EXPLICIT LOCAL SEGMENTATION BASED IMPULSIVE NOISE REDUCTION FOR COLOR IMAGES

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ABSTRACT

A family of local segmentation vector filters for color image noise suppression and detail preservation is proposed. Most state-of-the-art filters alleviate impulse noise well but tend to destroy thin lines, edges and fine image details. The proposed filters facilitate local segmentation to preserve image structures and noise suppression. First the K-VMF is developed and used for local segmentation, and then a selection of vector filters is used to reconstruct the current pixel. In addition, once pixels have been marked as being noisy, their values are not used in processing subsequent pixels. The proposed filters also demonstrated acceptable results for both objective and subjective assessments.

1. INTRODUCTION

In the specific area of color image restoration, filters are either categorized as component-wise or multivariate [1]. Component-wise methods deal with each channel separately, whereas multivariate filters process color pixels as vectors. Since color channels are strongly correlated, vector filters tend to perform better and produce fewer artifacts such as color bleeding and distortions. When dealing with impulsive noise, where the original pixels are completely replaced by random noise, some people advocate that the most efficient filtering approach is based on the vector order-statistic theory [2].

One of the most popular vector filters is the Vector Median filter (VMF) [3]. Other filters include Vector Direction filter (VDF/GVDF) [4], Directional Distance filter (DDF) [5], Hybrid Directional filter (HDF/AHDF) [6] and Adaptive Nearest Neighbour filter (ANNF) [7]. These classic filters remove impulse noise adequately but they tend to introduce new artifacts to image structures such as blurring, smearing and shifting. This happens because they do not classify pixels as been clean, noise, blotch of noises, or high image detail. The Multiple Window Configuration (MWC) [8] solves this drawback by the use of detection and switching. However, this filter depends on the reference image and fine tuning on specific images to achieve optimal results for that image. Another switch based filter is Neighbour Adaptive Vector filter (NAVF) [9]. All of these filters implicitly or explicitly assumed that the current window is homogeneous. This is true on most parts of the image, but there are edges, thin lines and outliers as well. Thus, the assumption of homogeneity will lead to the removal of not only noise but also the image structure. The Peer Group filter (PGF) [10] uses Fisher's Discriminant to segment pixels explicitly into groups with similar intensity and to reconstruct using the VMF and a weighting function.

2. VECTOR MEDIAN FILTER

VMF is one of the most efficient and popular filter because of its simplicity and low computational cost. It is extensively used, for example, as an impulse detector, and in hybrid and switch based filters.

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

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

The distance $d(x_i, x_j)$ is often the Euclidean distance. Let the $d_w(x_i)$ be sorted in ascending order to produced $\{d_1, d_2, ..., d_n\}$. The pixel associated with d_1 is the most 'inlying' value and is chosen as the vector median (VM) and used as the output of the VMF.

Although the VMF can remove most impulsive noise, it tends to destroy image structure and blur the image as in Figure 1. When there is no noise within an image the VMF will destroy thin lines and edges. The VMF and its

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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 other vector filters as well. The motivation of this paper is to overcome these drawbacks by using local segmentation.

3. FORMULATION OF LOCAL SEGMENTATIION VECTOR FILTERS (LSVF)

The structure of the proposed filter is in Figure 2. It comprised of the homogeneity detection, the local segmentation process and the vector filters for reconstruction.

3.1. Homogeneity Detection

If equation (2) is true, the region is classified as being homogeneous and no filter is required. Otherwise, it will be treated as containing two segments. The threshold $\delta_R = 55$ is chosen from [9].

$$d_n - d_1 \leq \delta_R \tag{2}$$

3.2. Local Segmentation (LS)

In color image processing, the K-median method can extended to K-VMF for local segmentation in the RGB color space.

Since we are only trying to find two classes, k=2. The 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 steps 2 to 4.

For initial vectors, there are two ways. One is to choose the two pixels in the mask which are the furthest apart (TYPE1). Another is to choose the centre pixel (CP) as one initial value and the pixel at the furthest distance from it is another (TYPE2). This latter method will require less computation than the first. In additional, if the CP is the sole pixel in the segment then it is considered to be noise.

3.2.1. Pixel Marking (PM)

When images are processed by rows, by the time a pixel is to be processed pixels in rows before the current row and in column of the current row up to but not including the current pixel, are known. It can be remembered whether these pixels were 'noisy' or 'clean'. For a 3x3 mask, 4 of the 9 pixels have already been processed and they will only be used in the LS process if they were 'clean'. This is shown in Figure 3.

