Current Trends in Technology and Science
ISSN : 2279-0535
8thSASTech 2014 Symposium on Advances in Science & Technology-Commission-IV Mashhad, Iran

Extraction of Imaging Sensors Temporal Noise Curve Through Segmentation of Non-uniform Targets and its use in an Innovative Adaptive Filter

Mohammad Reza Mobasheri[1]
Ali Rabiee[2]
1. Department of Remote Sensing Engineering, KNToosi University of Technology
(Mobasheri@kntu.ac.ir) (corresponding author)
2. Master's Student at Khavaran Institute of Higher-education (KHI)
(ali.rabiei520@gmail.com)

Abstract — Noise can severely damage the data contained in the images. To remove these noise from digital images, firstly the nature of the noise is must be recognized, then it can be removed from the image either based on the location or frequency procedures. In the approach proposed in this paper, a method for estimating the temporal noise in raw data obtained from imaging sensors with CCD and CMOS detectors is suggested. The method is based on the automatic segmentation of non-uniform targets. Unlike conventional methods such as ISO 15739, in which a special known charts for imaging and noise estimation is required, this technique takes advantage of automatic segmentation; therefore, it does not need uniform and known targets, special laboratory isolation and uniform illumination over the entire target. In this paper, an innovative adaptive filter is proposed for noise reduction in digital images. This filter uses the estimated noise curve to significantly reduce noise in the images. Finally, the performance of the proposed adaptive filter in reducing noise is compared with that of conventional filters using two parameters of MSE and PSNR. Results show that the proposed filter has a better performance in reducing noise with different variances.

Keywords — digital imaging sensor, noise estimation, temporal noise curve, adaptive filter

1. INTRODUCTION

Presence of noise in digital images is inevitable and can pose problems in extracting information from images. Several factors can cause noise in the imaging sensors. Some noise is caused by electronic circuits and some comes from surrounding sensors like the unwanted electromagnetic waves, sensor environment heat and atmospheric effects in satellite imagery. Electronic parts of satellite sensors are prone to high degrees of noise due to overheating and their inability to quickly transfer heat. Due to lack of access to satellite sensors, noise estimation is done using images captured. Removing noise from digital images is one of the main objectives to improve image data. In a classification, digital image noise (satellite and digital camera images) are divided into two categories. The first is fixed-pattern noise (FPN) which varies in the sensor cells and is an offset variation of pixel outputs in transition curves and often has a consistent pattern in the image array[1]. The second is temporal noise which is the result of the non-uniform response of a detector to constant illumination over time [2][3]. The filter used to remove or reduce noise depends on the nature and type of the noise. However, the process follows the following general pattern.

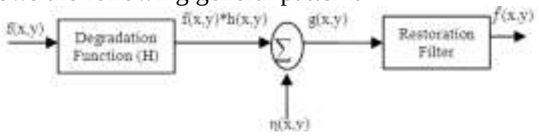


Fig. 1. General pattern of noise removal

To remove noise from digital images, first the nature of the noise must be recognized, then noise can be removed from the image through procedures involving either location or frequency. On the other hand, adaptive filter algorithms can be applied to the raw data generated by non-advanced and noise-vulnerable sensors to achieve an image with a quality comparable to those captured by advanced sensors [4]. A requirement for optimal use of this technique for improving image quality is that of recognition and estimation of the noise components which in turn shows the importance of addressing noise estimation[5][6]. Temporal noise leads to fundamental limitations in performance of the imaging sensor, particularly in low illumination and in video applications [4]. In imaging sensors with CCD detectors, temporal noise is mainly due to the photo detector shot noise, the output amplifier thermal and 1/f noise. Due to the additional pixel and column amplifier transistor thermal and 1/f noise, CMOS image sensors have higher noise than CCDs [2] [3][4][7].

1.1 Overview of Temporal Noise Estimation Through ISO15739

In the proposed approach in this paper, a method is suggested for estimating noise in the raw data obtained from imaging sensors with CCD and CMOS detectors. Unlike conventional method of ISO 15739 ([4] [8]), which require special known charts for imaging and noise estimation, this technique takes advantage of automatic segmentation; therefore, it does not need uniform and known targets, special laboratory isolation and uniform illumination over the entire target. Furthermore, unlike previous methods in which obtaining noise of a certain sensor at any illumination level requires a separate test, the method suggested in this study uses only one test to obtain sensor noise curve for a wide range of illumination levels. In summary, this method has the following advantages over previous methods:

1. It does not need a specific and already known target. In fact any fixed target or landscapes can be used.
2. It does not require calibration before measurements.
3. There is no need for uniform illumination over the entire target. Only the illumination intensity should be constant over time.
4. Fixed pattern noise has no effect on the temporal noise measurements.
5. Only one test can be used to achieve standard deviations for all parts of the image (DNs).
6. This method does not require advanced laboratory, isolation and advanced light source.

In this paper, a novel method is suggested for measuring the temporal noise in raw data obtained from imaging sensors with CCD and CMOS detectors. This method is specifically designed so that it can estimate the variance function representing the dependence of noise on signal received from the raw data. This method presents the noise standard deviation as a function of expected values of the output. Fig. 2.showsthe chart used in ISO15739.

