

A NOVEL MULTI ALGORITHMIC APPROACH FOR THE CLASSIFICATION OF DIGITAL MAMMOGRAMS



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ABSTRACT

A structure-adaptive hybrid vector filter is proposed for digital color image restoration. At each pixel location, the image vector (i.e., pixel) is first classified into several different signal activity categories by applying modified quad tree decomposition to luminance component (image) of the input color image. A weight-adaptive vector filtering operation with an optimal window is then activated to achieve the best tradeoff between noise suppression and detail preservation. Through extensive simulation experiments conducted using a wide range of test color images, the filter has demonstrated superior performance to that of a number of well known benchmark techniques, in terms of both standard objective measurements and perceived image quality, in suppressing several distinct types of noise commonly considered in color image restoration, including Gaussian noise, impulse noise, and mixed noise.

Index Terms—Adaptive vector filtering, digital color image restoration, modified quad tree decomposition, structure-adaptive hybrid vector filter.

1. INTRODUCTION

For over a decade, the vector filtering technique based on multivariate order statistics has become increasingly popular for color image restoration. The well-known Vector Filters include the Vector Median Filters (VMF), the Vector Directional Filter (VDF), and the Directional-Distance Filter (DDF). Adaptive Vector Filtering

techniques have been developed to deal with variations of color image characteristics and noise distribution. Fuzzy restoration techniques have also been reported demonstrating robust performance for restoration of digital color images corrupted by different types of random noise. Hybrid vector filtering techniques, such as Adaptive Hybrid Multivariate Filter (AMF), Hybrid Directional Filter (HF) Adaptive Hybrid Directional Filter (AHF), and Vector Median-Rational Hybrid Filters (VMRHF), have been advanced as a robust solution to suppression of different types of noise corrupting color images. However, these hybrid vector filters have very limited capabilities in structure adaptations. For instance, they are often implemented with a fixed filtering window dimension (e.g., 3×3 or 5×5) to restore image structures of varying scales.

II. NOISES IN DIGITAL COLOR IMAGES

Color images can be contaminated by various types of noise.

Nevertheless, the noise models frequently reported in digital

image restoration literature are the impulse noise, which is of either fixed or random value, the additive noise with a zero mean Gaussian or other distributions, and the *mixed noise* as a combination of the impulse and the additive noise.

A. Impulse Noise

Impulse noise often occurs in digital image recording or transmission process as a result of photo-electronic sensor

faults or channel bit errors [16], [17]. The intensity of image corruption by the impulse noise is often measured by the noise ratio, which represents the percentage of image pixels corrupted by the impulse noise. Let $C = \{c=(c1,c2) \mid 1 \leq c1 \leq H, 1 \leq c2 \leq W\}$ denote the pixel coordinates of a color image, where H and W are the height and the width of the image, respectively. At each pixel coordinate $c \in C$, a multivariate value is used to represent input RGB values at the current position. The impulse noise corruption of RGB color image can be expressed by a multivariate model [5], [6]

$$\begin{aligned} X(c) &= \{s(c), && \text{with probability } (1-pI) \\ X(c) &= \{N_i(c), && \text{with probability } pI \end{aligned} \quad (1)$$

Where $s(c)$ and $x(c)$ and represent the original and the observed pixel values at coordinate c , respectively, and pI is the impulse noise ratio. The value of $N_i(c)$ is generated by substituting at least one color component of the (s) pixel by a distinct value d . If d equals the maximum or the minimum value of the digital image (e.g., 255 or 0 for an 8-bit channel of 24-bit RGB color images), the impulse noise is referred to as pepper-and-salt (PS) impulse. A more generalized impulse noise model was also proposed in the literature [5], [17], where impulse values vary between 0 and 255, following a specific statistical distribution (e.g., uniform distribution). A color channel correlation technique is often used to simulate the impulse corruption in natural color images [5]. First, each RGB channel of image pixels is independently corrupted by the impulse noise with a uniform distribution between $[0,255]$ and a selected noise ratio (e.g., 10%). Thereafter, a factor $p=.5$ is used to simulate the error correlation between color components of the corrupted pixel, that is, for each pixel value, if any of other two R/G/B channels has been corrupted by the impulse noise, the current channel will likely suffer a further corruption with a probability of 50%.

