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Random Valued Impulse Noise Reduction in Satellite Color Images Using Fast Degree of Aggregation Filtering Approach

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Abstract: The suppression of random valued impulse noise in satellite data is the main focus of this article. When it comes to decreasing random valued impulsive noise in images, the vector median filters are often regarded as the highest standard. The degree of aggregation filter is a contemporary variation of this family of filters; it works by assigning each pixel a weight that is proportional to the degree to which it represents the signal component in the image. This method has the potential to enhance filtering quality by giving larger weights to pixels that seem to be similar to one another. Nevertheless, there is a major drawback to this method: filtering must be done on all of the pixels in a sequential order, which results in a very high computational cost. In this paper, we suggest a faster degree of association method that vastly improves upon the filter in concern. It is expected that the simulation would demonstrate the effectiveness of the proposed strategy. Using a combined metric of time and precision, we compared the suggested technique to the state-of-the-art approaches.

Keywords: *Anomaly Detection, Computational Time, Noise Reduction, Vector Median Filtering, Time Scaled Root Mean Square Error.*

1. Introduction

There are several technical fields that rely heavily on digital image processing, but none more so than satellite imaging [1, 2]. Noise often contaminates the satellite camera's recorded images. In this context, noise may be thought of as a chance occurrence that alters the luminance values of a given pixel, either the red, green, or blue luminance values or all three [3, 4]. Pre-processing images, in which noise reduction is the major focus of this article and it impulse noise model [5, 6, 7] that is of importance in this research. Impulse noise is a quick, unpredictable shift in brightness across individual pixels. All or part of the colour information of one damaged pixel might be off [8].

Vector median filters (VMFs) [9, 10] and variations are the most often used filters for reducing impulsive noise. The filters have been around since the 1990s, but they continue to be popular because of the ease with which they may improve aesthetic aspects like edges. The similarity detection concept is used inside a window is the basis for these filters.

The test pixel, which is often the window's geographic centre, is then given an alternate result that is the average of all of its neighbouring pixels in the window with comparable data. When figuring out how closely related a pixel is to a certain window, many different distance measures are taken into account. The actual image is reconstructed pixel by pixel from the noisy one using this method. In order to function, the VMF and variants like the basic vector directional filter (BVDF) [11, 12] and the -trimmed VMF [13] swap out the central pixel in a chosen window with another pixel whose sum of an acceptable distance measure is lowered. It is possible to get good results using filters from this family when it is important to maintain colour correlations amongst the three inputs. the PGFs have recently shown great promise in the reduction of impulse noise. This is because the PGFs initially identify the peer group that most strongly suggests a potential replacement for the central test pixel. After that, this peer group is filtered. However, there are many thresholding strategies used in the PGF approach. The selection of these criteria has a significant impact on the PGF's performance [14, 15]. Bogdan Smolka and associates did much of the early pioneering work in eliminating noise from digital color images. Two of their more recent filters, the adaptive rank weighted switching filter (ARWSF) [16] and the adaptive switching trimmed (AST) [17], are effective in reducing noise in digital colour photographs. These techniques rank the combined distances such that only the highest-ranked pixels are used in the filtering process.

The most current degree of aggregation filter DOAF [18] optimises pixel selection by weighing (or ranking) pixels inside the window to find those that are most like the chosen one. The ranking of pixels is ideal in that it

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reduces the amount of clustering inside the window's individual pixels to a minimum. Thus, it is hypothesised that this method performs better [19]. The DOAF method's main flaw is that it requires sequentially processing each pixel.