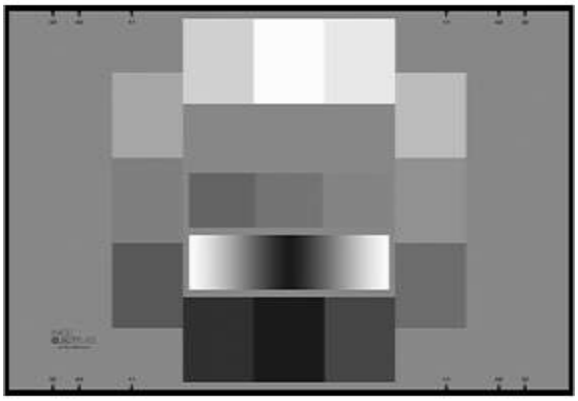


Fig. 2.the chart used in ISO15739 method for estimating imaging sensor noise [8]

1.2 Overview of Local Noise Reduction Adaptive Filter

The simplest statistical measures of a random variable are its mean and variance. Because these components are related to the appearance of an image, using them to construct an adaptive filter is logical. The mean represents the average illumination intensity in the area where the mean is calculated and the variance represents the contrast rate in the area. If the filter is applied into a local region of the image (x, y) the filter response in the center of the image is based on four quantities [9]:

1. g (x, y) the value of the noisy image at (x, y)
2. ^{2}a variance of the noise corrupting f(x,y) to form g(x,y)
3. $m_l$the local mean of the pixels in S_{xy}
4. $^{2}_{l}$thelocal variance of the pixels in S_{xy}.

It is expected that the behavior of the filter is as follows:

- If ^{2}is zero, the filter only returns the value of g (x, y). It is a noise-free case where g (x, y) equals f (x, y).
- If the local variance of $^{2}_{l}$is high relative to ^{2}, the filter should have a value close to g(x, y). Usually high local variance is related to the edges and should be preserved.
- If the two variances are equal, we expect the filter to return the arithmetic mean value of the pixels in the S_{xy}. This occurs when the local area has the same properties as the whole image and the local noise can be reduced via averaging.

Based on the above assumptions, an adaptive statement for obtaining $\hat{f}$ (x, y) can be written as follows [9]:

$$\hat{f}(x,y) = g(x,y) - \frac{\square_{\square}^{2}}{\square_{l}^{2}} [g(x,y) - m_l] \qquad (1\text{-}1)$$

quantity that needs to be known or estimated is the overall noise variance ($\square_{\square}^{2}$). Other parameters are computed from the pixels in S_{xy}, at each location (x, y) on which the filter window is centered. An assumption in this equation is that $\square_{\square}^{2} < \square_{l}^{2}$. In this model, the noise is additive and position independent, so this assumption is reasonable because S_{xy} is a subset of g(x, y). However, we seldom know the exact value of $\square_{\square}^{2}$. Thus, in practice, this condition may be violated. Therefore, measures should be taken in the equation so that if the condition $\square_{\square}^{2} < \square_{l}^{2}$ occurs, the ratio is set to 1. This makes the filter nonlinear. “However, it prevents nonsensical results (i.e., negative intensity levels, depending on the value of m_l due to a potential lack of knowledge about the variance of the image noise”. We can also allow the negative values to occur, and, at the end, rescale the intensity values. This results in a loss of dynamic range in the image [9]. Smart changes in the performance of this filter can lead to its better performance. In this equation, instead of using a variance for the entire image ($\square_{\square}^{2}$), noise standard deviation curve on the intensity levels $\square_{\square}^{2}$ (x, y) can be used. Therefore, it is definitely expected that the filter output values are more realistic. The proposed filter will be introduced in the following sections. The method for obtaining this curve is explained as follows.

2. METHODOLOGY

2.1 Proposed Method for Estimation of Temporal Noise

In this method, first, N images are captured from a constant target at a fixed intensity at time, and then they are averaged. The larger the N, the closer the image to desired properties. This average image is noise-free. In other words, it determines mathematical expectation for each pixel. Then segmentation is done on the average image in Δ intervals (according to DNs). Finally, the segments created on the average image are applied to each of the N images and a standard deviation is obtained for each segment. At the end, the standard deviations on the N images are averaged and STD curve according to DNs is obtained. In this part of the study, first, mathematic foundations of the proposed method for temporal noise estimation are introduced. Next, the method is tested using simulated data. Then, temporal noise curve for a given sensor (Sony laptop camera) is estimated. The mathematical model used in this paper for the output of the sensor cells is as follows:

$Z(x) = y(x) + \sigma(y(x))\,\zeta(x) \qquad x \in X$ (2-1)

where x is a set of active cell sensor positions, Z is the output actual raw data, Y is the ideal output, ζ is random noise with mean of 0 and standard deviation of 1, and finally σ is a function of y which modulates standard deviation of the entire noise component. There is no restrictions on the distribution of ζ(x) and different points may have different distributions. We know that as long as $E\{\zeta\} = 0$:

$E\{Z(x)\}=y(x)$

$STD\{Z(x)\} = \sigma(E\{Z(x)\}) = \sigma(y(x))$

(2-2)

A good estimation for y(x) can be a pointwise average of a large number N of observations $Z_n(x)$ [3]:

$1 / N \sum_{n=1}^{N} Zn(x) n = 1 : N$

$Z_n(x) = y(x) + \sigma(y(x))\,\zeta_n(x)$ (2-3)

For practical realization of Equation (2-3), the deterministic terms of the equation have to be invariant with respect to the replication index n. The signal y (x) should not change over time. During this test the detector should be fixed and parameters such as gain, aperture and exposure should remain constant. In this study, these conditions were observed and N image were captured in raw-data format, and were averaged to get a good estimate of y.

