NEWS DIRECTIONAL FILTERING FOR NOISE REDUCTION IN DIGITAL COLOR IMAGES WITH APPLICATION TO MEDICAL DIAGNOSTICS IN MRI SCANNING

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Abstract

The paper proposes a new approach for filtering out impulse noise in digital color images, focusing on medical diagnostics for magnetic resonance imaging (MRI) scans. The conventional filtering methods operate by applying a noise reduction scheme, generally the median filtering approach, for the center pixel of a suitably chosen window that iteratively slides along the entire image. The method proposed in this paper operates by comparing the center pixel with pixels along the four right angle directions, the north, east, west, and south directions, then applying a marginal median filter along the direction that minimizes the aggregate deviation from the center pixel (hence the title NEWS directional filtering). Simulations using GNU Octave 6.4.0 on Corei3 computer with 4 GB RAM show that the proposed method performs comparably with several directional filtering methods in terms of noise reduction and thus validates the proposed approach. Moreover, the method is validated on real MRI scan images.

Keywords: Impulse noise, vector median filters, directional filters, noise reduction, root mean square error, random valued impulse noise, fixed valued impulse noise.

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1. Introduction

Medical imaging refers to scanning different parts of a person under examination and diagnosing his health condition. This may be done by observing the person's magnetic resonance imaging (MRI), positron emission tomography (PET) scans, thermal/infrared imaging, etc. The images used in these applications often get corrupted by impulse noise during the scanning or measuring process or when transmitted from one point to another, thus leading to high information loss and, consequently, flawed diagnosis [1]. Impulse noise can be random spikes or lows of pixel intensities at random pixel locations. Impulse noise with spikes or lows is called fixed valued impulse noise (FVIN) and is otherwise called random valued impulse noise (RVIN) [2]. From this standpoint, the basis of this paper is to develop novel methods for reducing noise in digital images for medical diagnostic applications. That said, the method set herein applies to all classes of image processing applications.

The median filtering approaches are by far the most popular image filtering approaches due to their noise robustness. The general idea of these methods is to examine and correct a test pixel's (usually the center pixel) representativeness of a selected window (a set of surrounding pixels) within the image. The simplest noise reduction filter in this category is the standard median filter that computes the pixel median for each selected window over each color component and replaces the test pixel with the median [5, 6]. The vector median filter (VMF) is a prominently used order reducing scheme that processes color images as a vector field [7]. This method replaces the test pixel with another pixel in the window, minimizing the aggregate distance across all pixels. An alternative to using distance is the use of direction as proposed in the basic vector directional filter (BVDF) [8]. This filter uses the angular distance between the pixels rather than the vector magnitudes and minimizes the aggregate angular distance across all pixels in the window. Another approach to image filtering includes directional distance filtering (DDF) that utilizes a weighted product of VMF and BVDF [9]. The directional VMF (DVMF) is another directional scheme that operates by performing vector median filtering across the pixels that lie within 0^0, 45^0, 90^0 & 135^0 degrees from the canter test pixel and then taking the VMF for the resultant [10]. The filters of this family, especially the VMF and directional filters, can perform quite robustly, especially when the correlation between the three color components must be preserved [11]. The problem, however, in these methods is that the vector pixel is processed jointly as a multichannel. Consequently, any smoothing performed therein is accounted for equally in all the color channels. This could be problematic because outliers in one color component may influence the others, corrupting some good pixels.

Other techniques for noise reduction include extended versions of VMF like the alpha trimmed VMF [12], the adaptive switching filters [13], the peer group filters [14], and the adaptive weighted directional difference methods [15]. We neglect these as they are either limited to gray scale images, perform comparably to the techniques mentioned above, or are not specific to filtering based on directional approach. Moreover, research into noise reduction in images is twofold: (a) detecting whether a pixel is corrupted by impulse noise which is relatively complex in random valued impulse noise, and (b) filtering out the noise [16]. The focus of this paper is only on the latter. Most of the work pertaining to noise reduction in digital color images can be attributed to Bogdan Smolka et al. Their recent work in noise reduction in digital color images includes the adaptive rank weighted switching filter (ARWSF) [13] and the adaptive switching trimmed (AST) [18] filters. These methods have shown promise and superiority in reducing impulsive noise. These methods operate by multiplying the distance measure representing the similarity of pixels within the window with a weight function. The more similar pixels are given very high weighting, and the less similar ones very low weighting. Incorporating this weighing within the distance measure leads to improved minimization of the aggregate.