Problem identification: In terms of computational complexity, the lower constraint for this is polynomial, and it is equal to $O\left(MN\prod_{i=1:M,j=1:N} F_{i,j}\right)$ with M rows and N column of the image identifies the image's row and column counts, respectively, and $F_{i,j}$ is the interval of the DOAF calculation of $(i,j)^{th}$ pixel. Because of this heavy computing need, using VMFs in real-time pre-processing is challenging. For this reason, the fundamental contribution that this research makes is the proposal of a fast DOAF algorithm, which is several times quicker than the original DOAF. Distinctive from of the state-of-the-art methods, the key concept is to access DOAF just over the noisy pixels (anomalies) of the row using a predetermined set of previously filtered pixels, thereby limiting the effect of the impulse noise to the anomalous rows itself. This restricts the sequential operation to as few rows as possible. Moreover, processing over a single colour channel is sufficient due to the impulse noise's coherence across the colour channels, which eases faster filtering.

The remaining sections of the paper are as follows. The signal model represented in section 2. This followed by state-of-the-art methods in section 3. The proposed method describes in section 4. This is followed by evaluation and results in section 5. Finally, we concluded this in section 6.

2. The Noise Model

Here we define several key terms, introduce the impulse noise model, and explain a color image. Let $\mathbf{X}$ indicates the digital color image of the size $M \times N$ containing MN pixels where M the number of rows and N denotes the number of columns in the image respectively. Hence, the resulting colour image will be a collection of vector pixels

$$\mathbf{X} = \{\mathbf{x}_{i,j}, i = 1, 2.....,M, j = 1,2,.......,N\} \quad (1)$$

colour information is stored in a pixel as a joint vector including the red, green, and blue components of the colour,

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

For the signal values in this study, we use a double-precision format.

$$\mathbf{x}_{i=1,....,M,j=1,.....,N} \quad (3)$$

in the intermission $(0,1)$ where a 0 indicates the lowermost intensity and a 1 the strongest. For those who prefer to follow the formula in (1).

Let $\mathbf{z}$ be the color image tainted by random valued impulse noise (RVIN).

$$\mathbf{Z} = (\mathbf{z}_{i,j}, i = 1,..., M, j = 1, ..., N) \quad (4)$$

In this study, we focus on the random valued impulse noise model for the $(i,j)^{th}$ pixel, which is described as

$$\mathbf{z}_{i,j} = \begin{cases} \mathbf{x}_{i,j} & \text{if } q \geq p \\ \mathbf{v}_{i,j} & \text{otherwise} \end{cases} \quad (5)$$

Where $i = 1,......., M$, $j = 1,.........., N$. Within this range of $(0,1)$, the model's variables are equally distributed. Here $\{p, q\} \in U(0, 1)$ and $U(.)$ signifies a uniform distribution function. According to this explanation, the closer the value of signifies the noise probability p of an image to one, the greater the noise, and the nearer the value of denotes the noise probability p of an image to zero, the less the noise. If the pixel is uncorrupted, it will continue to display the value $\mathbf{x}_{i,j}$ that it had before the corruption occurred; otherwise, the generated noise will manifest in each of the colour channels to produce a noisy pixel.

$$\mathbf{v}_{i,j} = (v_{i,j,r}, v_{i,j,g}, v_{i,j,b}), v_{i,j,.} \sim U(0,1) \quad (6)$$

Here the noise intensities various any random value in $(0,1)$ in equation (6). When an image becomes noisy, noise reduction methods are used to bring it back to its pre-noise state. The main aim of denoising approach is to reconstruct the original image $\mathbf{X}$ from the corrupted image $\mathbf{Z}$.

3. Conventional Vector Median Filtering

Traditional noise-reduction filters are discussed here. According to a different description of (1), the noisy image $\mathbf{Z}$ may be represented as a vector in the form of

$$\mathbf{Z} = \{\mathbf{z}_\mathbf{i} = (z_{i,r}, z_{i,g}, z_{i,b})\ i = 1,......, MN\} \quad (7)$$

In order to filter this noisy image, a window W comprising of size $\sqrt{n} \times \sqrt{n}$ with n pixels are used. Consider the window's W pixel contents a flair. The most common kind of window 3×3 will be utilised in this chapter.