$\overline{Z(x)} = 1/N \sum_{n=1}^{N} Zn(x) = y(x) + \frac{(y(x))}{\sqrt{N}} \widetilde{\zeta(x)} \quad x \in X$ (2-4)

Once again, $\widetilde{\zeta(x)}$ is random noise with mean of 0 and variance of 1. The larger the number of images taken the smaller $\frac{(y(x))}{\sqrt{N}}$. If N is large enough:

$\overline{Z(x)} = E(Z(x)) = y(x)$ (2-5)

In this step, the average image $\overline{Z(x)}$ is segmented into a number of uniform segments (S). Ideally, the value of $\overline{Z(x)}$ should be constant within these segments.

$S(y)=\{x:\overline{Z(x)}=y\}$

(2-6)

But this kind of segmentation can lead to uncertain results because there may be very few or none samples that meet the equality $\overline{Z(x)} = y$. Thus, it is better to follow the following segmentation form so that a large number of pixels are included:

$S_\Delta(y) = \{x: \overline{Z(x)} \in [y-\Delta/2 , y+\Delta/2]\} \qquad \Delta>0$ (2-7)Here, it is assumed that y, and Δ are fixed and this segment contains M number of pixels with coordinates of X_m (m = 1, …, M). According to Equation (2.3) we have:

$Z_n(x_m) = y(x_m) + \sigma(y(x_m))\,\zeta_n(x_m) \qquad = y + \Delta^* d + \sigma(y(x_m))\,\zeta_n(x_m) \quad d \in [-1/2, 1/2]$ (2-8)

It is very reasonable to assume that d has uniform distribution. Therefore, the result is equation (2-8) is as follows:

$Z_n(X_m) = y + \sqrt{\frac{\Delta^2}{12} + \square^2(y(Xm))}\,\zeta'n(Xm)$(2-9)

where $\zeta'n$ is zero-mean random noise with standard deviation equal to 1. Next, the variance of the equation (2-10) is calculated in N shot over all pixels contained in S.

$Svar_n(y) = \sum_{m}^{M} \frac{\left(Zn(xm)-\widetilde{Zn}(y)\right)^2}{M-1}$ (2-10)

$\{X_m\}_{m=1}^{M} = S_\Delta(y) = \{X: \overline{z(x)} \in [y-\Delta/2, y+\Delta/2]\}$

$\widetilde{Zn}(y)$is the mean value of Zn over $S_\Delta(y)$:

$\widetilde{Zn}(y) = 1/M \sum_{m=1}^{M} Zn(xm)$(2-11)

Based on Equation (2-10) and (2-9) and assuming that in the segment σ (y (X_m)) can be well approximate to (y) σ:

$E\{Svar_n(y)\}= \Delta^2/12 + {}^2(y)$ (2-12)

The estimate $\hat{\square}$ (y) of the STD σ (y) is obtained based on (2-12), by average of N shots:

$\hat{}(y) = \sqrt{\frac{1}{N} \sum_{n=1}^{N} Svar\ n\ (y) - \Delta^2/12}$ (2-13)

Here it is assumed that under the square-root is not negative. By choosing a significantly small Δ:

$\hat{}(y) = \sqrt{\frac{1}{N} \sum_{n=1}^{N} Svar\ n\ (y)}$ (2-14)

To obtain the STD curve or the total variance function, the above steps are repeated for different values of y. It should be noted that segments should not be overlapping.

$y \in \{\Delta i , i \in N\} \cap [\min\{\bar{z}\}, \max\{\bar{z}\}]$ (2-15)

2.1.1. Simulation

In this step, to test the accuracy of the proposed method, the recognized noise is applied to simulated image and the proposed method is used to estimate the noise curve. First, a simulated image was created in MATLAB with array of 900*2560 pixels such that each adjacent 10 columns had the same intensity. For example, columns 1 to 10 had the same intensity equal to 0 which continues with interval of 1/256 to last column (columns 2550 to 2560 has an intensity equal to 1). Fig. 3, shows the simulated image along with its histogram curve.