This paper proposes a new directional filtering approach to reduce impulse noise in digital color images, focusing on utilizing only the pixels most representative of the signal/information by employing a direction oriented median operator. The method operates by minimizing and maximizing the distance of the center pixel to any of the four directions at right angles, namely the north, east, west and south directions. Hence we name this method North-East-West-South (NEWS) directional filter (NEWS-DF). The key rationale of this approach is to utilize only those pixels that contribute to the similarity measure within the chosen local window and discard the others. As a consequence, we possibly utilize only those pixels that contribute to information and discard those that contribute to noise and then apply filtering across those useful pixels, as against the conventional scheme of detecting whether the center pixel is noisy or not and then apply filtering for that pixel using all other pixels in the local window. Once the right angle direction that minimizes the distance from the center pixel is obtained, we compute the median of the pixels lying along that direction taken individually over each color component as used in the IVMF [5]; we compute the median along each color channel separately in order to mitigate the effect of smoothing in one color component on another color component. Our simulation results show that the proposed method compares favorably with state-of-the-art impulse noise reduction filters.

The rest of the paper is organized as follows. Section 2 sets the notation and describes the impulse noise followed by the conventional impulse noise reduction methods in section 3 and the proposed NEWS directional filter in section 4. We then present the results in section 5 and conclude in section 6.

2. The Impulse Noise Model

This section sets the notation and describes the impulse noise model for a digital color image. Let $\mathbf{X}$ be the color image of $M \times N$ pixels containing MN pixels where M denotes the number of rows and N the number of columns. Then the color $\mathbf{X}$ image will be a set of vector pixels

$$\mathbf{X} = \{\mathbf{x}_{i,j}\ i = 1,\dots,M,\ j = 1,\dots,N\} \qquad (1)$$

With each pixel being a joint vector containing the color intensities in the red, green and blue components as

$$\mathbf{x}_{i,j} = (x_{i,j,r},\ x_{i,j,g},\ x_{i,j,b}),\ i = 1,\dots,M,\ j = 1,\dots,N \qquad (2)$$

Let $Z = \{z_{i,j}\ i = 1,\dots,M,\ j = 1,\dots,N\}$ be the image corrupted by impulse noise. As discussed earlier, impulse noise is mainly classified as fixed valued impulse noise (a.k.a. salt and pepper noise) and random valued impulse noise. In the FVIN, a pixel is corrupted with probability $p \in (0,1)$.

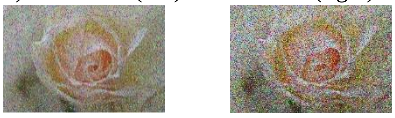
A corrupted pixel implies that one of its red, green or blue components gets corrupted by railing to 0 (full black) or 255 (full white) with uniform probability across the color components. In the RVIN, the corrupted pixels takes any random value between 0 to 255 instead of railing to high or low values. The impulse noise model in general, can be described as

$$\mathbf{z}_{i,j} = \begin{cases} x_{i,j} & \text{if } q \ge p \\ (x_{i,j,r}, x_{i,j,g}, a) & \text{if } q < p, r < \frac{1}{3} \\ (x_{i,j,r}, a, x_{i,j,b}) & \text{if } q < p, \frac{1}{3} \le r < \frac{2}{3} \\ (a, x_{i,j,g}, x_{i,j,b}) & \text{if } q < p, \frac{2}{3} \le r \end{cases} \qquad (3)$$

Where $(r,q) \in (0,1)$ are continuous random numbers chosen uniformly and $a = 1$ or 255 is uniformly chosen for FVIN, $a \in (0,255)$ is uniformly chosen within the interval for RVIN.

a) The original image

b) The RVIN (left) & The FVIN (right) images with p=0.2



c) The RVIN (left) & The FVIN (right) images with p=0.8

Fig.1: An example of the RVIN and the FVIN images

Figure 1 shows an example of an image corrupted by RVIN and FVIN at noise probabilities $p = 0.2$ and $p = 0.8$. It can be observed that increasing values of p results in increased noise. The case $p = 0$ implies a fully clean and un corrupted image with no noise and the case $p = 1$ implies a fully corrupted image with no signal. It can also be observed that the image corrupted by FVIN has sharp spikes of the three red, blue and green color intensities because the noise spikes to 0 or 255 intensity values only. In contrast, the image corrupted by RVIN is not as spiky as the FVIN because the noise takes any value between o to 255. This description indicates that p denotes the noise probability of an image, and the closer the value of p to one, the higher the noise, and the closer the value of p to zero, the lower the noise. Noise reduction techniques aim to restore the original image $\mathbf{X}$ from the noisy image $\mathbf{Z}$.