$$W = \{\mathbf{z}_i,\ i = 1,.......,n\} \quad (8)$$

The VMF [13], by far the most used filtering method, swaps the test (centre) pixel in the given window W with one from the window W that lessens the total pixel-to-pixel aggregate distance. One might think of the average distance between each pixel to every other pixel in the selected W as

$$D_i = \sum_{j=1}^{n} d(\mathbf{z}_i, \mathbf{z}_j), i = 1, 2, ..., n \tag{9}$$

Here $d(.,.)$ represents the Minowski's distance of the order λ between two joint pixels

$$d(\mathbf{z}_i, \mathbf{z}_j) = \left(\sum_{k=\{r,g,b\}} \left(z_{i,k} - z_{j,k} \right)^{\lambda} \right)^{1\backslash\lambda} \tag{10}$$

Let us consider the Euclidean distance by Setting λ = 2. After the minimum total aggregate distance has been established, the index $\hat{i} = arg\ min_i\ D_i,\ i = 1, 2, ..., n$ and the recovered image's central pixel in the middle of the window is changed to $y_c = \mathbf{z}_{\hat{i}}$ where $Y = \{y_{i=1, \cdots, MN}\}$ is denotes the reconstructed image from the noisy image. To do this, it uses the coherence of the signal components to determine which pixel should be used as the central test pixel. All other VMF operations are derived from this fundamental procedure.

In subsequent developments of the VMF, emphasis was placed on establishing better distance measurements used in (10) and better methods in calculating the aggregate distance in (9); the ARWSF [13] enhances filtering by assigning ranking the respect to distances, while the DOAF [200] enhances by ranking the aggregates. After calculating the total distance between each pixel and each further pixel in the selected window in accordance with (8), the ARWSF reorders the series based on a rank weighting of the distances, as follows: $\{\{\mathbf{z}_i, D_i\}: D_{i-1} \le D_i \le D_{i+1}, i = 1, ..., n\}$ and assign relative importance to each element in the sequence

$$D_i = D_i / i^2,\ i = 1, ..., n \tag{11}$$

$\mathbf{z}_i$ is chosen that, the index minimises $D_{i=1,....,n}$. On the other hand, the DOAF assigns a value to each distance-associated entity; in this case, we calculate the adjacency matrix.

$$D_i = d(\mathbf{z}_i - \mathbf{z}_5), i = 1, 2, ..., n \tag{12}$$

and set the diagonal elements to $D_{i,i} = \sum_{j=1...n} D_{i,j} + \delta$ where $\delta = 0.005$ is a small regularization value. The polynomial from of the normalized weighted vector $\mathbf{w} = \{w_{i=1:N}\}$ is calculated as

$$w_i = \frac{1/D_{i,i}^2}{\sum_{i=1}^{n} 1/D_{i,i}^2}, i = 1, ...n \tag{13}$$

$\mathbf{g} = D\mathbf{w}$ is used to obtained the weighted distances. The $\mathbf{g}$ is selected as the filtered output that minimizes $\mathbf{z}_i$.

Both the ARWSF and the DOAF variations of the VMF enhance performance over the original by giving more weight to pixels that are extremely comparable to the window. This allows for very precise filtering. Nevertheless, because of its great computing cost, the DOAF involves filtering iteration over all the pixels. The workaround we suggest in the following paragraphs is effective in avoiding this issue.

4. The Proposed Method

To supress the random valued impulse noise in colour images efficiently, we give the solution here. Assume that the noisy colour image defined by (1) has M rows and N columns of MN pixels, as

$$\mathbf{Z} = (\mathbf{z}_{i,j}, i = 1, ..., M, j = 1, ..., N) \tag{14}$$

colour information is stored in a pixel as a joint vector including the three colours red, green, and blue components,

$$\mathbf{z}_{i,j} = \left(z_{i,j,r}, z_{i,j,g}, z_{i,j,b} \right), i = 1, ..., N, j = 1, ...M$$