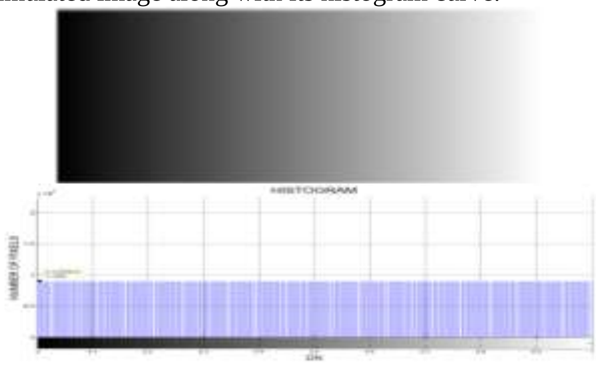


Fig. 3. The original image and its histogram curve (built, In MATLAB)

Then, according to temporal noise charts released by the manufacturer, a noise of similar pattern is added to each part of the image. Fig. 4, shows the temporal noise for two types of imaging sensors, i.e. CMOS sensors U and V used in Nokia mobile phones. A zero-mean Gaussian noise with variance (power) function according to (2-15) is added to (2-1). The resulting noisy image along with its

ISSN : 2279-0535
8thSASTech 2014 Symposium on Advances in Science & Technology-Commission-IV Mashhad, Iran

histogram curve is shown in fig. 6. The curve of noise applied to the original image is shown in Fig. 5.

i = 0 : 1 : 255

var = 1/1000 + 1/10000 * i (2-16)

□ = √ var

Here, the noise applied to the image has a higher power (variance) than the noise in imaging sensors (Fig. 4). The purpose is to evaluate the capability of the proposed method in conditions more difficult than reality. As seen in the histogram curve (Fig. 6), because the noise applied to each part of the image has relatively large standard deviations, The majority of image pixels are either 0 or saturated (i.e. 1). Indeed, the number of pixels that are 1 is higher, because the noise in brighter parts has a higher STD.

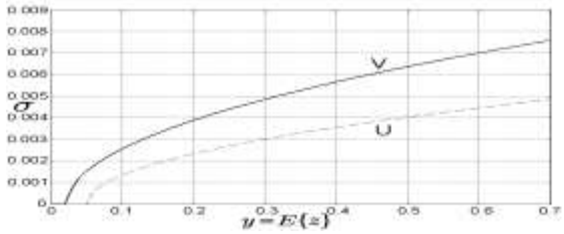


Fig. 4.temporal noise curves of two common sensors. U: Old sensor: 660 * 490 (VGA), sensor 1.4", pixel pitch = 5.4 µm, with integrated valve; V: later sensor, 1040 * 1296 (1.3 MP), 1/3.3", pixel pitch = 3.3µm, moveable valve (both sensors had Bayer CFA color filter array with a color filter (R G1 G2 B))[4].

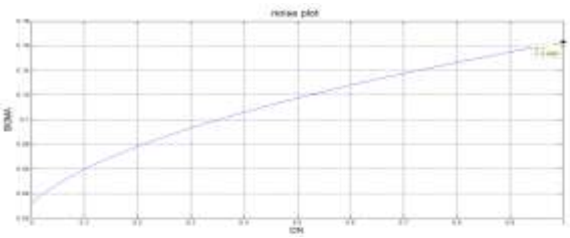


Fig. 5. Gaussian noise applied to each segment of the image based on intensity and using (2-16)

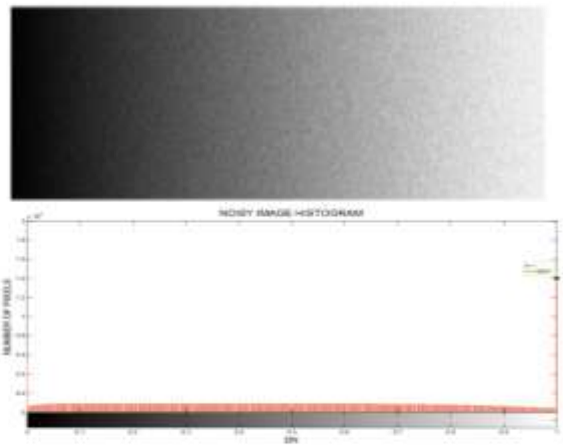


Fig. 6. A sample noisy image with equation (2-15) and its histogram curve

Now, N noisy image is generated by applying Equation (2-15) to the original image. In practice, these images amount to N consequent shots (from a fixed landscape with constant light) by a digital camera. At this stage, the N noisy images are averaged. Fig. 7, shows average images with their histogram curves for different Ns. As can be seen in Fig. 7, and according to mathematical equations mentioned (equation (2-4)), with increasing N, the average image approximates the original (ideal) image (i. e. the noise effect reduces). Also, the number of pixels with intensity of 0 and 1 (saturated), which was high in the histogram curve of Fig. 5, reduces with increasing N. By segmenting and estimating based on the proposed method in previous sections, the temporal noise in the images is estimated. It should be noted that the estimation is done by different intervals (Δ). Fig. 8, shows estimation results with different intervals for different N. As seen in Fig. 8, with N = 2 we cannot obtain a good approximation of the noise applied to the image. Of course as expected, with increasing N, the noise estimates improve. In addition, as seen in the Figure, the proposed estimation method has almost no sensitivity to segmentation interval. Fig. 9, shows the difference between the standard deviation of the applied noise and the estimated noise curve in three values of N = 2, 20, 100. Minimum distance is equal to 0.0143 at N = 2, 0.0015 at N = 20 and 2.48 at e^{-4} N = 100.