3. Conventional Noise Reduction Filters

In this section, we briefly describe the conventional impulse noise filtering methods. The filtering process, in general, uses a sliding window W containing n pixels of size $\sqrt{n} \times \sqrt{n}$. For convenience, we donate the set of pixels contained in the window as

$$W = \{\mathbf{x}_i, i = 1,\dots,n\} \qquad (4)$$

Where the joint vector is $\mathbf{x}_i = (x_{i,r}, x_{i,g}, x_{i,b})$. With this notation, the digital color image in (1) is now modified as

$$\mathbf{X} = \{\mathbf{x}_i, i = 1,\dots, MN\} \qquad (5)$$

The filtering methods detect and process the center pixel within the test window W. An example of the test window is shown in Figure 2. The filters aim to replace the center pixel with a value that is confirmative to the pixel intensities in the window. The most popular window is a square, with the center pixel being the test pixel of interest. A 3 x 3 or 5 x 5 or bigger sized windows can be used in the filtering process. A small window size could lead to neglecting critical image details, and a large window could possibly lead to averaging out sharp edges and peaks. In this paper, we chose the popularly used 3 x 3 window.

$\mathbf{x}_1$	$\mathbf{x}_4$	$\mathbf{x}_7$
$\mathbf{x}_2$	$\mathbf{x}_c = \mathbf{x}_5$	$\mathbf{x}_8$
$\mathbf{x}_3$	$\mathbf{x}_6$	$\mathbf{x}_9$

Fig. 2: An example 3×3 test window with $n=3^2=9$. The center pixel is the test pixel.

The most prominent of all filtering schemes is the VMF method. Here the aggregated distance of each pixel from every other pixel is computed as

$$\mathbf{s}_i = \sum_{j=1}^{n} d(\mathbf{x}_i - \mathbf{x}_j), i = 1,2,\dots,n \qquad (6)$$

Where $d(\mathbf{x}_i - \mathbf{x}_j)$ is the Minowski's distance with order λ between two joint pixels $\mathbf{x}_i$ and $\mathbf{x}_j$ is given by

$$d(\mathbf{x}_i - \mathbf{x}_j) = ((\mathbf{x}_{i,r} - \mathbf{x}_{j,r})^{\lambda} + (\mathbf{x}_{i,g} - \mathbf{x}_{j,g})^{\lambda} + (\mathbf{x}_{i,b} - \mathbf{x}_{j,b})^{\lambda})^{1/\lambda} \qquad (7)$$

Then we reorder the aggregate as

$$s_{\hat{i}=1,\dots,n} \Rightarrow \mathbf{x}_{\hat{i}=1,\dots,n} : s_{\hat{i}=1} \le s_{\hat{i}=2} \le \dots \le s_{\hat{i}=n} \qquad (8)$$

Then the center pixel is replaced with the pixel having the minimum aggregate distance from all other pixels as

$$\mathbf{x}_c = \mathbf{x}_{\hat{i}=1} \qquad (9)$$

The operation utilizes the correlation between the signal components, takes the pixel with the most coherence, and replaces the center test pixel with that pixel. This leads to the desirable property of overlaying an increased coherency in the center pixel with all the pixels in the window. At times, it could be the case that the center pixel is indeed the most coherent [17]. The BVDF, on the contrary, uses the aggregate angular distance between the pixels as

$$\theta_i = \sum_{j=1}^{n} \cos^{-1}\left(\frac{\mathbf{x_i}\mathbf{x_j}}{\|\mathbf{x_i}\|\|\mathbf{x_j}\|}\right), i = 1,2,\dots,n \qquad (10)$$

and replaces the center pixel with the pixel that minimizes $\theta_{i=1,\dots,n}$ as described in (8) and (9). The DDF uses the weighted product of the Minowski's distance and the angular distance as

$$A_i = S_i^{\gamma}\theta_i^{(1-\gamma)}, i = 1,2,\dots,n \qquad (11)$$

where $\gamma \in (0,1)$. The DVMF filter operates by taking the VMF of the pixels lying in 0°, 45°, 90° & 135° degrees to the center pixel, as shown in Figure 3, and then taking the VMF of the resultant.