Let us consider a i^{th} univariate data row of k^{th} color component consists of N pixel concentrations be

$$\mathbf{a}_i = \{a_1, a_2, ..., a_N\} = \mathbf{z}_{i,j=1,...,N,k} \tag{15}$$

Absolute differences between elements (pixel intensities) in a data slice and their immediate neighbours are then calculated.

$$\mathbf{d}_i = \left|\mathbf{a}_i - \{\mathbf{a}_{i,2}, ...\mathbf{a}_{i,N}, \mathbf{a}_{i,N}\}\right| - \left|\mathbf{a}_i - \{\mathbf{a}_{i,1}, \mathbf{a}_{i,1}, \mathbf{a}_{i,N-1}\}\right| \tag{16}$$

Then, the indices where the sum of the differences is more than a predetermined limit t_h are identified as

$$\mathbf{j}_i = \{j : \mathbf{d}_i(j) \ge t_h\} \tag{17}$$

Remember that the critical understanding of this method is to locate the out-of-place pixels in the data slice. Anomaly identification requires a signature of at least the first index in $\mathbf{j}_i$ represents the distance from the left clean pixel to the noise anomaly, the second represents the distance from the noise anomaly to the clean pixels (there can be more than one), and the third represents the distance from the noise anomaly to the right clean pixel.

Therefore, the $\mathbf{j}_i$ will include not just the indices of the abnormal pixels but also the indices for the regions to the left and right of those regions, which are not anomalous. We then identify the irregular pixels using

$$\mathbf{b}_i(j) = \begin{cases} 1 & if \quad \{\mathbf{j}_i(j)+1, \mathbf{j}_i(j)-1\} \in \mathbf{j}_i \\ 0 & else \end{cases} \tag{18}$$

for $j = 1,......,|\mathbf{j}_i|$ here $|.|$ represents cardinality function of given set. The vector $\mathbf{b}_i$ represents set of 1's and 0's, with a 1 at the j^{th} index for when the corresponding $\mathbf{d}_i(j)$ has attained, or surpassed, the threshold is zero otherwise. Anomaly locations (those pixels where the sum of the differences exceeds a predetermined threshold) are represented by ones, while normal locations are represented by zeros. Then, we get the anomaly indices by $\mathbf{c}_i = \{\mathbf{j}_i(j) : \mathbf{b}_i(j) = 1\}$. The non-anomalies have been eliminated, as can be seen.

This lays the groundwork for filtering out just the out-of-the-ordinary pixels by leveraging two neighbouring ones: This is the restored output vector of i^{th} data slice is

$$y_{i,j\in c_i} = \mathrm{DOAF}(\mathbf{w}^{<i,j>}) \tag{19}$$

$$y_{i,j\notin c_i} = \mathbf{z}_{i,j} \tag{20}$$

for $j = 1,2,...,N$, where (19) compute the DOAF output for anomalous pixels using the 3×3 window

$$\mathbf{w}^{<i,j>} = \bigcup_{i\in\{-1,1,1\}} \left\{ \bigcup_{j\in\{-1,1,1\}} \mathbf{z}_{i,j} \right\} \tag{21}$$

Contains the neighbours of the $(i,j)^{th}$ pixel and (19) preserves the non-anomalous pixels unaffected. The proposed approach from (15) to (20) is recapitulated across all rows $i = 1,.......,M$ and all color spaces. Impulse noise is consistent in all colours; hence the technique only has to be executed on a single colour channel. One of the main advantages of this approach is that it requires less computational capabilities to $O\left(\prod_{i=1}^{M} F|\mathbf{c}_i|\right)$. The $F|\mathbf{c}_i|$ represents the summation over the i^{th} row in a calculation. This computational time improvement can be achieved with omitting the common filtering of all pixels and all colour channels.