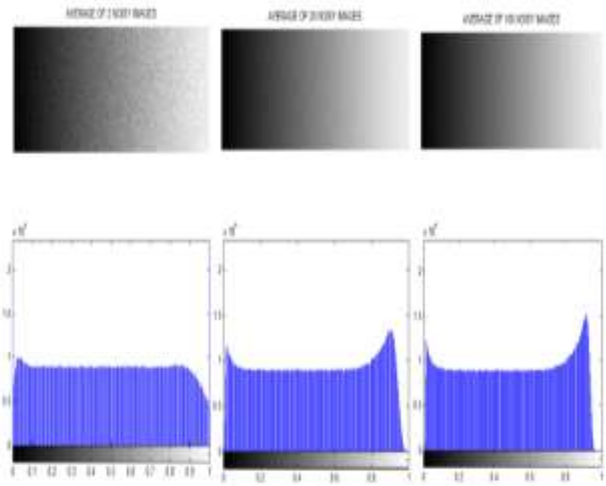
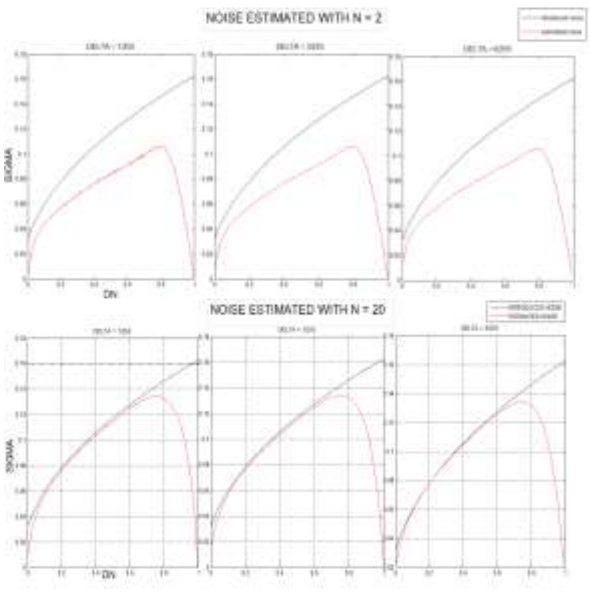


Fig. 7.average images with their histogram curves for 2, 20 and 100 noisy image based on Equation (2-15)



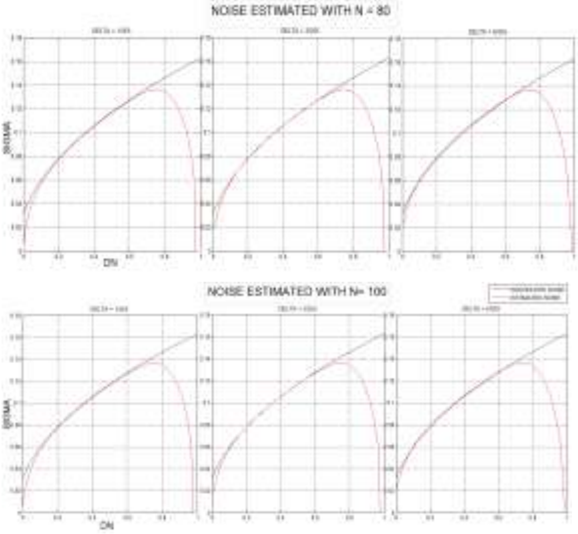


Fig. 8. Estimations of noise applied based on Equation (2-15) with different N and segmentation intervals (Δ)

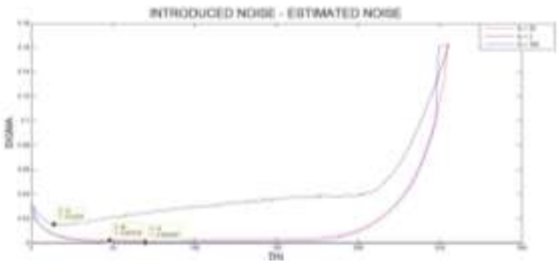


Fig. 9. The difference between standard deviation of the applied noise and the estimated noise curve in three values of N = 2, 20, 100 and Δ= 1/255(images of Equation (2-15) have become noisy).

2.1.2. Method Implementation

In this section, the mentioned noise estimation method is implemented for a given imaging sensor (Sony laptop camera). The results are investigated for two modes. In both, the same fixed targets are used. The only difference is the lighting intensity and conditions. An important point when capturing images is that the angle, exposure time, camera locations and subject location should remain fixed.

First Mode: In this mode, the exposure is less than in the latter. Fig .10, shows the main target with its histogram curve. N consecutive images were taken of this target and then were averaged. Averaged images for different N are shown in Fig. 11. Segmentation is then done for averages images based on the steps mentioned before. In Fig. 12, the results of noise estimation for various segmentation intervals are shown.

The second mode: In this mode the camera location and target remain unchanged. Only the exposure is slightly higher than in the first mode. Here, only the final results of noise estimation are shown in Fig. 13, and the averaged images and the target are not shown here. The noise estimation in the first mode are also shown for comparison.

