

Color Image Restoration Using Explicit Local Segmentation

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Abstract. A local segmentation structure is proposed for color image denoising and restoration. Most state-of-the-art filters suppression impulse noise well but tends to destroy thin lines, edges and high image details. The proposed filters facilitate local segmentation technique to preserve image structures and noise reduction. Firstly, the K-VMF is used for local segmentation and then the selection of vector filters for reconstruction of the current pixel. The proposed filters demonstrated acceptable results for both objective and subjective assessments.

1 Introduction

Traditionally, in the area of image restoration noise removal is achieved by linear operations because of their simplicity and ease of implementation. Nonlinear filters generally perform better than linear filters due to the fact that most imaging systems produced non-stationary and nonlinear signals. The Vector Median Filter (VMF [2]) is one of the most popular nonlinear vector filters for impulse noise removal because of its simplicity. Fuzzy VMF (FVMF [3]) is an extended VMF. Other order statistic vector filters include the Vector Directional filter (VDF/GVDF [4]), Directional Vector filter (DDF [5]), Hybrid Directional filter (HDF [6]) and Adaptive Nearest Neighbor filter (ANNF [7]). These classic filters perform well in suppressing impulse noise, but they tend to degrade the high image details and introduce new artifacts such as blurring, smearing and shifting of the image structures.

The Multiple Window Configuration (MWC [8]) and Neighborhood adaptive vector (NAVF [9]) filters are detection and switch based filters which utilize a detector and switch the output between component filters according to the detection results. MWC is one of the most efficient impulse noise removal filter but it depends on the estimated reference image (corrupted image filtered by standard median filtering). Thus any distortion remaining in reference image will be introduced into the final reconstruction, resulting in image blurring, edge shifting and chromatic distortions [9].

Seemann and Tischer [1] proposed an explicit local segmentation filter for removal of Gaussian noise in grey-scale images. They used the k-means technique to segment pixels in the local window and utilized the estimated global noise variance in order to reconstruct the corrupted pixels. The Peer Group filter (PGF [10]) is another explicit local segmentation filter for impulse noise suppression in color images. It used the

Fisher's discriminant to classify the pixels into groups. It employs a standard filter to reconstruct the noisy pixel from the pixels in the peer group.

In this paper, the concept of local segmentation is incorporated into existing vector filters in order to suppress impulse noise in both natural and textured color images. Section 1.1 describes some limitations of the VMF. Section 2 presents the structure of the proposed filter. Section 3, describes the simulation results and in Section 4, some remarks and conclusion.

1.1 VMF Drawbacks

The VMF is regarded as one of the most popular vector filters and there are many extensions and variations of it in the literature. For example, detection based filters utilize it with a noise detector. Hybrid or switch based filters use it as a component filter for reconstruction. VMF can also be used as a noise detector and for reconstruction, as in [9]. Its definition is as follows:

Let \underline{x} be a multichannel sample vector and W be the window (x_1, x_2, \dots, x_n) . For pixel x_i , its total distance to the other pixels in the window is given by (1).

$$d_w(x_i) = \sum_{j=1}^n d(x_i, x_j) \quad (1)$$

Often, the distance $d(x_i, x_j)$ is the Euclidean distance. Let the $d_w(x_i)$ be sorted in increasing order to produce $\{d_1, d_2, \dots, d_n\}$. The pixel associated with d_1 has the smallest total distance to all the pixels in the window. In one sense, it is the most 'in lying' value and thus the best representative value. This value is chosen as the vector median (VM) and used in the VMF.

Although it has been used extensively, the VMF has its drawbacks as demonstrated in Fig.1. Even when there is no noise within an image the VMF will destroy thin lines and edges. The VMF and its variants may destroy underlying image structure when the mask contains pixels from more than 1 segment. For example, suppose the mask contains 9 pixels which belong to two segments. The VM will be chosen from the pixels which belong to the segment which has more members in the mask. Thus structure like corners and thin lines, which only have a small number of pixels in the mask, get erased. For a 3x3 mask, if the centre pixel is part of a segment whose intersection with the mask contains at most 4 pixels, the centre pixel will be replaced by a pixel from the other segment. Any feature whose intersection with the 3x3 mask never has more than 4 pixels will be completely erased. These drawbacks not only occur with the VMF but also with VDF, DDF, and ANNF, to name a few.

2 Formulation of the Local Segmentation Vector Filters

The motivation for the proposed filter is to overcome the drawbacks of the vector filters. Hence, it aims to preserve as much of the image structure as possible and to minimize chromatic distortions. To preserve local image structure, our filters must identify this structure and segments within the mask. In this paper we will only consider situations where the mask covers at most two segments.