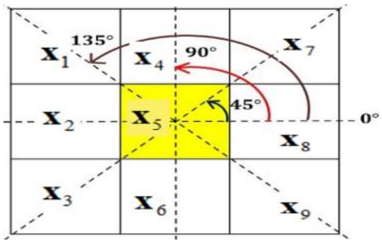


Fig. 3: A pictorial representation of DVMF

Along the zero degrees, the pixels that lie along that axis are $\mathbf{x}_2, \mathbf{x}_5, \mathbf{x}_8$. We perform median filtering over these pixels to obtain a new value $\mathbf{x}_0 = VMF(\mathbf{x}_2, \mathbf{x}_5, \mathbf{x}_8)$, Where $VMF(.)$ is the sequence of operations (6) - (9) on the pixels inside the argument. Similarly, along the 45 degrees axis we perform $\mathbf{x}_{45} = VMF(\mathbf{x}_3, \mathbf{x}_5, \mathbf{x}_7)$, along the 90 degree axis, we perform $\mathbf{x}_{90} = VMF(\mathbf{x}_4, \mathbf{x}_5, \mathbf{x}_6)$, and finally, along the 135 degree axis, we perform $\mathbf{x}_{135} = VMF(\mathbf{x}_1, \mathbf{x}_5, \mathbf{x}_9)$. The resultant will be the VMF output of the four resultants as

$$\mathbf{x}_c = VMF(\mathbf{x}_0, \mathbf{x}_{45}, \mathbf{x}_{90}, \mathbf{x}_{135})$$

4. Proposed News Directional Filtering

4.1. *Motivation*

Conventional image filtering methods, including directional filtering, operate on the joint vectors of pixels. Therefore, any smoothing introduced by the filter is accounted for in all the color components. Therefore, a directional approach is needed to marginalize its filtering operation over the individual color components, like the scalar median filter and the IVMDF. Moreover, the conventional methods compare each pixel against every other pixel [7] or a few select peers [14]. There exists a need to develop a directional scheme that compares pixels at right angles to the center pixel while also marginalising the filtering process over the color components. The filtering method proposed in this paper is as such.

4.2. *The proposal*

Consider a sliding window W containing n pixels. We categorize the pixels into four groups, each lying at right angles to the center pixel, namely the north, east, west, and south directions. Define $\eta_{D=1,2,3,4}$ where η_D contains the indices of the pixels lying in the D^{th} direction to the center pixel $\mathbf{x}_c$. We set the set of directional indices as

$$\eta_D = \{Set\ of\ pixels\ indices\ to\ the\ D^{th}\ direction\ to\ the\ centre\ pixel\ x_c\}$$

$$\eta_{D=1} = \{1,4,7\}\ north\ side\ pixel\ indices \quad (12)$$

$$\eta_{D=2} = \{3,6,9\}\ south\ side\ pixel\ indices \quad (13)$$

$$\eta_{D=3} = \{1,2,3\}\ west\ side\ pixel\ indices \quad (14)$$

$$\eta_{D=4} = \{7,8,9\}\ east\ side\ pixel\ indices \quad (15)$$

Figure 4 shows our direction set up within a sliding window. We then compute the aggregate of the absolute deviation of the pixels in the D^{th} direction to the center pixel for each color component individually. This is described as

$$d_{r,D} = \sum_{i \in \eta_D} |x_{r,c} - x_{r,i}| \quad (16)$$

$$d_{g,D} = \sum_{i \in \eta_D} |x_{g,c} - x_{g,i}| \quad (17)$$

$$d_{b,D} = \sum_{i \in \eta_D} |x_{b,c} - x_{b,i}| \quad (18)$$

We then obtain the direction that minimises and maximises the aggregate for all color components as

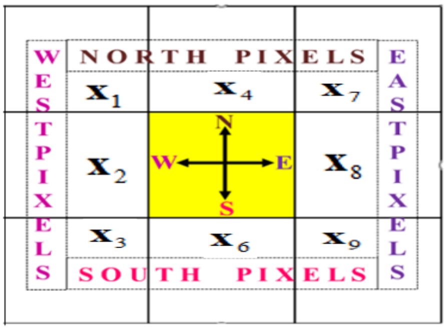


Fig. 4: A pictorial representation of direction set up within a 3×3 sliding window.

$$\hat{D}_{r,\min} = \arg\min_D \left\{d_{r,D}, D = 1,..,4\right\} \quad (19)$$

$$\hat{D}_{r,\max} = \arg\max_D \left\{d_{r,D}, D = 1,..,4\right\} \quad (20)$$

$$\hat{D}_{g,\min} = \arg\min_D \left\{d_{g,D}, D = 1,..,4\right\} \quad (21)$$

$$\hat{D}_{g,\max} = \arg\max_D \left\{d_{g,D}, D = 1,..,4\right\} \quad (22)$$

$$\hat{D}_{b,\min} = \arg\min_D \left\{d_{b,D}, D = 1,..,4\right\} \quad (23)$$

$$\hat{D}_{b,\max} = \arg\max_D \left\{d_{b,D}, D = 1,..,4\right\} \quad (24)$$

Then the center test pixel can be replaced in two ways: (a) Scheme 1: By taking the median of the pixels that lie along the direction that minimises the distance to the center pixel as

