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JOINT GAUSSIAN NOISE REDUCTION AND DEFECTS CORRECTION IN RAW DIGITAL IMAGES

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Abstract

In dim light conditions, digital images are prone to high noise levels, especially if a low cost imager is used. Gaussian and impulsive noises are the most likely to appear. Furthermore, defective, stuck pixels are quite unpleasant as well. In low illumination conditions, impulsive noise is particularly annoying; because of the high signal amplification, more than one defective pixel is likely to show up in the filter mask at the same time. A spatial filter is proposed, capable of removing Gaussian noise, impulsive noise and stuck pixels by using the same processing kernel.

1. Introduction

Basically, noise affecting digital images lowers the perceived overall quality of the acquired pictures [1][2]. Hence, a smart noise reduction algorithm capable to remove noise without affecting the tiny details of the image is of primary importance. Unfortunately, different kinds of noise having different characteristics are usually superimposed to the image signal. In order to remove noise, the design of a good filter requires knowledge of the particular distribution and properties of the unwanted signal. In our earlier solutions [3][4][5][6], noise was always assumed to be *AWGN* (*Additive White Gaussian Noise*); unfortunately other noise types are likely to surface as well. Defective impulsive pixels can appear anywhere in the image array and no assumption can be made about their possible location. A further complication arises in the case of very defective images in which the filter mask may contain more than one faulty pixel simultaneously. A solution for getting rid of both Gaussian noise and defective pixels consists in handling them separately using different cascaded filters, removing a different kind of noise at each pass. Another solution is to scan the image once, with every pixel processed by multiple different filters. In both cases it must be checked that no unwanted interaction between the filters exists. Furthermore, the possibility of having a mask with central and neighborhood outliers complicates the problem and this issue is usually not addressed.

In this paper a novel solution is proposed in which the same filter aims to the reduction of different noise types simultaneously. Specifically, a mixture of Gaussian and impulsive noise has been considered. Stuck elements are also taken into account.

The paper is organized as follows: next section describes in detail the noise mixture that the filter aims to remove. Paragraph 3 explains the proposed denoising method. A section with experimental results closes the paper.

2. Gaussian And Impulsive Noise Mixture

Noise level typically increases in low light conditions because the image signal has to be amplified. This is normally achieved by increasing gains in the imaging pipeline that strengthen the signal so as to yield an acceptable picture. Obviously, the gain values are applied to the image signal and to the superimposed noise as well; hence, one cannot boost the image signal without pushing up the noise level too.

In digital cameras a color filter is placed on top of the imager enabling color sensitivity to one primary color per pixel (*CFA Color Filter Array*); typically red, green and blue components are chosen as illustrated in Fig. 1; this arrangement is known as Bayer pattern [8].

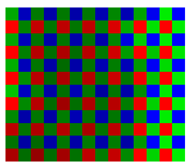


Fig. 1 Bayer pattern color filter array.

A color reconstruction algorithm interpolates the missing information at each location and reconstructs the full RGB image [9][10]. The proposed filter processes noisy *CFA* data directly. Therefore, filtering is performed as the first *IGP* step allowing the subsequent algorithms to process denoised data; this improves the overall performances, especially in terms of achievable image quality [3][4][11]. As an example, noisy *CFA* data appears as shown in Fig. 2.

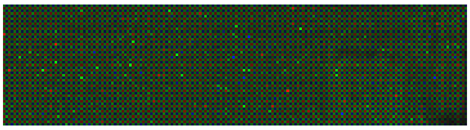


Fig. 2 Noisy Bayer data (in false colors).

Pixels deviate from their correct value by some constant drawn from a Gaussian distribution. Furthermore, a certain number of flawed elements exist; we define them as *spikes* or *outliers*. From now on the term "outlier element" will refer to:

- pixels whose value is randomly affected by impulsive noise; such elements can appear anywhere in the image array and there is no prior knowledge about their position.
- Pixels whose value is always flawed and are located at known positions of the image array.

Particularly in low light conditions, bright outliers can be close to each other as shown in Fig. 3.

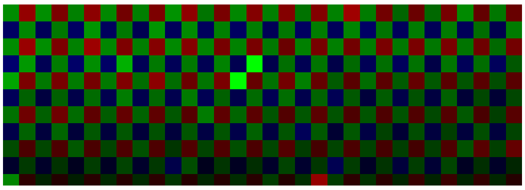


Fig. 3 Magnified portion of noisy Bayer data (in false colors) showing two adjacent impulsive defective pixels, along with Gaussian noisy pixels.

