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Vector Isolated Minimum Distance Filtering for Image De-Noising in Digital Color Images

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Abstract*: Image de-noising forms a crucial component of digital image processing. The state-of-the-art vector median filtering based image de-noising approaches like the median filtering, the vector median filtering and the basic vector directional filtering and their extensions process the vector pixels jointly in the red, green and blue components. Consequently any smoothing applied therein is leveraged on all the color components equally. In this paper we propose that processing the vectors in isolation, that is, each color component taken separately, and then smoothed by minimising the aggregate distance between the pixels in each color component will lead to more efficient de-noising of noisy images. We demonstrate the superiority of the proposed method compared against vector filtering approaches using several images and test measures.

Keywords: Image Processing, Image de-noising, Vector Median Filtering, Isolated Vector Minimum Distance Filtering, Impulse Noise.

I. INTRODUCTION

Digital image processing is a fundamental engineering domain in several applications including computer vision, robotics, biomedical engineering and target tracking [1]. The images used in these applications often get corrupted by noise. Noise in this context, can be defined as a random event that corrupt the original pixel intensity values, either the red, green, blue intensities or all of them, to another value within the visible range. The noise is not part of the ideal system and is treated to be independent of the original signal, and is generally caused due to transmission errors, system errors, etc. Image de-noising forms an important part of image processing and the interest of this paper is in de-noising of digital color images [2].

There are several noise models that apply to image corruption depending on the applications. The noise model of interest to this paper is the impulse noise model [3, 4]. The impulse noise is sudden burst or slump of energy at the pixels. Each pixel may be corrupted or not, and the corrupted one may be so in either of its color components. Owing to the uncertainty in pixel corruption, the impulse noise model can be modeled using probabilistic measures.

There are several nonlinear filtering approaches for reducing impulse noise [5]. The median filter is a nonlinear digital filter applicable for noise removal in both color and gray-scale images [6].

The idea here is to examine a window (or mask) of the image and measure if that window is representative of the image. Several measures such as the mean, the median, etc. have been used, but in particular, the median filtering techniques applied to the joint vector pixels have gained prominence due to their ease of operation and robustness to noise [7]. The vector median filter (VMF) is a nonlinear method prominently used to process the color images as a vector field in order to mitigate the multichannel dependence [8, 9]. The family of vector filters inspired by the VMF that includes the directional vector filtering, the method works by selecting an output vector in a given population which is the nearest one to the rest of the vectors in terms of a distance measure. The filters of this family, and especially the VMF, can perform quite robustly in impulse noise reduction without introducing color artifacts, since they appropriately consider the color components correlation [10]. In particular, these methods are used to improve their ability to preserve image details but many noise free pixels are unnecessarily modified. Another version of the VMF is the basic vector directional filter (BVDF) that rather uses the angular distance between the pixels than the vector magnitudes [11]. The method is shown to be more effective when vector angles dominate the vector magnitudes.

The problem however in state-of-the-art methods in vector median filtering is that the vector pixel is processed jointly, i.e., the red, green and blue pixel intensities are taken together as a multichannel. Any smoothing performed therein is accounted in all the color channels equally. This could be problematic since there is every possibility that skewness in one color component is smeared into other color components, thereby distancing the pixel from the true intensity in its individual color components.

In this paper we propose the isolated vector minimum distance filter (IVMDF) to solve this problem by processing the test windows in isolation. They key idea here is to minimise the aggregated distance of pixels with all the other pixels in the test window, and this process is done by keeping the vector pixels in isolation. That is, any smoothing performed therein affects only the corresponding color component but not the others. The merit of this proposal is improved accuracy in image reconstruction and fewer artifacts.

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The rest of the paper is organized as follows. In Section II we describe the image signal model. We then describe the aforementioned image de-noising methods in Section III. This is followed by our proposed IVMDF method in Section IV and comparative results in Section V. We finally conclude in Section VI.