5. Evaluation and Results

Here, we use two test statistics to compare the suggested approach termed as fast DOAF (FDOAF) with ARWSF & DOAF. Root mean square error (RMSE) and time-scaled root mean square error (TRMSE) are two standard metrics for evaluating precision.

$$RMSE(\mathbf{X},\mathbf{Y}) = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\|\mathbf{X}_{i,j} - \mathbf{Y}_{i,j}\|^2} \tag{22}$$

In which the two sets of values, $\mathbf{X}$ and $\mathbf{Y}$, represent the original data and the reconstructed version of the image, respectively. We want the RMSE to be modest since it means the difference between the filtered and original images is minimal. We then define the time-scaled root-mean-squared-error (RMSE) as

$$TRMSE = T \times RMSE \tag{23}$$

Where T is the amount of time it takes for the filter to apply its transformation to the whole image in terms of computing time (in seconds).

All of the techniques were written in MATLAB 2018b and tested in Intel Core i5 CPU with 8 GB of Memory. Three satellite pictures are shown as examples. Figure 1 depicts these values: Statistics for SAT-I: M = 128, N = 128, total = 16384 pixels, M = 270, N = 269,total = 72630 pixels, and M = 659, N = 658, total = 433622. In our suggested FDOAF, the threshold value is t_h = 0.05.

Fig. 1. Three satellite imagery examples used for testing.

In Table 1, we provide the computing time T (in sec) required by each of the presented approaches. It has been determined that for the standard ARWSF and DOAF approaches, T is almost constant regardless of p. Nevertheless, it was discovered that T for the suggested technique grows proportionately with p due of the higher filtering computation caused by the greater number of outliers when dealing with high noise.

Table 1: The computational time of the filter T (seconds) corresponding to figure 1 with varying noise probabilities.

p	0.1	0.2	0.3	0.4	0.5
SAT-1					
FDOAF	2.4531	3.3438	4.5156	5.1094	5.7500
ARWSF	10.656	10.718	10.656	10.546	10.546
DOAF	8.1250	8.0938	8.0469	8.1094	7.9219
SAT-2					
FDOAF	16.094	19.234	23.438	25.047	29.406
ARWSF	34.141	33.484	33.609	34.828	33.672
DOAF	44.719	45.219	45.422	45.234	44.938
SAT-3					
FDOAF	76.297	98.562	120.28	138.18	165.28
ARWSF	228.17	215.85	197.73	209.54	208.62
DOAF	421.79	282.54	263.67	276.39	279.73

For SAT-1 image, the suggested approach FDOAF displays a decrease of 76.92%, 68.81%, 57.61%, 51.52% & 45.41 % compared to the ARWSF and a decrease of 69.81 %, 58.62 %, 43.81 %, 36.91 %, and 27.42 % compared to the DOAF at p = 0.1, 0.2,.., 0.5. At p = 0.1, 0.2,., 0.5, the suggested FDOAF for SAT-2 exhibits a decrease of 64.10%, 57.41%, 48.42%, 34.52%, and 52.81%, 42.51%, 30.22%, 28.01%, and 12.61% when compared to ARWSF and DOAF, respectively. The suggested FDOAF exhibits significant improvements in noise reduction of 81.91%, 65.12%, 54.31%, 50.11%, & 40.91% and 66.51%, 54.32%, 39.12%, 34.12% & 20.71% compare with ARWSF & DOAF correspondingly at p = 0.1,0.2, .., 0.5. for SAT-3 image.

It seems to reason that MN will have an impact on T. When comparing the SAT-2 having MN = 72630 pixels with SAT-1 having MN = 16384. At p = 0.5, the suggested FDOAF from ARWSF and DOAF approaches reduces the number of false positives by roughly two and three times, respectively. These findings demonstrate the significant efficacy of the FDOAF in quickening the filtering process. The root-mean-square-error (RMSE) values for the three satellite images at different noise probabilities are shown in Table 2. The suggested FDOAF, the RMSE values are similar to the other approaches for low values of p, as can be shown.