B. Additive Noise

The thermal effect of various electronic circuits and the random photon-fluctuation of photo-electronic sensors [16], [17] Induce additive noise in digital color images. A generalized model for color images contaminated by the additive noise is given by [12], [16], [17]

$$X(c) = s(c) + Na(c) \quad (2)$$

Where $s(c)$ and $n(c)$ is the original pixel value and a multivariate additive noise value at pixel coordinate c respectively. Without losing generality, it is assumed that the additive noise is introduced in each of RGB channels

independently, with a zero mean and the same standard deviation in each channel [16], [17].

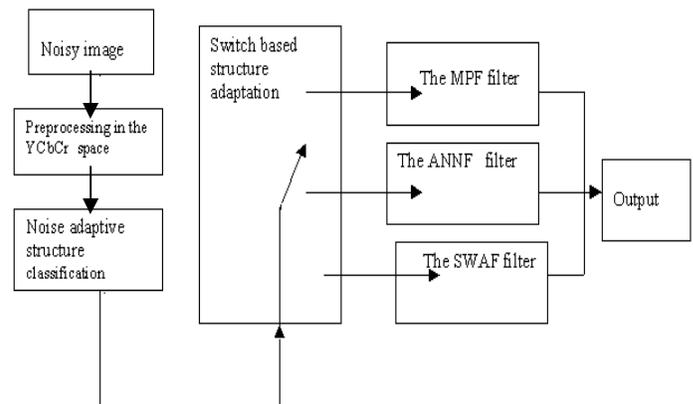
C. Mixed Noise

In many situations, color images suffer from both sensor faults and transmission noise [17]. Such scenarios can be described as a mixed noise contamination. A generalized model for the mixed noise contamination has been given by [12], [17]

$$\begin{aligned} X(c) &= s(c) + N_i(c), && \text{with probability } (1-pI) \\ X(c) &= Na(c), && \text{with probability } pI \end{aligned} \quad (3)$$

Where $Na(c)$ denotes a multivariate additive noise as in (2), $N_i(c)$ is an impulse corrupted value as defined in (1), and is the noise ratio to control the occurrence between additive noise contamination and impulse noise corruption. Image corruption by the mixed noise has been recognized as one of the most challenging cases for color image restoration [17].

III THE BLOCK DIAGRAM



A. Noise-adaptive preprocessing

The proposed noise-adaptive preprocessing will be performed in two steps. The additive noise deviation of the input image is first estimated. Then a presmoothing filter is used to filter each channel of the input image independently.

The local statistics filters have been used in monochrome image. They were able to recover primary ergodic image structures from zero mean additive noise contamination, while keeping high frequency image details and structure untouched. An efficient way to use local statistics filters in the RGB color space is to implement in a scalar filtering structure with a color de-correlation scheme. However, the RGB to $YCbCr$ transformation is more popular in digital

imaging and Video applications for its computation efficiency and color de-correlation performance.

B. Structure classification

The purpose of the structure activity classification is to partition the local structures so that a proper filtering structure and dimension can be determined for each pixel position. The luminance channel (image) of the preprocessed input color image, which contains most of image structure information, is first decomposed by a modified quad tree decomposition technique. Then, a structure activity index is calculated for each pixel position according to the decomposition results. Modified Quad tree Decomposition, decomposed the preprocessed input image into no overlapping rectangular homogeneous blocks. The block size from the modified quad tree decomposition has provided an effective structure description for the input image. However, directly using such dyadic size values as the structure activity index may introduce unpleasant block artifacts to the reconstructed image. The structure activity index is calculated as the ensemble mean of the local decomposition results centered at each position.

C. Switch based structure adaptation

Switch Based Structure Adaptation selects a partition based on the structure classification. It selects The Modified Peer Filter (MPF) for Low activity areas. The Adaptive Nearest Neighbor Filter (ANNF) for Medium activity areas. The Structure Weighted Average Filter (SWAF) for High activity areas Modified Peer Filter was proposed for image enhancement and in reducing image degradation in the high activity areas. Adaptive Nearest Neighbor Filter removes the noise while preserving the image edge structure in the medium activity areas. Structure Weighted Average Filter was designed to smooth the small distortion in the low activity areas.

IV STRUCTURE ACTIVITY CLASSIFICATION

The purpose of the structure activity classification is to partition the local structures so that a proper filtering structure and dimension can be determined for each pixel position to achieve the best visual quality. The luminance channel (image) of the preprocessed input color image, which contains most of image structure information, is first decomposed by a modified quad tree decomposition technique. Then, a structure activity index is calculated for each pixel position according to the decomposition results. Classification is finally applied to the activity index of each pixel to partition it into one of three signals activity areas,

namely, the high-activity area, the medium-activity area, and the low activity area. Each of them will relate to a well-designed filtering process, which provides the optimal restoration solution for the partitioned pixel.

