MSE and the ISNR are given by, [6]

$$MSE(S, \hat{S}) = \frac{1}{p\,m} \sum_{i=1}^{p} \sum_{j=1}^{m} (s_{ij} - \hat{s}_{ij})^2, \qquad (7)$$

$$ISNR = 10 \log \frac{MSE(S, C)}{MSE(S, \hat{S})} . \qquad (8)$$

The main problem with both the MSE and the ISNR is that they require a reference-image, S, to assess how good is the estimation process. Taking this point into the NUC problem, we need to perform the TPC in order to obtain the uncorrupted image, which is not always possible. Correctly, the NUC capability is measured without using a reference by means of the roughness parameter of an estimated image, $\hat{S}$, ρ, that is defined by

$$\rho(\hat{S}) = \frac{\left\| h * \hat{S} \right\|_1 + \left\| h^T * \hat{S} \right\|_1}{\left\| \hat{S} \right\|_1}, \qquad (9)$$

where h is a horizontal mask $[1, -1]$, $\|.\|_1$ is the L_1 norm, ^{T} is the transpose, and $*$ represents the discrete convolution. Note that $\rho(\hat{S})$ is zero for a uniform image and increases with the detector-to-detector variations in the image $\hat{S}$. Moreover, ρ can be used as a measure of NUC in real infrared data as well as simulated data. This index can only show if the correction is producing a smooth image or not, leaving out any radiometric modifications. For this reason is not a really useful metric, because must be used in conjunction with a naked-eye evaluation.

3. REFERENCE-FREE INFRARED QUALITY INDEX

The NU problem comes from both bias and gain disparities in the IRFPA. Accordingly with the literature and our experience, the gain nonuniformity is considered to be known and having a small spectral variation. As a consequence, in several NUC methodologies the gain is considered simply as a fixed variable equal to one as in [8]. Therefore, the FPN can be solely modeled as an additive noise, where a Gaussian distribution with fixed variance over the whole dynamic range of operation can be assumed.

In addition to producing dynamic range deviations, NUC methods typically generate ghosting artifacts while reducing the original FPN content. This problem also degrades the quality of some corrected images, introducing image structures into the estimated FPN statistical distribution, that differs from any expected canonical distribution. Thus, the basic idea behind the proposed Reference-Free Infrared Quality Index (RIQI) is to compare the noise distribution found after applying any NUC method, with the expected theoretical noise distribution. This is performed by measuring the difference (i.e. distance and shape) of the probability mass function (pmf) between the expected FPN distribution and the measured FPN.

The RIQI can be defined considering that in any metric vector space the inequality $|a - b| \leq |a| + |b|$ holds for any two points a and b. Then, we can easily note that the ratio between $|a - b|$ and $|a| + |b|$ will be always in the interval $[0,1]$. Using this ratio and recalling that we need to compare probability distributions, we can define our quality index

$$RIQI \triangleq \frac{\sum_{n=1}^{k} |p_N(n) - p_E(n)|}{\sum_{n=1}^{k} |p_N(n)| + \sum_{n=1}^{k} |p_E(n)|} , \quad (10)$$

where $p_N(n)$ is the histogram that follows the noise distribution generated by the FPN, and $p_E(n)$ is the histogram of the additive NU noise estimated by the NUC method, i.e. $E = Y - \hat{X}$. (Recall that the gain is assumed to be one.)

From our experience over several cameras that were fabricated using different technologies, the noise histogram, $p_N(n)$, can assumed as the histogram of a Gaussian distribution that follows the real noise statistics. Then, the vestigial noise $E = Y - \hat{X}$ will follow a Gaussian-like statistical distribution, i.e. $E \sim f(b, \theta)$ were θ define the parameters of such distribution.

The RIQI varies between 0 and 1, being 0 the best case of adjustment between distributions, and 1 for the opposite case. Using this information, the proposed metric is capable of: (i) perform a comparative evaluation of the level of NU that is being compensated by the NUC method under study, (ii) follow the behavior of the NUC algorithm and evaluate the radiometric stability of the corrected images in compare with the original data, and (iii) quantify the modifications in the dynamic range, the modifications in the image structure and time evolution of the NUC, since is performed in a frame-by-frame basis.

4. RESULTS OVER SIMULATED NOISE

In order to quantify the RIQI abilities, we present results over simulated FPN, providing us the real image and the corrupted frame. The estimation process is performed using tree classical methodologies: the recursive version of the constant-statistics method (RCS) [1], the Scribner NUC algorithm (SNA) [3], and the enhanced Scribner method (ESNA), [5]. The capabilities of our index are quantified using the reference-based quality indexes MSE and ISNR, [6], and the reference index roughness, [7].