Similar arrangements of impulsive adjacent noisy pixels are particularly though to remove, as one of the two "spikes" could be preserved and considered in the final weighted average.

3. Proposed Filter

In order to remove the noise mixture described in section 2, the filter must be designed so that it can take into account the possibility that the central pixel and probably one of its neighborhoods are defective. Hence, a strategy to detect outliers amid a sequence of Gaussian noisy pixels is necessary. Details must be preserved, therefore, edges and textures must not be confused with impulsive noise nor with Gaussian noise.

A key property of the Gaussian distribution is given by the following rules:

- ~ 68 % of samples fall within the interval [$\mu-\sigma$, $\mu+\sigma$]
- ~ 95 % of samples fall within the interval [$\mu-2\sigma$, $\mu+2\sigma$]
- ~ 99 % of samples fall within the interval [$\mu-3\sigma$, $\mu+3\sigma$]

where μ and σ are the mean and standard deviation respectively.
Consider a 3x3 filter support as illustrated in Fig. 4.

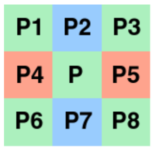


Fig. 4 A normal 3x3 filter mask cannot be used on Bayer Data.

In order to include 9 valid pixels, due to the particular layout of the Bayer data, the aforementioned 3x3 mask has to be extended to 5x5. Furthermore, two working windows must be considered; a diamond shaped mask for green elements and a rectangular mask for red and blue pixels (Fig. 5).

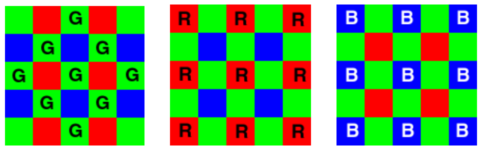


Fig. 5 Bayer Filter masks.

The proposed solution performs a neighborhood preprocessing step in order to reject outliers. After neighborhood adjustment, the central pixel is checked for defectiveness and it is corrected in case of positive response. Finally a weighted average is computed.
In Fig. 6, the method for the green channel is illustrated, being the red and blue cases perfectly equivalent.

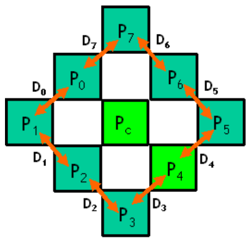


Fig. 6 Computation of the D_i differences.

The following absolute differences are computed in anti-clockwise order (but a clockwise order could be performed as well):

$$D_0 = abs(P_0\text{-}P_1),\ D_1 = abs(P_1\text{-}P_2),\ \ldots\ ,\ D_7 = abs(P_7\text{-}P_0)$$

Two further quantities are necessary:

- Among the D_i differences, the maximum variation D_{max} is determined.
- The Gaussian noise standard deviation σ is estimated [12][13][14][15].

Each difference D_i is compared to $K\sigma$, $K>0$. Differences lower than $K\sigma$ are considered to be safe and there is no need to modify the corresponding pixels. By using the $K\sigma$ threshold ($K>3$) both noise and texture can regularly coexist in the neighborhood because of the "~99% rule". Specifically we look for differences that are less than $K\sigma$. Each time D_i is found to be less then $K\sigma$, a counter is incremented. If the counter reaches 6, then two differences out of 8 are suspect; if they are consecutive then the neighborhood is likely to contain an outlier, i.e. an element having no similarity with the other mask elements.

The position of the defective pixel is indicated by the maximum difference D_{max} previously computed. In particular, the index "i", for which D is maximum, determines the position of the outlier.

In fact, D_{max} corresponds to a certain difference $D_i=abs(P_i-P_{i+1})$ that identifies two pixels, namely P_i and P_{i+1}. The outlier is located either in P_i or in P_{i+1} and it can be eliminated by storing the $median(P_{i-1},P_i, P_{i+1})$ in P_i and P_{i+1}.