A. Modified quadtree decomposition

The modified quadtree decomposition decomposed the preprocessed input image into non-overlapping rectangular homogeneous blocks according to a local dispersion criterion adopted from the variable block truncation coding (VBTC). The details of the modified quad tree decomposition process are depicted as follows.

1. Start from the entire image. Divide the ensemble deviation into four equally rectangular blocks. Denote it as v_i .

Select a predetermined threshold T , if

$$\max \{ v_i \} - \min \{ v_i \} \leq T \quad (4)$$

$$1 \leq i \leq 4 \quad 1 \leq i \leq 4$$

Then consider the block as homogeneous block otherwise further splitting is applied.

2) Repeat the splitting step on each divided block independently and recursively, until all the sub blocks are either homogeneous blocks, or reaching the minimum size of 1×1 pixels.

3) If 16×16 -pixel, split it into four equal-size rectangular blocks directly and recursively, until all the sub blocks reach 16×16 -pixel in size.

The threshold is given by the Median Absolute Deviation (MAD) scale estimation on the local ensemble deviation i.e.,

$$T = \eta \cdot MAD \{ \sigma_{3 \times 3}(c) / c \in C \} \quad (5)$$

Where $\sigma_{3 \times 3}(c)$ is the ensemble deviation obtained from a 3×3 local window centered at position c .

Where η is an empirically determined parameter used to reflect the structure dispersion of the input image η range was found to be $[0.7, 2.5]$.

B. STRUCTURE ACTIVITY PARTITION

The block size from the modified quad tree decomposition has provided an effective structure description for the input image. The structure activity index $I(c)$ is calculated as the ensemble mean of the local

decomposition results centered at each position c . The structure activity index is given by

$$I(c) = \frac{1}{2L+1} \sum_{c \in \Phi(c)} B(c) \quad (6)$$

where $B(c)$ denotes the decomposed block size at position c and $\Phi(c)$ denote a local area centered at the position c , with its size equal to $2L + 1$. Based on the obtained structure activity index $I(c)$, each obtained pixel $x(c)$ is finally classified into one of the following different structure groups.

1 High activity area (HAA)

If $1.0 \leq I(c) \leq 2.5$, then it is in high activity area. This group often relates to high-frequency details or impulse noise. In order to preserve fine image structure while suppressing impulse noises, a high nonlinear filter with a small processing window should be employed to detect and restore the original image pixel value.

2 Medium activity area (MAA)

If $2.5 \leq I(c) \leq 2.5$, then it is in medium activity area. This group usually includes primary image edge structures and textures. Moderate nonlinear filtering will be used to remove possible impulse noise, to smooth the texture area, and to preserve the primary structure. Its processing window should also be adaptive to the different structure distribution.

3. Low activity area (LAA)

If $5.5 \leq I(c) \leq 16.0$, then it is in low activity area. This group relates to the flat background area with, little variance or distortion. In order to favor the human perception without losing computation efficiency, a linear (weighted) filter with a relatively big processing window should be considered to provide sufficient smooth effect for the concerned area.

C. HYBRID VECTOR FILTERING STRUCTURE

In order to match the restoration requirements of different structure groups, it is proposed to use three sub adaptive-vector-filters. The three subfilters are

1. The Modified Peer Filter (MPF)
2. The Adaptive Nearest Neighbor Filter (ANNF)

3. The Structure Weighted Average Filter (SWAF)

Small windows and high-detail preservation nonlinear subfilters are proposed for effective removal of noises contained in image edges and detail areas, while large windows and more linear filtering scheme are proposed for sufficient smoothing of small distortions in flat background areas. The table 1 shows the different window dimension for the MPF, ANNF and SWAF.

1. Modified Peer Filter

The Peer Group Filter (PGF) was proposed for image enhancement. It consists of a Fisher discrimination based on the Euclidean distance and a standard Gaussian filter. The Euclidean distance cannot precisely reflect the visual similarity between two color image pixels. The Fisher discrimination may malfunction for pixel set consisting of two or more distinct clusters, e.g., a sharp edge with impulse noises. The fixed standard Gaussian filter tends to over-smooth fine image details. Therefore, the modified peer filter is formulated to provide better structure preservation for noise removal in image detail areas. The Modified Peer Group Filter is optimal in reducing image degradation in the high-activity areas. A 3×3 window size is generally used as shown in table 1