We use the statistics of the FPN estimated from a camera as a guide to establish the levels of noise in our simulations. The results under this scenario are presented in the Fig. 1.

From these results it can be noted that our metric is capable to show the adaptation process of the SNA and the radiometric adaptation of the correction, approaching to zero accordingly with the NUC behavior. This important result cannot be obtained from the roughness index.

The ISNR curve indicates that the Harris correction was suffering an error in the parameters calculation during the first frames. This is because the image was lacking of variability, but it fails to show the same problem with the Scribner's algorithm, instead the RIQI present the expected behavior of the correction in that conditions.

In the presented results we can identify two points in the curve, where the roughness index has local minima that allow us to show interesting conclusions. Such frames are the 1420 and 2880. The set of images for the frame 1420 are show in Fig. 2

Clearly, it can be observed that a better correction product of the number of frames used to estimate the parameter and the movement of the scene, which is represented by the behavior of the RIQI.

The set of data is almost running out of frame 2830 but it shows that the enhanced Scribner correction achieves a better stability during the observed images, product of visual corroboration of the NUC and the RIQI evolution curve.

5. CONCLUSIONS

In this work we presented a novel reference-free quality metric for NUC. We based our metric in order to solve a constant problem that we had during developments of our own NUC algorithms. The problem is that the reference imagery is commonly unavailable in order to use the reference-based metrics that are the best alternative when you need to rank the NUC capabilities achieved by any particular method. In addition, the reference-free metrics that can be found in the literature are commonly designed for images captured in the visual-range and present the problem that they require a naked-eye evaluation in order to assess the correct interpretation of such metric.

As a big difference with classical metrics used in NUC research, our metric can track the time evolution of any NUC algorithm under evaluation. The presented curves indicate that RIQI can clearly track the variations in the dynamic range
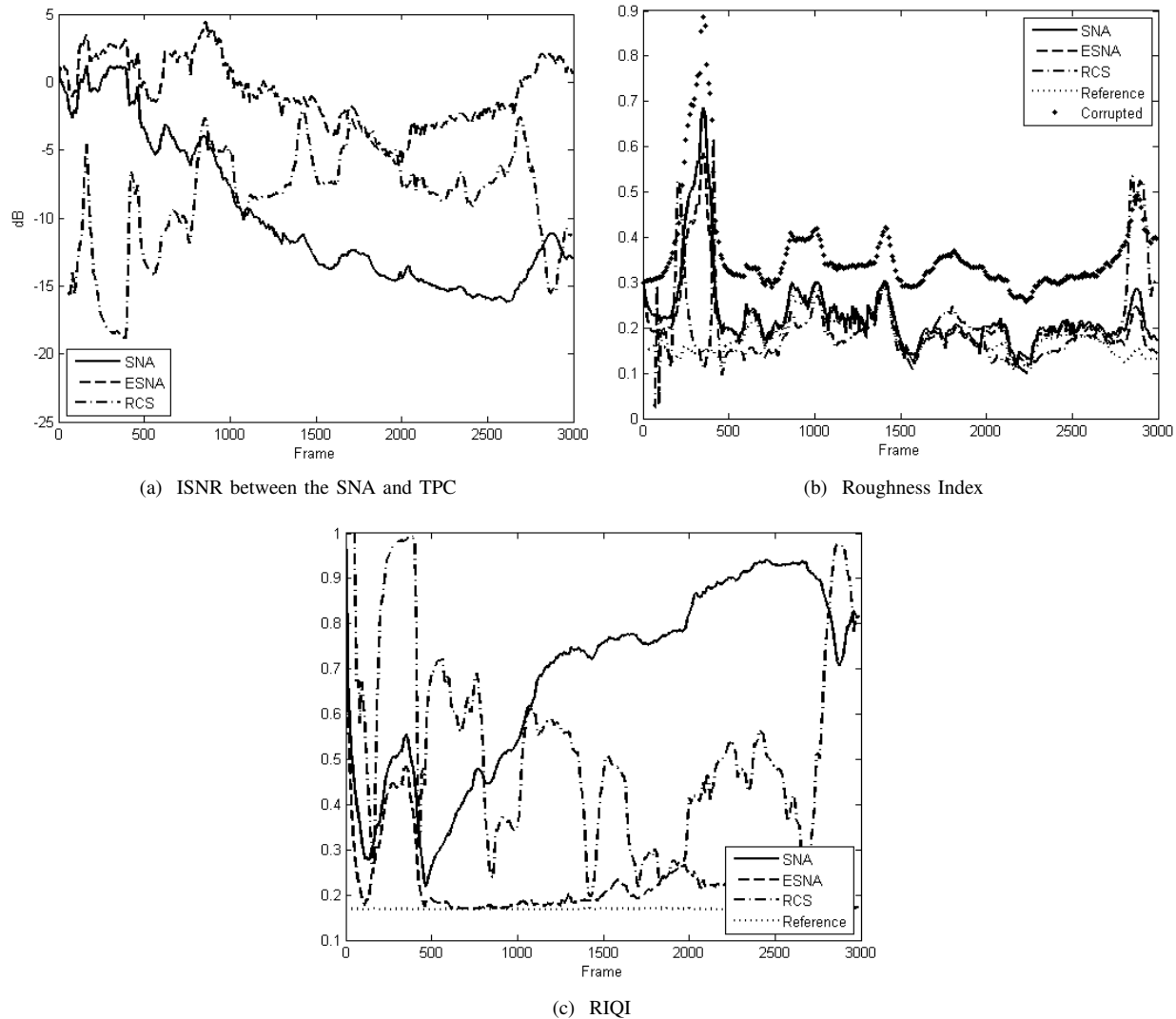
(a) ISNR between the SNA and TPC