II. THE SIGNAL MODEL

It is likely that digital images get corrupted by noise during transmission from one point to another. There are several types of noise that are of concern and this paper focuses on the impulse noise. The impulse noise in digital images represents random burst or slump of energy that occur during the transmission. Here a pixel may be corrupted with some probability. If I is the original uncorrupted image, then the noisy image I_n at the (i, j) pixel can be described as

$$I_n(i,j) = \begin{cases} I(i,j), & \text{if } x \geq p \\ \left(I_r(i,j), I_g(i,j), z\right), & \text{if } y < \frac{1}{3} \text{ and } x < p \\ \left(I_r(i,j), z, I_b(i,j)\right), & \text{if } \frac{1}{3} \leq y < \frac{2}{3} \text{ and } x < p \\ \left(z, I_g(i,j), I_b(i,j)\right), & \text{if } \frac{2}{3} \leq y \text{ and } x < p \end{cases}$$

where I_r, I_g, I_b are respectively the original red, green and blue intensity components. The probability of noise $p \in (0,1)$ models whether a pixel is corrupted or not. The larger the value of p the noisy the image gets and the lesser the value of p its value the less noisy the image. The numbers $x, y \in (0,1)$ are uniform continuous random variables drawn from the specified interval and are probability supports to model that color component that is corrupted. The number $z \in (0,255)$ is a uniform continuous random number drawn from the specified interval and specifies the corruption of the pixel.

III. IMAGE DE-NOISING METHODS

In this section we describe the three popular vector median filter based image de-noising methods.

A. Median Filtering

The median filtering was first popularised by J. W. Tukey [4]. The filtering process works by considering a $n \times n$ window (or mask), denoted as W, within the noisy image I_n and then replacing a test pixel (usually the centre vector pixel) by the vector median of the entire window.

Let $\mathrm{x}_i, i = 1,\ldots,n$ be the vector pixels in the $n \times n$ window W. Each of the vector pixel is a 3-tuple and consists of the intensities in each of the three color components as

$$\mathrm{x}_i = \left(x_{r,i}, x_{g,i}, x_{b,i}\right), i = 1,\ldots,n$$

where $x_{r,i}, x_{g,i}, x_{b,i}$ respectively correspond to the red, green and blue intensities in the i th pixel. Then the median is computed as

$$m = median(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_n)$$

and the test pixel x_T is replaced with the median vector pixel m.

This filtering process has proved to be robust to the presence of noise because it cancels the effect of pixel skewness induced by the impulse noise. Moreover the method iteratively converges to a single root signal.

B. Vector Median Filtering

The vector median filter and its extensions are derived from maximum likelihood estimation (MLE) principles of exponential distributions. The method is as follows. Let $\mathrm{x}_i, i = 1,\ldots,n$ be the vector pixels in the $n \times n$ window W. For each vector pixel we calculate the sum of the distances to other pixels using an appropriately chosen distance measure. In this paper we chose the L_2 norm Minowski's distance measure. The distances are then added to obtain

$$S_i = \sum_{j=1}^{n} \left\| \mathrm{x}_i - \mathrm{x}_j \right\|^2, i = 1,\ldots,n$$

We then compute the index that minimises the sum as follows,

$$\hat{i} = \min_i S_i$$

and the test pixel x_T is replaced with the vector median $\mathrm{x}_{\hat{i}}$.

It can be observed that the VMF method minimises the aggregated distance between the pixels in the text window and consequently the outliers caused due to noise are smoothed out.

C. Basic Vector Directional Filtering

The BVD filter is a rank ordered method in which the angle between two vector pixels is used as the distance measure as against the Minowski's distance in the VMF. The method is as follows. Let $\mathrm{x}_i, i = 1,\ldots,n$ be the vector pixels in the $n \times n$ window W. For each vector pixel we calculate its angle to other pixels and then obtain the aggregated sum as

$$A_i = \sum_{j=1}^{n} \cos^{-1}\left(\frac{\mathrm{x}_i \mathrm{x}_j}{\left\|\mathrm{x}_i\right\| \left\|\mathrm{x}_j\right\|} \right), i = 1,\ldots,n$$

We then compute the index that minimises the angle as follows,

$$\hat{i} = \min_i A_i$$

and the test pixel x_T is replaced with the vector median $\mathrm{x}_{\hat{i}}$.

It can be observed that the BVDF method minimises the aggregated angular distance between the pixels in the test window such that the directional error between the pixels is minimised. The BVDF method if particularly useful when directional processing is more appropriate and dominant in multichannel image processing.