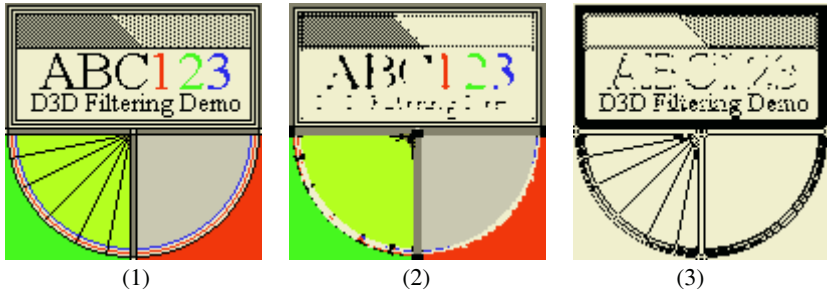


Fig. 1. (1) Noiseless *Letter* image, (2) Result of VMF and (3) Difference image

2.1 Homogeneity Detector

There are numerous ways to check whether a local window is homogeneous or not. If equation (2) is true, the region is classified as being homogeneous and unaffected by impulse noise and no filter is required. Otherwise, it will be treated as containing two segments and local segmentation. The threshold $\delta_R = 55$ is chosen from [9].

$$d_n - d_1 \leq \delta_R \quad (2)$$

2.2 Local Segmentation (LS)

In grayscale images there are many ways to cluster data. The K-means and K-median are among the popular choices because of their simplicity and low computation cost. K-means minimizes the mean square error, whereas K-median minimizes the mean absolute error. In color image processing, the K-median method can be extended to K-VMF for local segmentation in the RGB color space.

Since we are only trying to find two classes, $k=2$. Our algorithm is as follows:

1. Choose two initial vectors to represent each class.
2. Assign each pixel in the mask to the representative vector which is closer.
3. Re-compute the representative vector for a class as the VM of the pixels in that class.
4. Repeat as long as the class representatives continue to change.

For initial vectors, we choose the two pixels in the mask which are the furthest apart.

2.3 Reconstruction Filters

If we have split the pixels into two segments our program allows any vector filter (E.g. VMF, VDF, DDF, ANNF, etc) to be applied, but it can only use pixels from the same segment as the pixel to be filtered. However, the vector filter will only be applied if the segment is considered to be 'valid'. If the pixel to be filtered is in the segment by itself, it could either be part of a one pixel feature or it could be adversely affected by impulsive noise. There is no way to distinguish between those two situations. Therefore, we need to set a limit on how small a valid segment can be. If the segment has 3 or more pixels, it is considered valid. If it has 2 pixels or fewer, it is considered invalid and the vector median of the other segment is used as the filtered value.

3 Simulation Results

In this section, the proposed local segmentation filter structure is evaluated and compared with existing filters for color image denoising. The performance analysis carried out in two ways:

- 1) A comparison of the classic vector filters (VMF and ANNF) with their proposed variants, LS-VMF and LS-ANNF.
- 2) A comparison of the proposed LS vectors with the state-of-the-art filters.

Several objective criteria are used to measure the distortion in image reconstruction, which includes the NMSE (normalized mean square error) and the NCD (normalized color difference). The NMSE and NCD are defined in [3].

3.1 Impulse Noise Corruption

In this paper, the corrupted noise model is assumed to be random impulse noise where the noise term is uniformly distributed over the range of all possible pixel values. All images in the simulation are corrupted by channel correlation method proposed by [4]. For example, a preset percentage is first corrupted by random impulse noise in an independent manner, then a correlation factor $C=0.5$ is used to introduce more noise into the other colour channels for each corrupt pixel. In another word, there is a 50% chance of further corruption if one channel has been already corrupted.

3.2 Experimental Performance

In the first experiment, the Mandrill image was corrupted by 5% and 10% of random impulse noise. In order to evaluate the fidelity of the LS vector filters, they are first compared with their corresponding classic vector filters. Table 1 shows the objective measures for VMF, ANNF and the proposed LS-VMF, LS-ANNF, respectively. It shows that the proposed filters have consistent improvement for both noise levels than their counterparts. Figure 2 demonstrates that the proposed filters perform better at preserving edges and at retaining image structures.

Table 1. Color Mandrill image corrupted by 5% and 10% random impulse noise. The measurements are scaled by $10e-2$

Noise	Random Impulse (5%)		Random Impulse (10%)	
Filter	NMSE	NCD	NMSE	NCD
None	1.492	2.702	2.864	5.178
VMF	1.602	5.247	1.671	5.414
LS-VMF	1.181	4.611	1.359	4.970
ANNF	1.489	5.640	1.548	5.940
LS-ANNF	1.114	4.954	1.279	5.440

In the second experiment, the proposed filters are compared with the state-of-the-art filters for the Letter image corrupted by 10% and 20% of random impulse noise. In Figure 3, the proposed filters performed exceptionally well for noise suppression and detail preservation. Most state-of-the-art filters showed unacceptable results as they destroyed lines, edges, and high image detail. Moreover, GVDF, DDF and

MWC even have chromatic distortions along with structure degradations. Table 2 shows evidence of these degradations. The main reasons for such poor performance could be that the images are different to those in the training set used to tune the filters or the image model used by these filters is not appropriate. However, it is conclusive that these filters do not preserve image structure well and even further degrade the image quality even with or without noise. The PGF also used explicit local segmentation is one of the top performer for both natural and texture images.