(b) Roughness Index

(c) RIQI

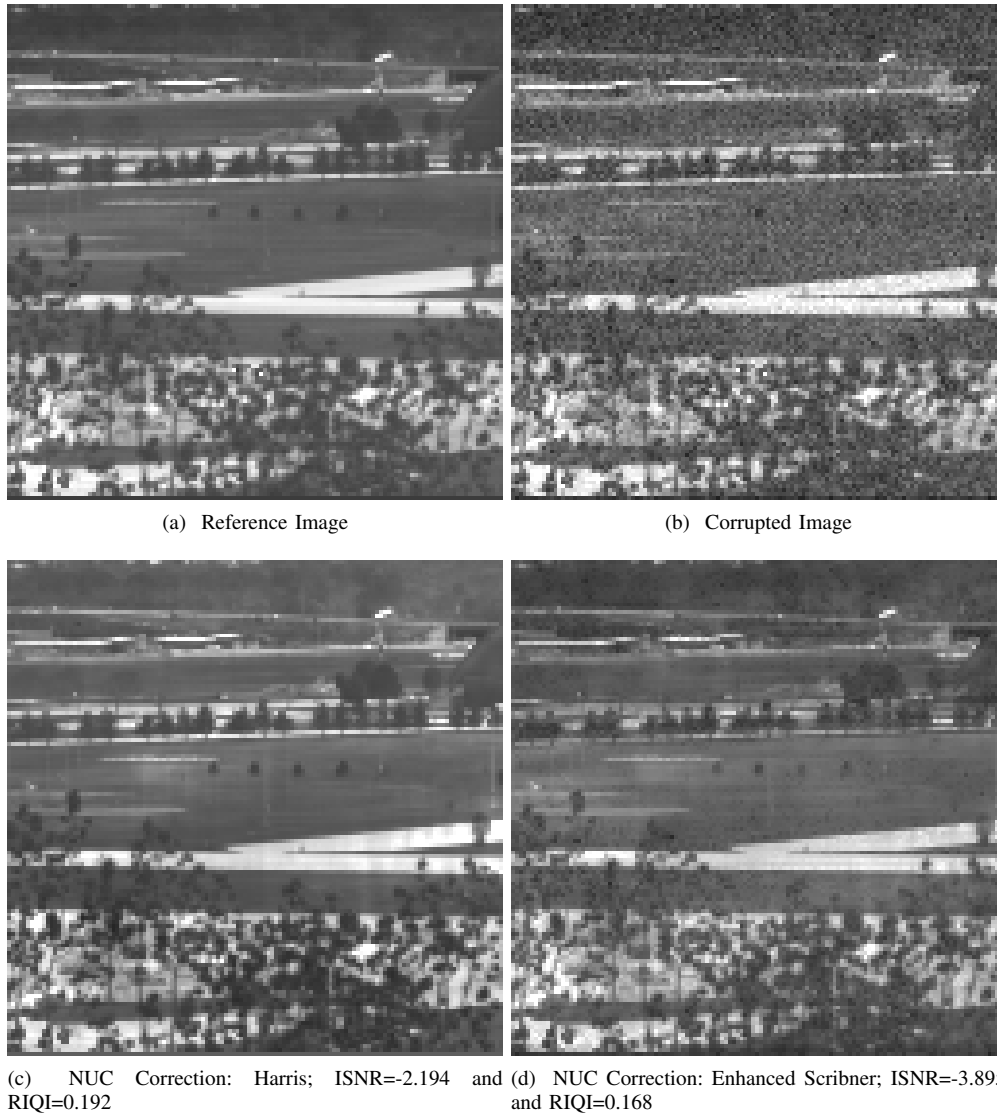**Fig. 1**. Different methods and NUC-quality indexes over a block of 3000 frames.

after the estimation process. We must point out that a main difference between our metric and the roughness index is that RIQI works over the vestigial noise instead of the estimated images. This fact is of major importance since if the estimation process gives rise to a flat image, which means that the correction does not work properly, our index will quantify it and the roughness will not.