Table 2: The RMSE values of the filter corresponding to figure 1 with varying noise probabilities.

p	0.1	0.2	0.3	0.4	0.5
SAT-1					
FDOAF	0.03848	0.04890	0.06025	0.07064	0.08977
ARWSF	0.03090	0.03432	0.03961	0.04435	0.06040
DOAF	0.03368	0.03835	0.04709	0.05585	0.07884
SAT-2					
FDOAF	0.04680	0.05699	0.06971	0.08727	0.11575
ARWSF	0.04335	0.04533	0.04915	0.05966	0.08309
DOAF	0.04764	0.05206	0.06017	0.07807	0.10865
SAT-3					
FDOAF	0.03835	0.04872	0.05860	0.07724	0.10722
ARWSF	0.03098	0.03299	0.03671	0.04863	0.07361
DOAF	0.03459	0.03968	0.04739	0.06681	0.09945

However, the method's scalability suffers significantly with large p numbers. Anomaly detection may produce false positives or genuine negatives, which might account for the observed phenomenon. Fig. 2 & 3 shows the result of applying the filter on test images SAT-1 & SAT-2.

Fig. 2. The filtered results of the SAT-1 image. A noisy, ARWSF, DOAF, and FDOAF image is shown from left to right. Starting at the top: p = 0.1, 0.2,., 0.5.

The Time scaled RMSE values of these techniques for different noise probabilities are shown in Table 3. Comparing the proposed FDOAF to the alternative approaches, also displays % difference in TRMSE. The proposed method shows a remarkable improvement in terms of TRMSE when applied to all three images collectively; the FDOAF shows a decrease of 70.10 percent for ARWSF and of 60.71 percent for DOAF at p = 0.1, 0.2,..., 0.5, respectively.

Fig. 3. The results of the SAT-2 image filtering. From left to right, noisy, ARWSF, DOAF, and FDOAF p = 0.1, 0.2, .., 0.5 from top to bottom.

Table 3: The TRMSE values of the filter corresponding to figure 1 for varying noise probabilities.

p	0.1	0.2	0.3	0.4	0.5
SAT-1					
FDOAF	0.09441	0.16352	0.27210	0.36096	0.51621
ARWSF	0.32934	0.36787	0.42212	0.46775	0.63710
% ↓	71.3358	55.5479	35.5392	22.8307	18.9754
DOAF	0.27369	0.31043	0.37893	0.45296	0.62457
% ↓	65.5048	47.3225	28.1924	20.3114	17.3498
SAT-2					
FDOAF	2.9266	4.8021	7.0485	10.6742	17.7221
ARWSF	13.0673	9.32340	9.68190	13.4429	20.5916
% ↓	77.6034	48.4942	27.1992	20.5958	13.9352
DOAF	7.8938	8.5657	9.3712	14.0015	20.7482
% ↓	62.9249	43.9381	24.7853	23.7634	14.5845
SAT-3					
FDOAF	0.75322	1.09626	1.63387	2.18597	3.40391
ARWSF	1.93894	2.05008	2.23278	2.69877	3.73395
% ↓	61.1529	46.5257	26.8235	19.0014	8.8390
DOAF	1.62663	1.74320	2.02229	2.71918	3.65854
% ↓	53.6942	37.1119	19.2071	19.6094	6.95990

Anomaly processing improves in high-noise conditions, accounting for the decrease at larger P values. Most importantly, the TRMSE convincingly demonstrates that the decreased time consumption of the suggested technique more than compensates for the larger RMSE. The ability to execute anomaly detection along a single colour channel and the dearth of sequential processing across every pixel in the image the primary reasons for this effectiveness.

6. 6 Conclusion

In this article, we looked at how to speed up the DOAF filter, which is often used to reduce impulsive noise in satellite images. Outliers (noisy pixels) in a particular data row will be the only ones subjected to the DOAF in an effort to separate the random valued impulsive noise. As random valued impulse noise is consistent across all colour channels, filtering it does not need processing the whole image at once. By applying the suggested approach to satellite images corrupted with noise, we demonstrate its efficacy and assess its time and accuracy costs.

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