After neighborhood preprocessing, the central pixel P_c has to be processed. The possible values for the central pixel P_c are as follows:

- P_c is correct
- P_c is affected by Gaussian noise
- P_c is an outlier

In each circumstance, the filter has to behave correctly. In order to solve this problem, a modified version of Duncan filtering method described in [5][6][7] is adopted. Briefly, the Duncan filter is designed to average only similar pixels of the filter working window. In the case of Gaussian noise, the method is depicted in Fig. 7.

Three ranges *Th1*, *Th2* and *Th3,* whose wideness is directly proportional to σ, are considered; they are centered on P and on the σ biased versions of P, i.e. $P+\sigma$ and $P-\sigma$. The rationale behind the use of the σ bias is that P itself may be affected by Gaussian noise. The interval maximizing the number of pixels is chosen; in Fig. 7 the interval centered on $P+\sigma$ has been chosen as it maximizes the number of pixels.

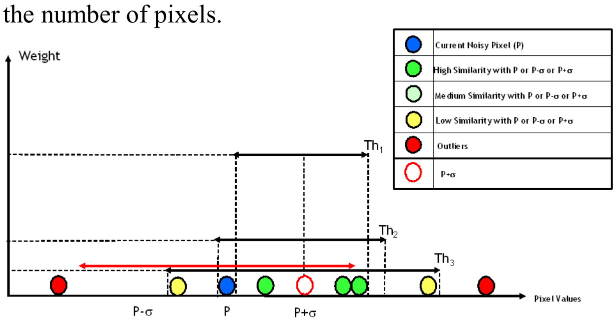


Fig. 7 The Duncan Filter selects the range maximizing the number of similar pixels.

The main problem with the aforementioned approach is evident in the case of spikes (Fig. 8).

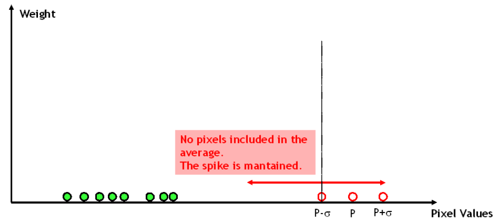


Fig. 8 Duncan Filtering method with central pixel outlier.

If P is an extreme outlier then (a spike in the case of Fig.7), even by considering $P-\sigma$, it will not be possible to include other pixels in the weighted average as there are no available elements near $P-\sigma$. Nonetheless, the interval centered on $P-\sigma$ is the one closest to the majority of the remaining pixels; this is because $P-\sigma$ is closer to the other pixels if compared to P's and $P+\sigma$'s distance. This suggests the way in which the outlier can be rejected. Each time the interval centred on $P-\sigma$ is selected and it is greater then the maximum element in the neighbourhood, then $P-\sigma$ is automatically rejected as it is supposed to be an outlier. The rationale for removing a dark outlier is analogous: the $P+\sigma$ centered interval is considered; $P+\sigma$ is checked by comparing it to the minimum element of the neighbourhood. If $P+\sigma$ or $P-\sigma$ are suspect outliers, they will be substituted by a weighted average of the remaining pixels. Clearly, no action is taken if the "maximizing interval" is:

- centered on P
- centered on $P-\sigma$ but this value is not brighter than the neighbourhood maximum.
- centered in $P+\sigma$ but this value is not darker than the neighbourhood minimum.

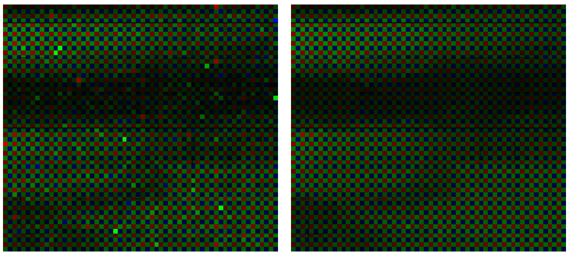
In these cases in fact, the central pixel is supposed not to be an outlier. A final weighted average using the preprocessed central and neighborhood pixels terminates the computation; the weights are computed by using the pixels included in the intervals centered on the appropriate value and controlled by the thresholds *Th1*, *Th2* and *Th3*.

This final step processes only pixels affected by Gaussian noise because the outliers have been suppressed in the previous preprocessing phase.