IV. OUR PROPOSED METHOD

In this paper we propose the isolated vector minimum distance filter method for digital image de-noising. The proposed method is as follows. Let $\mathrm{x}_i, i = 1,\ldots,n$ be the vector pixels in the $n \times n$ window W. We now isolate the vectors as follows, let the values $x_{r,i}, x_{g,i}, x_{b,i}$ for $i = 1,\ldots,n$ respectively correspond to the red,

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green and blue intensities of the i th pixel. For each pixel calculate the aggregate of the Minowski's distance to all other pixel intensities inside the filtering window as

$$z_{r,i} = \sum_{j=1}^{n} \left| x_{r,i} - x_{r,j} \right|$$

$$z_{g,i} = \sum_{j=1}^{n} \left| x_{g,i} - x_{g,j} \right|$$

$$z_{b,i} = \sum_{j=1}^{n} \left| x_{b,i} - x_{b,j} \right|$$

and then compute the index corresponding to the isolated minimum distance as

$$\hat{i}_r = \min_i z_{r,i}, i = 1,\ldots,n$$

$$\hat{i}_g = \min_i z_{g,i}, i = 1,\ldots,n$$

$$\hat{i}_b = \min_i z_{b,i}, i = 1,\ldots,n$$

We finally replace the test pixel according to

$$x_{r,T} = x_{r,i_r}$$

$$x_{g,T} = x_{g,i_g}$$

$$x_{b,T} = x_{b,i_b}$$

It can be seen that the key idea here is to isolate the joint vectors corresponding to the red, green and blue components and process them separately and thereafter minimise the Minowski's distance across each color component. Consequently the pixel that replaces the test pixel is more robust to noise in terms of its color intensity inasmuch as its immunity to skewness in the window. The result would be more accurate than that of the aforementioned vector median filtering methods because each color component is processed in isolation.

V. EXPERIMENTAL RESULTS

In this section we signify the proposed method in comparison with state-of-the-art vector median filtering methods. We employ two measures to test the methods.

A. Test measures

One important measure to test the amount of de-noising is the root mean square error (RMSE) that uses the original clean image and the filtered image to compute the error between the two. The RMSE is computed as

$$RMSE(I,R) = \sqrt{\frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j-1}^{N} \left\| I(i,j) - R(i,j) \right\|^2}$$

where I and R respectively are the original and filtered (or reconstructed) images and M, N respectively denote the number of rows and the number of columns in the image. A small value of the RMSE is desirable because it indicates that the error between the filtered image and the original is small.

The second important measure is the peak signal-to-noise ratio (PSNR) that computes the ratio of the signal power to the noise power. The PSNR in decibels is computed as

$$PSNR = 10 \log_{10} \frac{I_{MAX}^2}{MSE(R)}$$

where I_{MAX} is the maximum pixel intensity in the original image and $MSE(R)$ is the mean square error of the filtered image. A high PSNR is desirable because it indicates good signal recovery from the noise.

B. *Experimental results*

We use the image shown in Fig. 1 to experimentally analyse the proposed de-noising method. The Fig. 2 shows the RMSE of the de-noising methods versus the noise probability p. It can be seen that our method exhibits improved accuracy than that of the joint vector approaches and also performs increasingly well in high noise, i.e., for large values of p. This can be attributed to the fact that the skewness is dealt with for each color component separately leading to a more accurate reconstruction.

Fig. 1. Original image taken for test.