$$x_{r,c} = Median\left\{x_{r,i}, i \in \eta_{\hat{D}_{r,\min}}\right\} \quad (25)$$

$$x_{g,c} = Median\left\{x_{g,i}, i \in \eta_{\hat{D}_{g,\min}}\right\} \quad (26)$$

$$x_{b,c} = Median\left\{x_{b,i}, i \in \eta_{\hat{D}_{b,\min}}\right\} \quad (27)$$

and (b) Scheme 2: By taking the median of the pixels that lie along the directions that minimise and maximise the distance to the center pixel described as

$$x_{r,c} = Median\left\{x_{r,i}, x_{r,j}, i \in \eta_{\hat{D}_{r,\min}}, j \in \eta_{\hat{D}_{r,\max}}\right\} \quad (28)$$

$$x_{g,c} = Median\left\{x_{g,i}, x_{g,j}, i \in \eta_{\hat{D}_{g,\min}}, j \in \eta_{\hat{D}_{g,\max}}\right\} \quad (29)$$

$$x_{b,c} = Median\left\{x_{b,i}, x_{b,j}, i \in \eta_{\hat{D}_{b,\min}}, j \in \eta_{\hat{D}_{b,\max}}\right\} \quad (30)$$

What differentiates the two proposed schemes?. Let's only take the right angle direction that minimises the aggregated distance from the center pixel. It accounts only for the case where the pixels along the chosen direction are uncorrupted, and the center pixel is also uncorrupted, i.e., for low noise conditions. This approach can account negatively when the chosen pixels and the center pixel are corrupted, i.e., for high noise conditions.

Alternatively, let's take the two directions, one that minimizes and the other that maximizes the aggregate distance from the center pixel. We account for both cases where the chosen set of six pixels, three coming from the direction that minimizes. The other three come from the direction that maximises the distance to the center pixel by simply taking the median (or the mean of the two) and averaging the two cases where the set of pixels is corrupted and uncorrupted.

In summary, the filtering process can be elucidated as follows. The aggregate distance of the center pixel to the pixels lying in each of the four directions is computed. Then the median of the pixels along the direction that minimises the computed aggregate distance is taken and replaced with the center pixel. The aggregating, minimising and median operations are performed for each color separately. The conventional directional filtering methods compute this distance jointly, the problem of which involves inducing the color artifacts and noise corruption in one color component to be leveraged into the others during the averaging process. The proposed method does not suffer from the problem as color components are filtered separately as shown in (25), (26), (27) , (28), (29), and (30).

How does this method overcome the effect of smoothing in one color component to be leveraged in the others? Consider the noise model described in (3). The probability that a pixel is corrupted is set to be p. If a pixel is corrupted, then only one of its color components will be corrupted with equal probability. This implies that the three color components have an equal probability of ⅓ of being corrupted, but only one color component will be corrupted at any one time. Suppose the red component of the i th pixel is corrupted and the green and blue components are uncorrupted. The traditional joint filtering methods compute the median jointly. The pixel that minimises the aggregate distance using the VMF method is determined and replaces the center pixel in all three color components. Hence the median operation smears some unwanted information in the clean blue and green components. The proposed method operates on each color component in isolation; therefore, the averaging (smoothing) operation along one color component does not influence the others.

5. Simulation and Comparison

This section compares the proposed NEWS-DF with state-of-the-art vector median filters using three test statistics.

The proposed NEWS_DF method is outlined in **Algorithm 1** for ease of understanding.

Algorithm 1

Proposed NEWS-DF algorithm

Consider the window in red component.

$$W_r = \{\mathbf{x}_{r,1}, \mathbf{x}_{r,2}, ..., \mathbf{x}_{r,n}\}$$

for $D = 1,..,4$ **do**

$$d_{r,D} = \sum_{j \in \eta_D} | x_{r,5} - x_{r,j} |$$

end for

Compute direction that minimizes the aggregate as

$$\hat{D}_{r,\min} = \arg\min_D \left(d_{r, D=1,..,4} \right)$$

replace $x_{r,5} = Median\left(x_{r,i}, i \in \eta_{\hat{D}_{r,\min}} \right)$

The Same algorithm is repeated for blue and green components.