4. Experimental Results

In order to assess the effectiveness of the proposed filter, synthetic test images were corrupted by additive white Gaussian noise (*AWGN*); spikes and dead elements where also added to simulate impulsive noise and generally defective stuck pixels. Furthermore, experiments with real images were also performed. In the latter case, images were acquired by a *CMOS* image sensor in low light conditions so as to obtain a very degraded signal. In both cases the filter behaved correctly, reducing Gaussian noise and removing outliers.

In Fig. 9 the results of the overall filtering process on raw *CFA* data are shown.



(a) (b)

Fig. 9 Magnified portion of Bayer data, before (a) and after filtering (b). Outliers have been removed and Gaussian noise reduced.

Single and double outliers are cancelled, whilst Gaussian noise is reduced. The effects of the filter on the final color image are illustrated in Fig. 10.

Fig. 10 The noisy image (up) and its filtered counterpart (below).

The clean reference image was highly corrupted with artificial Gaussian noise and defective pixels; the results show the effectiveness of the proposed method. In our experiments the algorithm performed well also in terms of *PSNR*. By corrupting a clean reference image using high noise levels (σ=10) and lots of stuck elements, *PSNR* gains up to ~4/5dBs are obtainable.

5. Conclusions

A method for recovering highly corrupted noisy images has been presented. By using the same filter kernel, both Gaussian noise and defective pixels are corrected. Future work consists in improving the filter by introducing further rules able to recognize defects from real texture.

REFERENCES

[1] S. Battiato, M. Mancuso - "An Introduction to the Digital Still Camera Technology" - ST Journal of System Research. Vol.2, No.2, Dec.2001;

[2] G. Cortelazzo, G.A. Mian, R. Parolari, " Statistical Characteristics of Granular Camera Noise" , IEEE Transactions on Circuits and Systems for Video Technology, Vol. 4, No.6, December 1994.

[3] A. Bosco, M. Mancuso - "Adaptive Filtering For Image Denoising" - in IEEE Proceedings of ICCE2001 (pp.208-209), Los Angeles, June 2001;

[4] A. Bosco - "Adaptive Image Denoising On Bayer Pattern" - ST Journal of System Research. Vol.2, No.2, Dec.2001;

[5] A. Bosco, M. Mancuso, S. Battiato, G. Spampinato, "Temporal Noise Reduction of Bayer Matrixed Video Data" , In Proceedings of IEEE ICME'02 International Conference on Multimedia and Expo 2002 , pp.681-684 , Lausanne, Switzerland, August 2002;

[6] A. Bosco, M. Mancuso, S. Battiato, G. Spampinato, "Adaptive Temporal Filtering for CFA Video Sequences", In Proceedings of IEEE ACIVS'02 Advanced Concepts for Intelligent Vision Systems 2002, pp. 19-24, Ghent University, Belgium, September 2002

[7] A. M. Borneo, L. Salinari, D. Sirtori, "An Innovative Adaptive Noise Reduction Filter for Moving Pictures Based on Modified Duncan Range Test", ST Journal of System Research, Vol.1, No.1, 2001;

[8] B.E. Bayer, "Color Imaging Array", U.S. Patent 3,971,065-1976;

[9] R. Kimmel, "Demosaicing Image Reconstruction from Color CCD Samples", IEEE Transactions on Image Processing, Vol.7, No.3, 1999.

[10] R. Ramanath, "Interpolation Methods for the Bayer Color Array", MS Thesis, North Carolina State University, 2000.

[11] O. Kalevo, H. Rantanen, "Noise Reduction Techniques for Bayer-Matrix Images", Proceedings of SPIE 2002, Vol.4669;

[12] Aish Aishy Amer, Eric Dubois, Amar Mitiche, "Reliable and Fast Structure-oriented Video Noise Estimation", IEEE ICIP 2002;

[13] S.I.Olsen, "Noise Variance Estimation in Images" in Proceedings of the 8th Scandinavian Conference on Image Analysis, Troms∅, Norway 1993;

[14] A. Bosco, K. Findlater, S. Battiato, A. Castorina – " A Noise Reduction Filter for Full-Frame Imaging Devices" – IEEE Transactions on Consumer Electronics – Vol. 49, Issue 3, August 2003;

[15] A. Bosco, K. Findlater, S. Battiato, A. Castorina, - "A Temporal Noise Reduction Filter Based on Full-Frame Data Image Sensors" - in Proceedings of IEEE - ICCE 2003 (International Conference on Consumer Electronics) - Los Angeles, June 2003.