TABLE 1

STRUCTURE CLASSIFICATION AND THEIR HYBRID FILTERING AND WINDOW ADAPTATION

| $I(c)$ | 1.0-2.5 | 2.5-4.0 | 4.0-5.5 | 5.5-7.5 | 5.5-9.5 | 9.6-16.0 |
|-----------------------|--------------|--------------|--------------|--------------|--------------|----------------|
| Classification | HAA | MAA | | LAA | | |
| Subfilter | MPF | ANNF | | SWAF | | |
| Windows size | 3×3 | 3×3 | 5×5 | 7×7 | 9×9 | 11×11 |

2. Adaptive Nearest Neighbor Filter

For the classified medium-activity area, it is desirable to preserve its primary edge structure while applying a strict limitation on local deviations. This task is

accomplished by a well defined subfilter, the ANNF filter. The window dimension of the ANNF can be 3×3 or 5×5 , depending on the structure activity index value as shown in table 1.

3. Structure Weighted Average Filter

Structure Weighted Average Filter (SWAF) was designed to smooth the small distortion in the low activity areas. The low activity areas are usually flat area of input image with small distortions or background containing impulse noise. The structure weighted average filter is designed to effectively suppress all small distortions and noises remaining in low-activity areas, while reducing significant amount of computation overhead. Since $I(c)$ is usually large for smooth areas such a weighting structure is able to avoid the distortion spreading of impulse noise corruption in flat areas and to provide smoother reconstruction for better perceptual image quality.

V. SIMULATION RESULTS

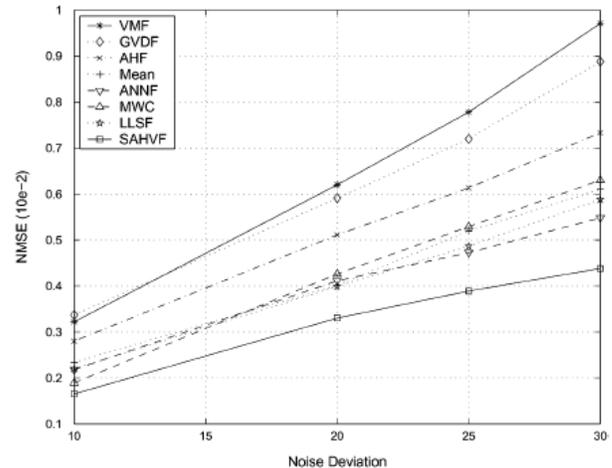
The proposed filter structure has been extensively evaluated using a wide range of 512×512 24-bit RGB test images. Two standard quantitative measures are employed in the performance assessment. The *normalized mean square error* (NMSE) [17] measures the image distortion in the RGB color space. Lets $s(c)$ and $y(c)$ denote the original and reconstructed pixel value at position $c \in C$ respectively, then

$$NMSE = \frac{\sum_{c \in C} \|s(c) - y(c)\|^2}{\sum_{c \in C} \|s(c)\|^2}. \quad (7)$$

The *normalized color difference* (NCD) [17] measures the image distortion in the perceptual uniform CIELAB color space .It is given by

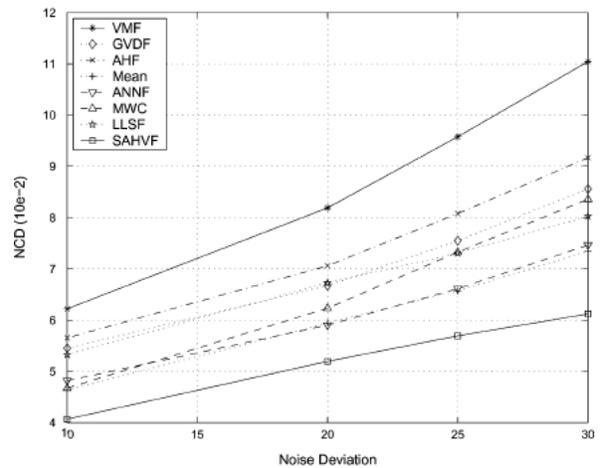
$$NCD = \frac{\sum_{c \in C} \|\Delta E_{Lab}(c)\|}{\sum_{c \in C} \|E_{Lab}(c)\|} \quad (8)$$

Where $\Delta E_{lab}(c)$ represents the difference between the original image pixel and its reconstruction at position c in the CIELAB color space, and $E_{lab}(c)$ denotes the original image pixel value in the CIELAB color space.