5.1. *Simulation*

The first is the root mean square error (RMSE) defined as

$$\text{RMSE}(X,Y) = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \| X_{i,j} - Y_{i,j} \|^2} \quad (31)$$

where X, Y respectively, are the original and filtered images. A small value of the RMSE indicates that the error between the filtered image and the original is small; hence, we desire small RMSE values. The second measure is the peak signal-to-noise ratio (PSNR) defined as

$$\text{PSNR}(X,Y) = 10\log_{10}\left(\frac{Max(X)^2}{MSE(X,Y)} \right) \quad (32)$$

where $\text{MSE}(X,Y)$ is the mean square error of the reconstructed image. A high PSNR is desirable because it indicates good signal recovery from the noise. The RMSE is the measure of error from the original image to the reconstructed image. This error is computed by taking the absolute difference or the square root of the squared mean of the difference between the original and the reconstructed image, pixel by pixel. Hence a low RMSE implies that the reconstructed image is close to the original. The PSNR is the ratio of the signal power to the noise power. Impulse noise severely distorts the pixel values, making it difficult to detect the signal since it is mixed up with the noise. Since the impulse noise model is assumed to be known, taking the ratio of the signal to the noise by leveraging the mean square error in the denominator helps us get a measure of the amount of signal protruding out of the noise. Hence the high value of PSNR denotes high signal power. The third measure is the correlation similarity index (CSI) defined as

$$\mathrm{CSI(X,Y)} = \frac{2C_{\mathrm{X,Y}}}{\sigma_{\mathrm{X}} + \sigma_{\mathrm{Y}}} \quad (33)$$

Where $\sigma_{(.)}$ denotes standard deviation and $C_{(.,.)}$ denotes co-variance.

The CSI measures the similarity between two images in terms of their correlative behavior. For increasing contrast in the reference image, there should be an equal contrast increase in the reconstructed image. While the RMSE and the PSNR test pixel by pixel, CSI measures the similarity between the original and the reconstructed image by a margin of a few pixels by taking the variance measure. We first demonstrate the superiority of the proposed NEWS-DF method over state-of-the-art filtering methods. In Figure 5 we display the test case image used for this purpose. For this test case, Figure 6 shows the noisy image and the filtered images at varying probabilities of noise, and it can be visually observed that the proposed NEWS-DF method, shown in the last column, outperforms favorably with the conventional methods. The proposed NEWS-DF takes useful pixels to operate so we can observe the filtered image better than the VMF, BVDF and DVMF.

Fig. 5: The original test image

Fig. 6: Left to right: (a) Noisy image, (b) Median filter, (c) VMF, (d) BVDF, (e) DDF, (f) DVMF, (g) Proposed NEWS-DF-1, (h) Proposed NEWS-DF-2. Top to bottom: Noise probability $p = 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$.

For the demonstration in Figure 6, the RMSE performance versus the noise probability is shown in Figure 7. It can be seen that the proposed NEWS-DF method exhibits accuracy (i.e., low

RMSE) equivalent to that of the conventional methods thus validating the scheme. Moreover, as discussed earlier, the process of taking the median of only those pixels that lie in the direction that minimises the aggregate distance from the center pixel works well in low noise conditions, and the second approach of taking the median of those pixels that lie in the direction that minimises and maximises the aggregate distance works well in high noise conditions. This switchover is noticed in the black solid and dashed lines at $p = 0.3$. It can also be seen that the DVMF does not scale well with noise because it does not guarantee the best pixels are taken to compute the final resultant.

The key contribution of this paper is developing a directional approach for the vector median filter technique. Therefore the method, in principle, should be directly compared with the BVDF which is also a directional approach. It can be observed that the true merit of the proposed method manifests after $p = 0.5$. At $p = 0.8$, the proposed NEWS directional filter is about 8 times better in terms of RMSE than the BVDF and also the VMF. The PSNR and CSI performance of image in Figure 5 versus the noise probability is shown in Figures 8 and 9. The black dashed line corresponds to the proposed NEWS-DF with the approach in (25), (26) and (27) and the black solid line to the approach in (28), (29) and (30). Again the switchover at $p = 0.3$ is observed in both the variants of the proposed NEWS-DF and also it can be observed that the proposed NEWS-DF variants compare favorably with the conventional methods. Moreover, the structural similarity is also high, indicating the proposed method is indeed valid in removing impulse noise in digital color images.