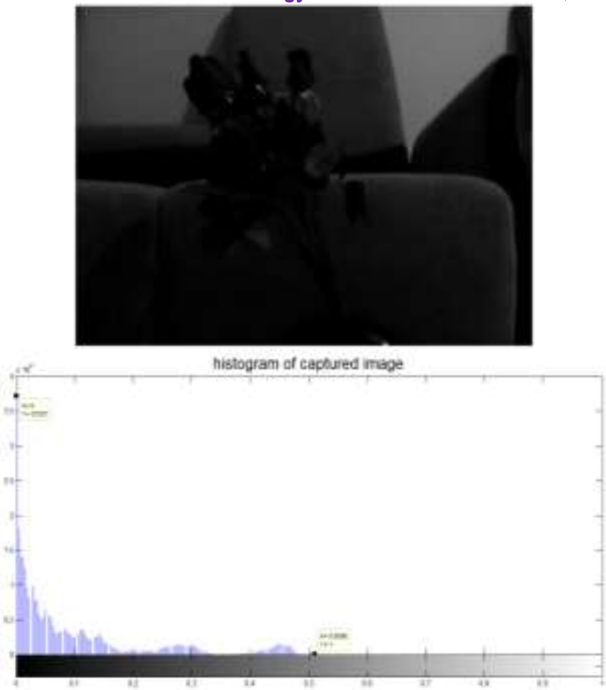


Fig. 10.An example of the image taken in the first mode (low light) with its histogram curve.

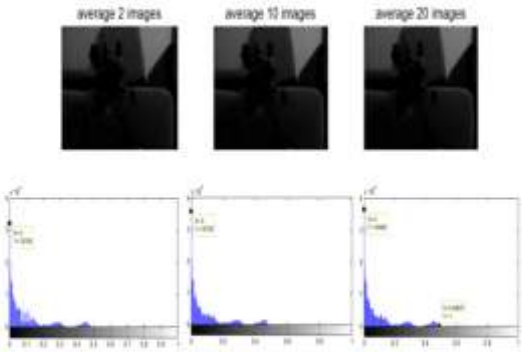


Fig. 11. Average images captured for different N along with their histogram curves.

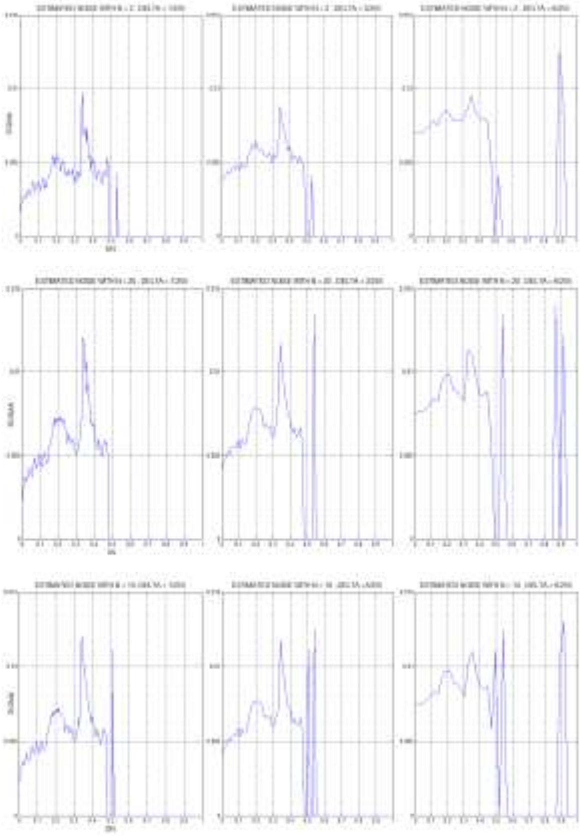


Fig. 12 results of noise estimation in the first mode

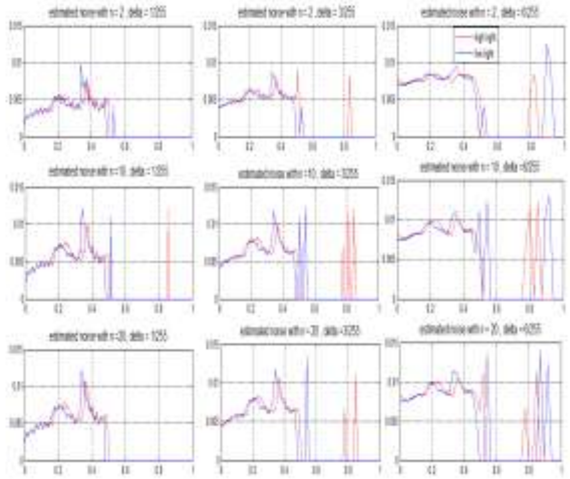


Fig. 13 comparison between the estimated noises in two modes (only exposure varies)

The blue curves are from the first mode (low light) and the red curves are from the second mode (high light). As can be seen in Fig. 13, the peaks created by blue curves are higher than those created by red curves. As a result, the noise input to the image in the first mode, where the light on the target is weaker, is higher than in the second mode. Therefore, it can be concluded that the lower the level of input signal in the sensor, the higher the amount and effect of noise in the final image quality.

Now that imaging sensor noise was obtained through this simpler and less costly method, a filter is introduced in the next section that uses the estimated curve to reduce image noise. The proposed filter is an evolved of the local noise reduction adaptive filter [9] described at the beginning of this article.