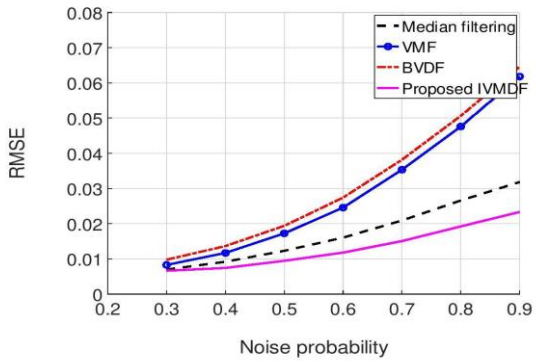

Fig. 2. RMSE versus noise probability

It can be observed that, in terms of RMSE, the proposed IVMDF is nearly 1.1 times superior to the VMF and BVD approaches at noise probability $p = 0.5$. This superiority is enhanced at higher noise as can be seen that the proposed IVMDF is twice superior to the VMF and BVDF methods and around 1.3 times superior to the median filter at noise probability $p = 0.9$, i.e., when 90% of the pixels are corrupted. The Fig. 3 shows the PSNR of the de-noising methods versus the noise probability p. It can be seen that our method again exhibits improved accuracy than that of the joint vector approaches and also performs increasingly well in high noise conditions. When 90% of the pixels are corrupted, i.e., at $p = 0.9$, our method is 1.3 times superior to the VMF and the BVDF and about ten percent superior to the median filter. These results specify the importance and efficiency of processing the digital color images in isolation. Moreover the efficiency of the proposed method improves at high noise when compared with the vector median filters.

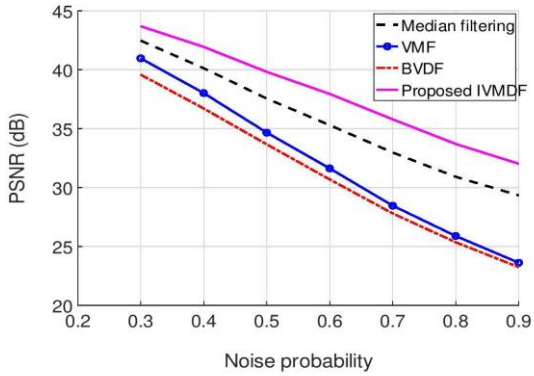

Fig. 3. PSNR versus noise probability

Fig. 4 shows the noisy images and the filtered images for the tested methods corresponding to the results shown in Fig. 2 and 3 for varying noise probabilities and it can be visually observed that the proposed IVMDF is more robust to noise than state-of-the-art methods.

Fig. 4. Left to right: (a) Noisy image, (b) Median filter, (c) VMF, and (d) Proposed IVMDF. Top to bottom: Noise probability $p = 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$.

To generalise the proposed method, we show the filtering output for a few other images in Fig. 5 for a noise probability of $p = 0.8$ and also report the RMSE and PSNR in Tables 1 and 2. It can be visually observed that the proposed IVMDF outperforms the other methods by virtue of performing minimum distance filtering for vector pixels in isolation.

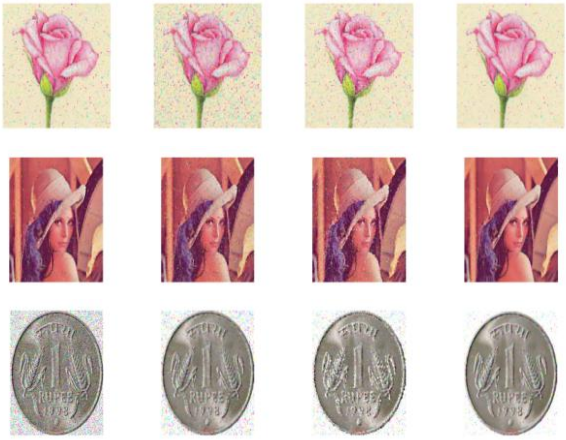

Fig. 5. Left to right: (a) Noisy Image, (b) Median filter, (c) VMF, and (d) proposed IVMDF.

Image No.	Median filter	VMF	BVDF	Proposed IVMDF
1	0.0624	0.0929	0.7609	0.0522
2	0.0572	0.0736	0.0915	0.0515
3	0.0913	0.1118	0.1276	0.0867

Table I. RMSE values for the images in Fig. 5

Image No.	Median filter	VMF	BVDF	Proposed IVMDF
1	23.981	20.562	22.351	25.560
2	24.818	22.323	20.738	25.730
3	20.789	19.092	17.879	29.233

Table 2. PSNR values for the images in Fig. 5.

VI. CONCLUSION

In this paper we presented the isolated vector minimum distance filtering method for digital image de-noising. The key idea here is to differentiate the idea of vector median filtering taken jointly and taken in isolation, and we have experimentally demonstrated that the filtering is more accurate than the conventionally used vector median filters when taken in isolation by virtue of accounting for each color component separately.

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