3.3. Vector Filtering (VF)

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 to the segment containing the current pixel, creating a whole family of Local Segment Vector Filter (LSVF). The vector filter will only be applied if the segment is considered to be 'valid'. If the segment has 3 or more pixels, it is considered as 'valid'. If it has 2 pixels or fewer, it is considered 'invalid' and the vector filtered value of the other segment is used as the filtered value. The PM feature can also be used. When a filter is applied to a segment, pixels marked as noise can be ignored. In this paper 4 types of LSVF are considered.

3.3.1. LSVF1 – LSVMF1

Local Segmentation - TYPE1
Vector Filter - VMF
Additional - Not Included

3.3.2. LSVF2 – LSANF1

Local Segmentation - TYPE1
Vector Filter - ANNF
Additional – Not Included

3.3.3. LSVF1 – LSVMF2

Local Segmentation – TYPE2
Vector Filter - VMF
Additional – Pixel Marking in both LS and VF

3.3.4. LSVF4 – LSANF2

Local Segmentation – TYPE2
Vector Filter - ANNF
Additional – Pixel Marking in both LS and VF

4. SIMULATION RESULTS

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

1) A comparison of the classic vector filters (VMF and ANNF) with their proposed variants, LSVMF1, LSVMF2, LSANF1 and LSANF2 in Table 1.

2) A comparison of the proposed LSVF(s) with the state-of-the-art filters.

Several objective criteria are used to measure the distortion in image reconstruction, which includes the MSE (Mean Square Error), MAE (Mean Absolute Error) and the NCD (Normalized Color Difference). NCD is defined in [3].

4.1. Impulse Noise Corruption

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 (0 to 255). All images in the simulation are corrupted by channel correlation method proposed by [4]. For example, for a preset percentage of pixels, the R, G or B channel of the pixel value is chosen at random and 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 color channels for each corrupt pixel. In another word, there is a 50% chance of further corruption if one channel has been already corrupted.

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4.2. Experimental Performance

4.2.1. Experiment One

In this experiment, the *Barbara* image was corrupted by 5% and 10% of random impulse noise. To evaluate the efficiency of the LS structure, the proposed filters are first compared with their corresponding classic vector filters. Table 1 shows the objective measures for VMF, ANNF and the proposed LSVMF(s) and LSANF(s). It shows that the proposed filters have consistent improvement for both noise levels than their counterparts. Figure 4 demonstrates that the proposed filters perform better at preserving edges and at retaining image structures, with less blurring.

4.2.1. Experiment Two

In this experiment, the proposed filters are compared with some of the state-of-the-art filters for the *Letter* image corrupted by 10% and 20% of random impulse noise. In Figure 5, the proposed filters performed 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. Table 2 shows evidence of these degradations.

5. CONCLUSIONS

The proposed filters using the LS structure perform better than their classic counterparts. Moreover, it is demonstrated that the PM improves the proposed filters by having higher accuracy in LS and in the reconstruction process. It shows that most filters do not preserve image structure well and even further degrade the image quality even with or without noise. The proposed filters perform better in for image structure preservation than other filters.

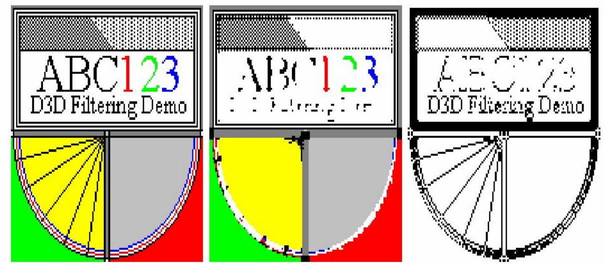

Figure 1: Results of VMF filter for *Letter* image.

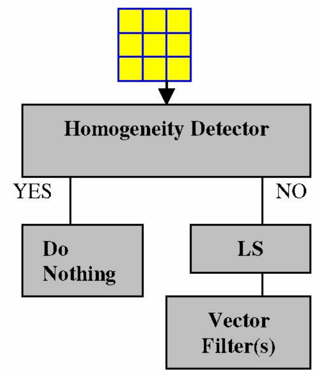

Figure 2: Proposed LSVF structure

Noise / Filter	Random Impulse 5%			Random Impulse 10%		
	MAE	MSE	NCD	MAE	MSE	NCD
None	7.8	922	2.87	15.6	1863	5.71
ANNF	22.6	594	3.86	23.9	624	4.24
LSANF1	**15.6**	**351**	**2.72**	**18.4**	**475**	**3.46**
LSANF2	**14.9**	**268**	**2.70**	**17.0**	**369**	**3.13**
VMF	21.2	624	3.55	22.1	656	3.70
LSVMF1	**14.6**	**361**	**2.54**	**17.0**	**490**	**3.07**
LSVMF2	**13.8**	**284**	**2.57**	**15.8**	**390**	**2.97**

Table 1: Results of color *Barbara* image. NCD scaled by 10e-2

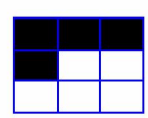

Figure 3: PM - Pixels with known status (black).