6. ACKNOWLEDGMENTS

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(a) Reference Image
(b) Corrupted Image

(c) NUC Correction: Harris; ISNR=-2.194 and RIQI=0.192
(d) NUC Correction: Enhanced Scribner; ISNR=-3.895 and RIQI=0.168

Fig. 2. Set of images obtained at frame 1420 of the video sequence.

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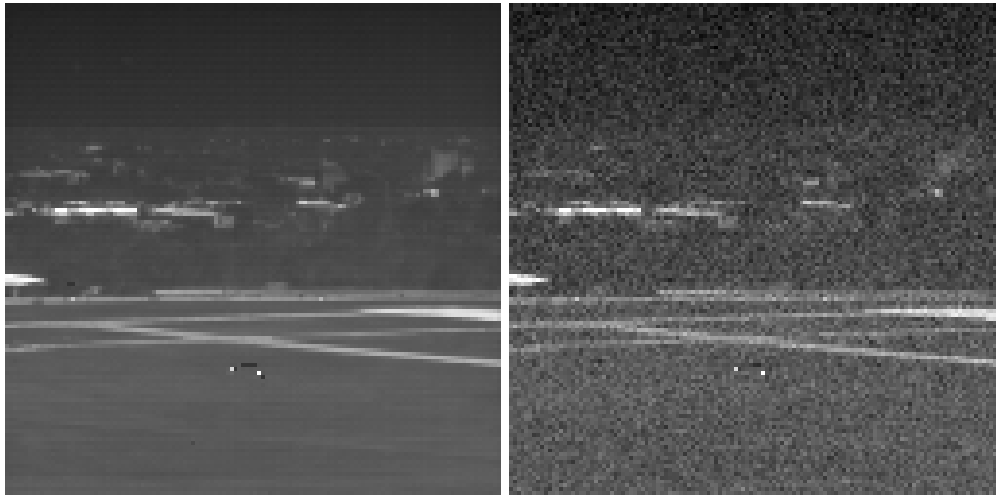
(a) Reference Image

(b) Corrupted Image
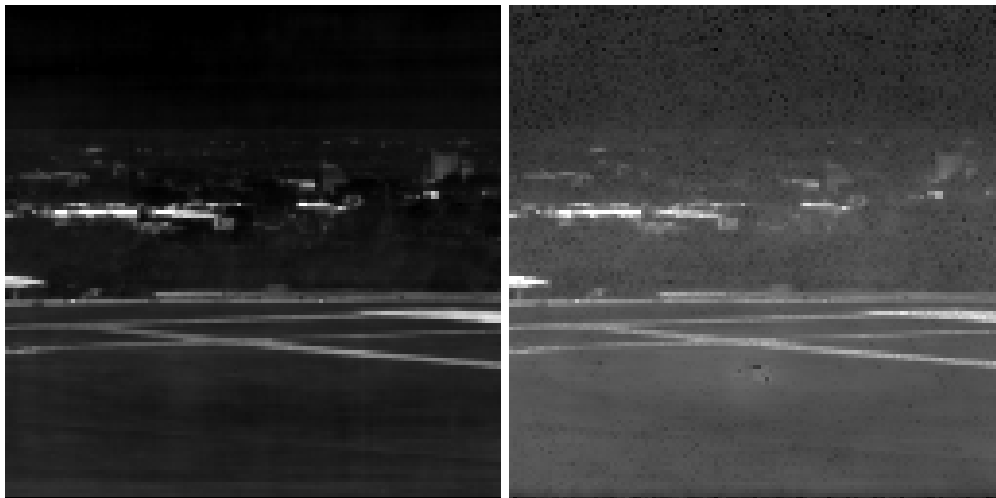
(c) NUC Correction: Harris; ISNR=-12.560 and RIQI=0.892

(d) NUC Correction: Enhanced Scribner; ; ISNR=2.214 and RIQI=0.191

Fig. 3. Set of images obtained at frame 2830 of the video sequence.