2.2 Proposed Adaptive Filter For Noise Reduction

A step by step process of the proposed algorithm to improve the performance of local noise reduction filter [9] are as follows:

1. Obtaining temporal noise standard deviation curves using the method described in the previous sections for a digital camera with a given imaging sensor (segmentation for non-uniform targets).
2. Taking an image with the same camera (noisy image)
3. During the filtering operations in the image edges, part of the filter window will be out of the image. Border replication technique has been used in this paper.
4. The 3 x 3 filter window is applied to the image obtained in stage 3. In this case, the average size of 9 pixels within the window is calculated. Next, referring to the estimated noise curve, the temporal noise standard deviation as related to the mean of the window or the nearest number to that mean is determined (σ_{η}^{2} (x, y)).
5. The variance obtained from the temporal noise curve is placed in the following relationship:

$$\hat{f}(x,y)=g(x,y) - \frac{\sigma_{\eta}^{2}(x,y)}{\sigma_{L}^{2}}\,[g(x,y) - m_{L}] \quad (2\text{-}17)$$

6. All conditions stated at the beginning of this section for the relationship (1-1), are true for relation (2-17).
7. All these steps are performed for all image arrayone by one.

Next, performance of the proposed filter is compared with that of the filter suggested in [9] using two parameters of MSE and PSNR. In addition, these two components are calculated in terms of normalized intensities and the conditions for both filters are the same. Equation (2-18) shows how to calculate these two parameters [6].

$$\text{PSNR (Img , Org)} = 10 \log_{10} \frac{S^2}{MSE(Img\,,Org)} \quad (2\text{-}18)$$

$$\text{MSE (Img, Org)} = \frac{\sum_{c=1}\sum_{i=1}\sum_{j=1}[Org(i,j,c)-Img(i,j,c)]^2}{3NM}$$

2.2.1 Evaluation of the Proposed Filter

In this step, the same image Fig. 3 is used for comparison of filters in terms of performance. It is worth noting that for the proposed filter, the same values of the estimated noise curve is entered into equation (2-17). For the local noise reduction adaptive filter [9], a number is used for the required standard deviation in (1-1). The number is obtained from mean of estimated standard deviation curve and, in this example, is about std = 0.06854. In Fig. 14, the original image, the noisy image and finally the filtered image for both filters are shown. In Fig. 15, a line from each image (the line in the middle of the image at row 450) from both filters are compared with one another. As can be seen fluctuations in the output of the proposed filter are less than in the conventional filter.

Table (2-1) uses numerical values for comparison using parameters of MSE and PSNR and demonstrates better performance of the proposed filter.

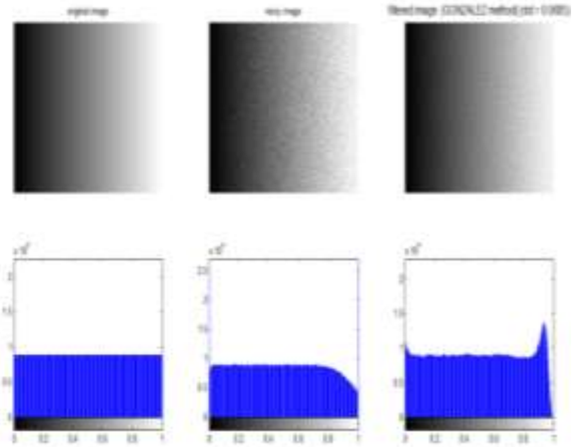


Fig. 14 output images of the proposed filter and the filter suggested in [9] with their histogram curve

Table (2-1) Comparison of local noise reduction filter and the proposed filter using parameters of MSE and PSNR

	MSE Intensities between 0 and 1	MSE Intensities between 0 and 255	PSNR (db)
local noise reduction filter	0.0013	85.7438	28.8031
Proposed filter	0.0008	52.2874	30.9538

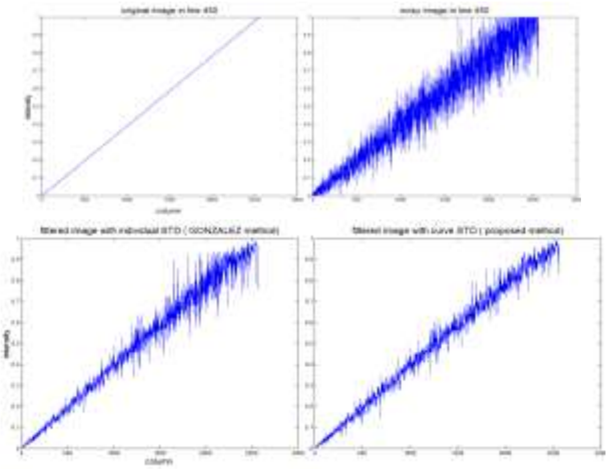


Fig. 15 comparison of a line from the output image of each filter

2.2.2 Evaluation for Different Noise Variances

The two filters are now compared in terms of their performance in removing noises with various powers. The original image (Fig. 3) is composed of 256 gray levels. Each level has 90000 (900*10) pixels, and each segment was altered with a different variation obtained from the relation (2-15). Now, the MSE component is calculated for the original image and the filtered image segment by segment so that a chart of these parameters in terms of different variances of the noise in the image is obtained. Fig. 16, shows the MSE of the filtered image in both methods by different standard deviations of both methods according of the noise in the image. As can be seen in the charts, in low-noise segments of the image, the filter presented in [7] and the proposed filter in this study have almost the same performance. In the entire image, as previously shown in Table (3-1), the noise reduction performance of the proposed filter is better.