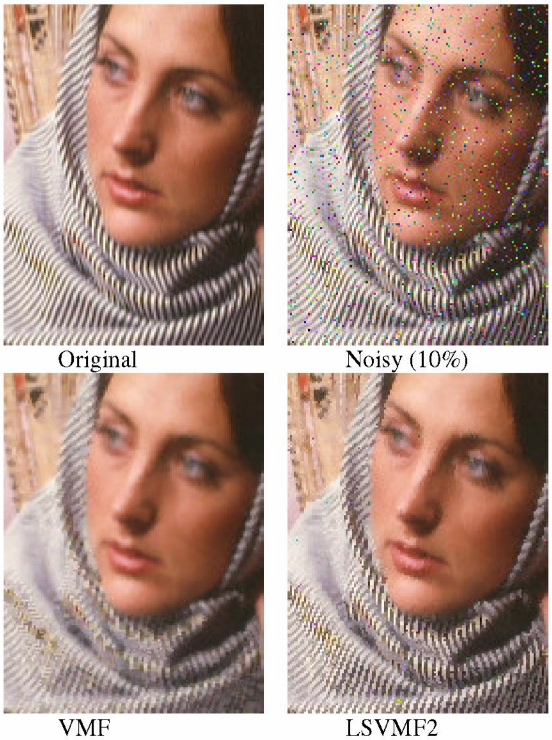

Figure 4: Results for parts of the *Barbara* image (10% noise).

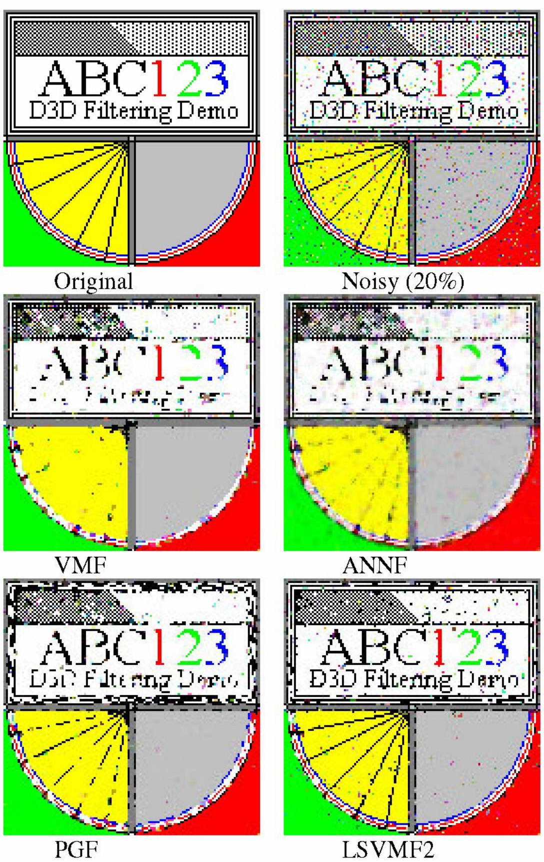

Figure 5: Results of *Letter* image (20% noise).

Noise / Filter	Random Impulse 10%			Random Impulse 20%		
	MAE	MSE	NCD	MAE	MSE	NCD
None	23.3	3794	7.3	45.5	7424	14.2
Mean	182.7	22761	32.4	193.9	23208	35.4
VMF	147.5	34779	27.3	150.6	34543	28.3
GVDF	142.4	32754	25.5	145.6	31954	26.3
DDF	138.5	32649	25.6	143.2	32991	26.5
HDF	147.0	34089	26.4	150.2	33734	26.8
AHDF	148.8	33856	26.8	151.2	32966	27.0
FVDF	145.5	32029	26.0	149.3	31211	26.9
ANNF	151.6	32587	28.3	157.7	31147	29.7
MWC	132.5	24513	27.7	131.2	24614	28.0
PGF	42.1	9909	7.8	70.6	16144	13.2
LSANF1	**28.0**	**5511**	**6.5**	**46.4**	**8088**	**11.4**
LSANF2	**23.7**	**5196**	**5.6**	**37.8**	**7431**	**9.3**
LSVMF1	**25.6**	**5676**	**5.5**	**41.0**	**8385**	**9.2**
LSVMF2	**22.5**	**5373**	**4.6**	**34.9**	**7803**	**7.5**

Table 2: Results of color *Letter* image. NCD is scaled by 10e-2

6. REFERENCES

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