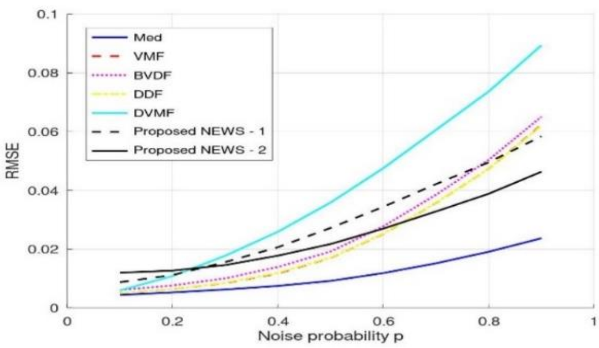


Fig.7: The RMSE versus the noise probability

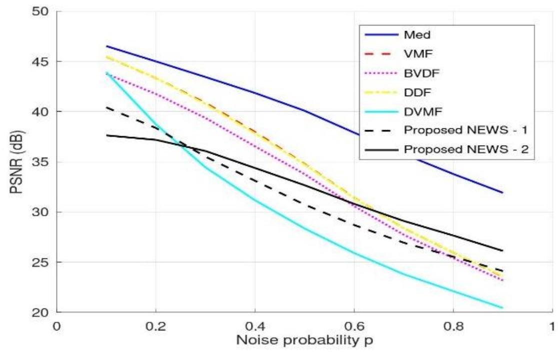


Fig.8: The PSNR versus the noise probability

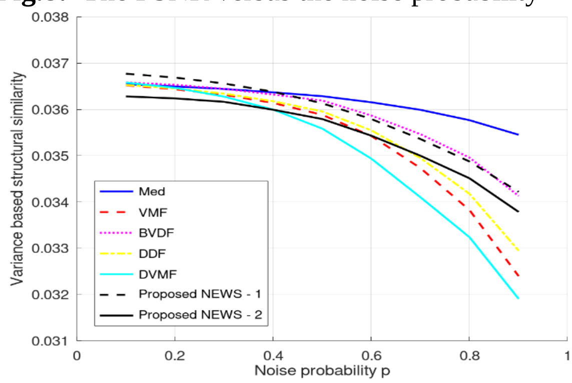


Fig.9: The CSI versus the noise probability

To generalise the proposed method, we show the filtering output for more images in Figure 10 for a noise probability of $p = 0.8$ and report the RMSE and PSNR values for Figure10 in Tables 1 and 2. It can be observed that the proposed NEWS-DF outperforms the DVMF and compares well with the other methods by virtue of utilising the information contained in informant (or useful) pixels. When averaged across all the images used in this paper the DVMF is 70% worse than the proposed NEWS-DF while the latter performs equivalently to the VMF and 1.2 times better than the BVDF in terms of the RMSE and PSNR.

The second variant of NEWS-DF eliminates the chance of selecting noisy set of pixels for the filtering process. Hence, the filter performs comparably well with all the conventional filters. Moreover, it can be observed from the images that the proposed NEWS-DF corrects more color artifacts than the joint vector median filters by virtue of leveraging the filtering process locally within each color component.

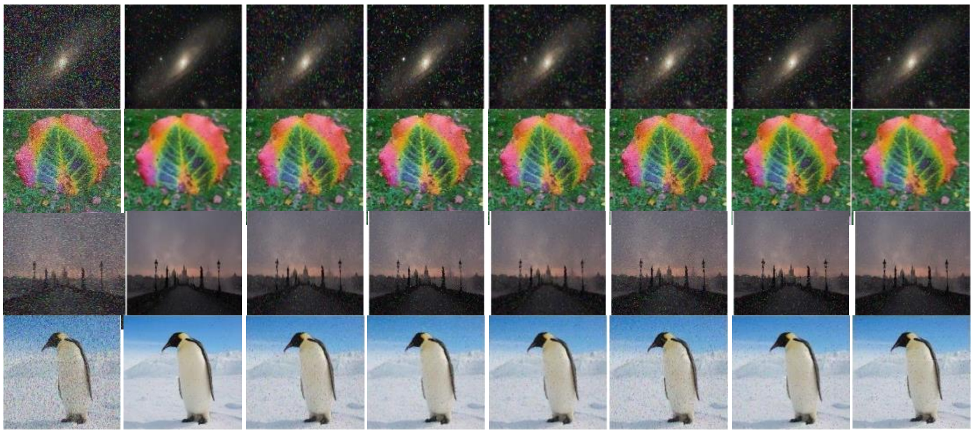


Fig. 10: Left to right: (a) Noisy image, (b) Median filter, (c) VMF, (d) BVDF, (e) DDF, (f) DVMF, (g) Proposed NEWS-DF-1, (h) Proposed NEWS-DF-2, At noise probability $p = 0.8$

Table 1. RMSE values for the images in Fig. 10

Image No.	*Median filter*	*VMF*	*BVDF*	*DDF*	*DVMF*	*Proposed NEWS-1*	*Proposed NEWS-2*
1	0.051210	0.076151	0.090712	0.077554	0.098255	0.079089	0.074099
2	0.087968	0.11275	0.129390	0.109510	0.127620	0.114150	0.117640
3	0.055044	0.102690	0.093069	0.095695	0.130240	0.104000	0.084407
4	0.054858	0.082310	0.094379	0.083452	0.104750	0.084523	0.076923
5	0.033615	0.070912	0.064469	0.066666	0.096698	0.072369	0.057560
6	0.034985	0.069470	0.064252	0.065154	0.096668	0.074192	0.060337