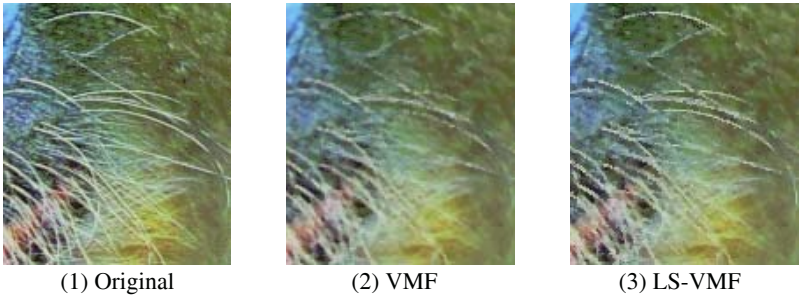


Fig. 2. Filtered Mandrill image (portion) for the VMF and LS-VMF filters

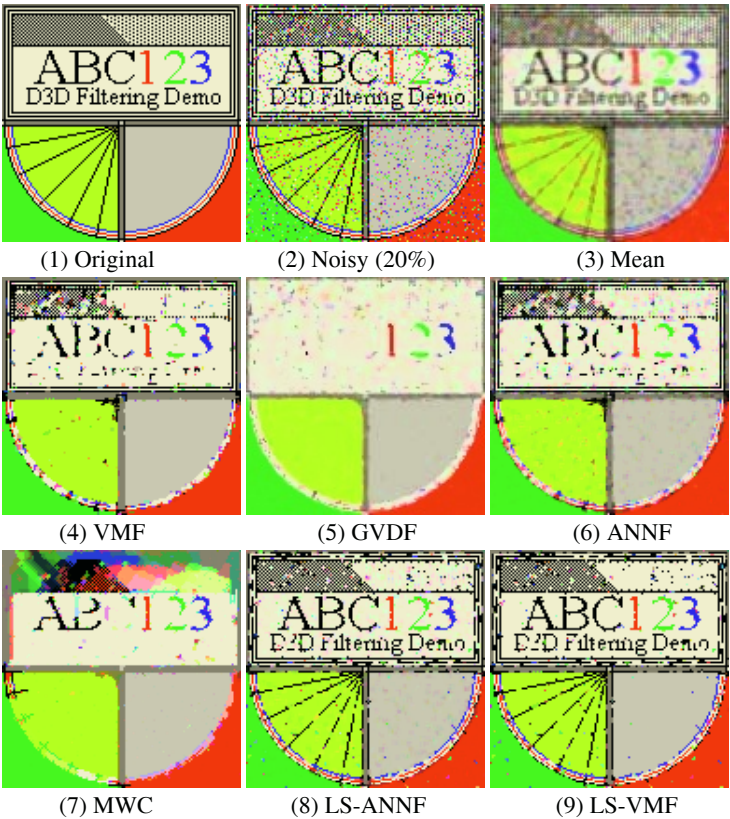


Fig. 3. Some resultant images of color *Letter* image corrupted by 20% random impulse

Table 2. Color *Letter* image corrupted by 10% and 20% random impulse noise. The measurements are scaled to 10e-2

Noise	Random Impulse (10%)		Random Impulse (20%)	
Filter	NMSE	NCD	NMSE	NCD
None	3.341	7.149	6.413	13.758
Mean	20.169	32.311	20.548	35.033
VMF	31.046	27.325	31.185	28.593
GVDF	29.165	25.437	28.415	26.325
DDF	28.971	25.706	29.357	26.495
HDF	30.477	26.400	30.552	27.278
AHDF	29.973	26.434	29.878	27.435
FVDF	28.415	25.920	27.773	26.902
ANNF	29.028	28.182	28.062	29.757
MWC	21.813	28.081	21.840	27.523
PGF	9.223	8.075	14.707	13.384
LS-ANNF	5.383	6.914	7.412	10.935
LS-VMF	5.673	5.664	7.830	8.552

4 Conclusions

In this paper, a local segmentation structure is proposed for use with existing vector filters for color image denoising and restoration. The proposed K-VMF technique is used for local segmentation and vector filters such as VMF and ANNF are used for reconstruction. However, the proposed structure is so diverse that it is not limited to these two filters. The proposed LS-VMF and LS-ANNF filters demonstrate greatly improved performance as compared to the VMF and ANNF filters. The proposed filters performed exceptional well for random impulse noise suppression and detail preservation, where most state-of-the-art filters showed unacceptable results as they destroy lines, edges, and high image detail.

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