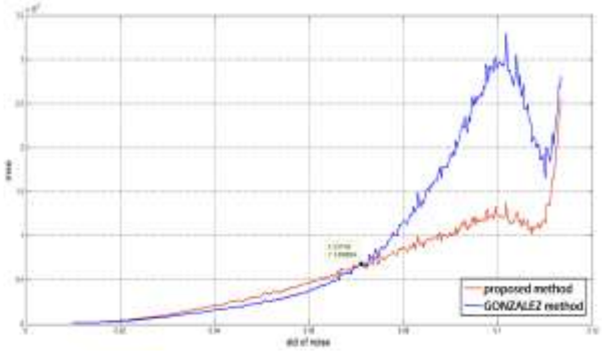


Fig. 16. Comparison of two filters in terms of their noise removal performance at different variances

2.2.3 Practical Application of the Proposed Filter

It was demonstrated that the proposed filter has a good performance in noise removal. Now, the filter is applied to the image taken by a conventional laptop camera. In previous sections, obtaining a temporal noise standard deviation curve for a given sensor through automated segmentation method of non-uniform targets was explained. Here, the curve is applied to the proposed filter and the image taken by the sensor is filtered. Fig. 17, shows the captured and filtered images with their histogram curve. Table (2-2) shows parameters of MSE and PSNR for the captured and filtered images. Here, to compare these parameters for the ideal and captured images, an average of 20 captured images is used. As can be seen, the filtered image is more similar to the ideal image compared to the captured image.

Table (2-2) Parameters of MSE and PSNR for the captured and filtered images

	MSE Intensities between 0 and 1	MSE Intensities between 0 and 255	PSNR (db)
Captured image	7.5943 e^{-5}	5.0144	41.1951
Filtered image	4.342 e^{-5}	2.9938	43.6629

Current Trends in Technology and Science
ISSN : 2279-0535
8thSASTech 2014 Symposium on Advances in Science & Technology-Commission-IV Mashhad, Iran

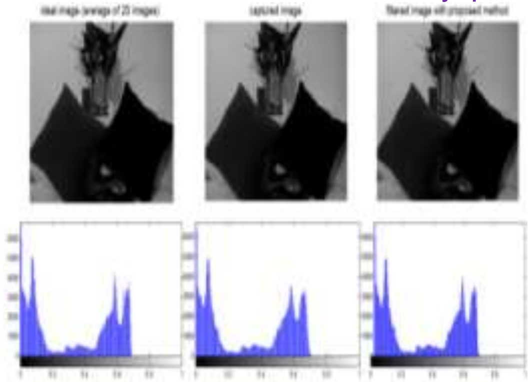


Fig. 17. Practical implementation of the proposal filter

3. Conclusions

In this paper, first, the necessity of recognizing qualitative and quantitative features of noise in images was discussed. Then a new method for estimation of temporal noise curve for a typical sensor was presented. This approach is based on automatic segmentation of non-uniform targets. The advantage of this method is that it does not have some of the difficulties and drawbacks of the previous methods such as (ISO 15739). Also, using simulation, performance of the proposed method in noise estimation was tested and found to be acceptable. Finally, an adaptive filter, that can use the above-mentioned estimated noise curve for a typical sensor to significantly enhance the quality of images captured by that sensor was proposed.

References

[1] Abbas El Gamal, Boyd Fowler, Hao Min, XinqiaoLiu ,“Modeling and Estimation of FPN Components in CMOS Image Sensors” , Copyright 2001

[2] “Noise in Sub-Micron CMOS Image Sensors”. Xinyang WANG. Master of Science University of Southampton, Southampton, UK Bachelor in Electrical Engineering Zhejiang University, Hangzhou, P.R. China. Copyright 2008 by © X. Wang

[3] Tian, H., B. Fowler, and A. El Gamal, .”Analysis of Temporal Noise in CMOS Photodiode Active Pixel Sensor”., IEEE Journal of Solid-State Circuits, vol. 36, no. 1, pp. 92.101, Jan. 2001.

[4] Foi, A. and Alenius, S. and Katvonik, V. and Egiazarian, K, "Noise Measurement For Raw_Data Of Digital Imaging Sensors By Automatic Segmentation Of Non_Uniform Targets", IEEE.

[5] R. C. Bilcu and M. Vehvilainen, “A New Method for Noise Estimation in Images,” Proc. IEEE EURASIP International Workshop on Nonlinear Signal and ImageProcessing, Sapporo, Japan, May 18-20, 2005.

[6] Hytti, H., .”Characterization of digital image noise properties based on RAW data”. Proc. SPIE-IS&T Electronic Imaging, Image Quality and System Performance III, vol. 6059, 60590A, Jan. 2006

[7] Abbas El Gamal, Khaled Salama, “Analysis Of Active Pixel Sensor Readout Circuit”, IEEE Transactions On Circuits And Systems—I: Fundamental Theory And Applications, Vol. 50, No. 7, July 2003

[8] Photography - Electronic still-image imaging - Noise measurements, ISO 15739:2003, May, 2003.

[9] RC Gonzalez and RE Woods, "Digital Image Processing," Prentice-Hall, Inc., New Jersey, USA, 2002.