(a)

Fig 1 Performance of various filters on restoration of the image contaminated different levels of noise. (a) The output distortion measured in NMSE



(b)

Fig 2 Performance of various filters on restoration of the image contaminated different levels of noise. (b) The output distortion measured in NCD

VI. CONCLUSION AND FUTURE WORK

In this paper, various noise types in digital color imaging are reviewed. Based on the human visual perception, a structure-adaptive filter named SAHVF is proposed for color image restoration. The filter includes a noise-adaptive structure activity classification, which provides a structure activity detection and partition for each pixel position. The

results of the classification are utilized by a switch-based hybrid filtering structure, which is able to select an optimal sub filtering and processing window to provide the best tradeoff between noise suppression and visual quality. The proposed SAHVF filter has demonstrated a robust performance in suppressing different types of noise contamination. For additive noise contamination; it can produce a reconstruction with smoother background and sharp texture, which is significantly better in perceived image quality. For impulse noise corruption, the filter provides a comparable performance to the state-of-the-art filters in noise removal and structure preservation. Beside its robust performance, the filter demands a moderate computation cost for most restoration applications, especially for high-corrupted color images, the SAHVF can provide better reconstruction, with less than half of the processing time than those classic vector filters. The simulation will be done in next phase. This consists of additive noise suppression, impulse noise removal and mixed noise suppression, to restore the original color image

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REFERENCES

- [1] V. Barnett, "The ordering of multivariate data," *J. Stat. Soc. Amer. A.*, vol. 139, no. 3, pp. 318–354, 1976.
- [2] I. Pitas and P. Tsakalides, "Multivariate ordering in color image filtering," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 1, no. 3, pp. 247–259, Sep. 1991.
- [3] R. C. Hardie and G. R. Arce, "Ranking in R and its use in multivariate image estimation," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 1, no. 2, pp. 197209, Jun. 1991.
- [4] J. Astola, P. Haavisto, and Y. Neuov, "Vector median filter," *Proc. IEEE*, vol. 78, no. 4, pp. 678–689, Apr. 1990.
- [5] P. E. Trahanias and A. N. Venetsanopoulos, "Vector directional filters: A new class of multichannel image processing filter," *IEEE Trans. Image Process.*, vol. 2, no. 4, pp. 5288–534, Apr. 1993.
- [6] D. G. Karakos and P. E. Trahanias, "Combining vector median and vector directional filters: the directional-distance filter," in *Proc. IEEE Int. Conf. Image Processing*, vol. 1, Washington, DC, Oct. 1995, pp. 171–174.
- [7] K. N. Plataniotis, S. Vinayagamoorthy, D. Androustos, and A. N. Venetsanopoulos, "An adaptive nearest neighbor multichannel filter," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 6, no. 6, pp. 699–703, Dec. 1996.
- [8] K. N. Plataniotis, D. Androustos, and A. N. Venetsanopoulos, "Adaptive multichannel filters for color image processing," *Signal Process.: Image Commun.*, vol. 11, no. 3, pp. 171–177, Jan. 1998.
- [9] "Color image processing using adaptive vector directional filters," *IEEE Trans. Circuits Syst. II, Exp. Briefs*, vol. 45, no. 10, pp. 1414–1419, Oct. 1998.
- [10] "Adaptive fuzzy systems for multichannel signal processing," *Proc. IEEE*, vol. 87, no. 9, pp. 1601–1622, Sep. 2009.
- [11] E. S. Hore, B. Qiu, and H. R. Wu, "Improved color image vector filtering using fuzzy noise detection," *Opt. Eng.*, vol. 42, no. 6, pp. 1656–1664, Jun. 2008.
- [12] K. Tang, J. Astola, and Y. Neuvo, "Nonlinear multivariate image filtering techniques," *IEEE Trans. Image Process.*, vol. 4, no. 6, pp. 788–798, Jun. 2002.
- [13] M. Gabbouj and F. A. Cheikh, "Vector median-vector directional hybrid filter for color image restoration," in *Proc. EUSIPCO*, vol. 2, Trieste, Italy, Sep. 10–13, 1996, pp. 879–881.
- [14] L. Khriji and M. Gabbouj, "Vector median-rational hybrid filters for multichannel image processing," *IEEE Signal Process. Lett.*, vol. 6, no. 8, pp. 186–190, Aug. 2009.
- [15] Y. H. Lee and S. A. Kassam, "Generalized median filtering and related nonlinear filtering techniques," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-33, no. 3, pp. 672–683, Jun. 1985.
- [16] W. K. Pratt, Ed., *Digital Image Processing*. New York: Wiley, 2011.
- [17] K. N. Plataniotis and A. N. Venetsanopoulos, Eds., *Color Image Processing and Applications*. Berlin, Germany: Springer, 2012.