Table 2. PSNR values for the images in Fig. 10

Image No.	*Median filter*	*VMF*	*BVDF*	*DDF*	*DVMF*	*Proposed NEWS-1*	*Proposed NEWS-2*
1	25.794	22.330	20.818	22.166	20.113	21.989	22.581
2	21.113	18.958	17.762	19.210	17.882	18.850	18.589
3	25.171	19.764	20.620	20.378	17.702	19.655	21.469
4	25.180	21.641	20.490	21.534	19.550	21.381	22.227
5	28.605	22.122	22.949	22.658	19.427	21.944	23.934
6	29.088	23.136	23.828	23.689	20.274	22.564	24.362

5.2. *Application to noise reduction in MRI scans*

Finally the proposed NEWS directional filter is applied to a MRI scan (courtesy https://openneuro.org/). The MRI scan images are generally corrupted by noise arising from thermal and electrical effects in the sensors and the sensing machinery. These effects appear as impulses in the scanned MRI images. These impulses, albeit random, are predominant near change point regions, e.g., tumors, and it becomes critical to remove this noise for effective medical diagnosis. Figure 11 shows a real MRI image corrupted by fixed valued impulse noise (FVIN) and random valued impulse noise (RVIN) and the performance of the VMF, the directional filtering and the proposed methods in reducing the noise. The corresponding RMSE and PSNR values are shown in Table 3.

It can be observed that the proposed NEWS directional filter method compares well and denoises the MRI images, more effectively especially at higher noise (p=0.85), thus aiding in accurate diagnosis.

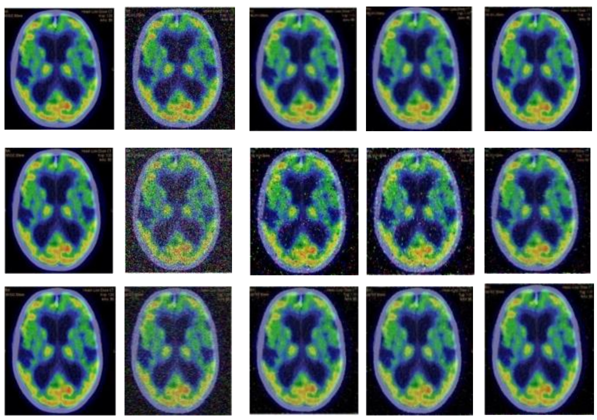


Fig.11: Panels from left to right, (a) original image, (b) noisy image, (c) VMF output, (d) DDF output, and (e) proposed NEWS DF method. The top panels correspond to F.V.I.N. at p=0.3. The middle panels correspond to F.V.I.N. at p=0.85. The bottom panels correspond to R.V.I.N. at p =0.5

Table 3. The table shows the RMSE and PSNR values for the results shown in Fig. 11.

	RMSE Values			***PSNR Values [dB]***		
	F.V.I.N.	***F.V.I.N.***	***R.V.I.N.***	***F.V.I.N.***	***F.V.I.N.***	***R.V.I.N.***
Noise Probability	p =0.3	p =0.85	p =0.5	p =0.3	p =0.85	p =0.5
VMF	0.0428	0.1612	0.0570	27.355	16.833	24.876
DDF	0.0483	0.2006	0.0577	26.309	15.850	24.773
NEWS DF	0.0509	0.1000	0.0564	25.849	19.998	24.648

As mentioned earlier, our method improves over the BVDF and hence is expected to show lower RMSE and higher PSNR than that of the BVDF. It can be observed that our proposed NEWS directional filter shows nearly 10% improvement over the BVDF. It compares equally with the standard VMF and shows minuscule improvement at higher values of noise probability p.

6. Conclusion

Although several methods have been proposed to reduce impulse noise in color images, directional approaches are still needed to utilize informant pixels in filtering. This paper presented a novel idea of utilizing the pixels along the right angle directions from the center pixel to compute the direction that conforms to the signal and then utilize those pixels in filtering out the impulse noise. We have validated our method using several simulations and implementation on real MRI scans and have shown that our proposal compares favorably with the conventional filtering methods. Moreover, our method marginalizes over the color components, so the color artifacts in the noisy versions are removed well. The possibility of adapting the proposed method to gray scale images will be explored in the future.

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