

Development of Image Fusion Algorithm for Impulse Noise Removal in Digital Images using the quality Assessment in Spatial Domain

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ABSTRACT

Now a days remote sensing plays very important role in satellite based communication. Satellite gives images in digital format. Digital images are often corrupted during acquisition, transmission or due to faulty memory locations in hardware. The noise density varies depending on various factors namely reflective surfaces, atmospheric variations, noisy communication channels etc. Impulse noise corruption is very common in digital images. In this paper, the images captured by different sensors, producing different impulse noisy images are considered. As order statistics filters exhibit better performance, these noisy images are filtered individually using non linear filtering algorithms namely, Vector Median Filter (VMF), Rank Conditioned VMF, Rank conditioned and Threshold VMF, Center Weighted VMF and Absolute Deviation VMF. These filtered images are combined to a single image called image fusion, which retains the important features of the images from individual sensors. The filtered images are fused into a single image by using the image fusion technique which is based on the quality assessment in spatial domain. Now this fused image is again filtered using absolute deviation VMF which performs better than fused image. The performance evaluation of the filtered and the fused image with respect to the original image is done using mean square error(MSE), peak signal to noise ratio(PSNR) and structural similarity index(SSIM).

Keywords- Median Filter, Fusion, Order Static filters

I. INTRODUCTION

Noise is undesired information that contaminates an image. Noise appears in image from various sources. The digital image acquisition process converts an optical image into a continuous electrical signal. This electrical signal sampled, is primary process by which noise appears in digital image. There are several ways through which noise can be introduced into an image, depending on how the image is created. This is the main problem in remote sensing applications. Satellite image, containing the noise signals and lead to a distorted image and not

being able to understand. So to study it properly, requires the use of appropriate filters to limit or reduce much of the noise. It helps the possibility of better interpretation of the content of the image.

The images captured by multiple sensors can be differently noised depending on the proximity to the object, environmental disturbances and sensor features. There are different types of noises are added to the image depending on the nature of sensor, application, hardware etc. Gaussian noise, uniform noise, impulse noise, gamma noise, exponential noise etc. are some of the noise models in image processing. Impulse noise is one of the common problems in digital images. In this paper an attempt has been made to remove impulse noise from images captured by different sensors. The impulse noise can be removed by using nonlinear filters. The median filter is mostly used nonlinear filter to remove impulse noise. However the direct extension of the median filter to color images is not a straight forward one. The ordering of the vector pixel data is carried by considering suitable distance measure. The vector pixels in a kernel are ordered depending on the sum of the distances between each vector pixel and the other vector pixels in a window or kernel. The vector pixel with smallest sum of distances forms the vector median.

In most of the imaging applications, for example remote sensing, the images captured by different sensors are combined to a single image, which retains the important features of the images from individual sensors. Only removal of noise is not sufficient for further processing in case remote sensing applications. The filtered images must be fused into a single image which is most suitable than individual image. This task accomplished by a process called image fusion. Image fusion is defined as the process of combining substantial information from several sensors using mathematical techniques in order to create a single composite image that will be more comprehensive and thus, more useful for a human operator or other computer vision tasks. Current technology in image sensors offers a wide variety of information that can be extracted from an observed scene.

II. ORDER STATIC FILTERS FOR COLOUR IMAGE PROCESSING

Vector Median Filter

In the vector median filter for the ordering of vectors in a particular kernel or mask a suitable distance measure is chosen. The vector pixels in the window are ordered on the basis of the sum of distances between each vector pixel and the other pixels in the window. The sum of the distances is arranged in ascending order and then the same ordering is associated with vector pixels. The vector pixel with the smallest distances is the vector median pixel. The vector median filter is represented as $X_{VMF} = \text{Vector Median}(a_A)$

$$a_A = \left(\text{rank} \left(\left(\sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{j=-\frac{w-1}{2}}^{\frac{w-1}{2}} \left(\sum_{k=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{l=-\frac{w-1}{2}}^{\frac{w-1}{2}} L_k = (a_A(k) - a_A(p)) + L_Q \right) \right) \right) \right) \text{IM}(x+i, y+j) \right)$$

Where $A = 1$ when $i = j = x + y = -2$
 $A = 1 + A$ when $k = m = 1$
 $L_Q = 0$ when $k = m = 1$
 $L_Q = L_K$ else

Where for the image IM with window size W, L_k represents the sum of distances from K^{th} pixel to all other pixels in the kernel

Where $(1 \leq i \leq W^2)$ and $a_A(k), a_A(p)$ the vectors, L_k is the distance measure is given by the city block distance which is more suited to non correlated noise. The ordering may be illustrated as

$$L_1 \leq L_2 \leq L_3 \leq \dots \leq L_{w^2}$$

And this implies the same ordering to the corresponding vector pixels i.e.

$$a_A(1) \leq a_A(2) \leq a_A(3) \dots \leq a_A(w^2)$$

Since the vector pixel with the smallest sum of distances is the vector median pixel, it will correspond to rank 1 of the ordered pixels i.e.,

$$X_{VMF} = a_A(1)$$

Rank Conditioned Vector Median Filter

The rank conditioned vector median filter improves the performance of the vector median filter. The vector median of the kernel replaces the central pixel when the rank of the central pixel is greater than a predefined rank of a healthy vector pixel inside the window. To find out a rank of the healthy vector pixel the code simulating RCVMF is executed on a noiseless image. Then, the mean value of the obtained ranks of the central vector pixel is calculated. This value is rounded off to a whole

number, and it is considered to be rank of the healthy vector pixel of a kernel. Then this rank is used for simulations at various noise percentages.

The rank of a healthy vector pixel is given as

$$M_\theta = \left(\sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{j=-\frac{w-1}{2}}^{\frac{w-1}{2}} \left(R_c = \left(\text{rank} \left(\sum_{x=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{y=-\frac{w-1}{2}}^{\frac{w-1}{2}} a_A = \text{IM}(x+i, y+j) \right) + R_c \right) \right) \right) / ((n \times r) - (\frac{w-1}{2}))$$

Where $R_c = 0$ when $i = j = w - \frac{w-1}{2}$

The vector median value X_{VMF} can be calculated as

$$a_A = \left(\text{rank} \left(\left(\sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{j=-\frac{w-1}{2}}^{\frac{w-1}{2}} \left(\sum_{k=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{l=-\frac{w-1}{2}}^{\frac{w-1}{2}} L_k = (a_A(k) - a_A(p)) + L_Q \right) \right) \right) \text{IM}(x+i, y+j) \right)$$

Where $A = 1$ when $i = j = w - \frac{w-1}{2}$
 $A = 1 + A$ when $x + y = -2$

Where $L_Q = 0$ when $k = m = 1$
 $L_Q = L_K$ else

The rank conditioned vector median filter can be expressed as:

$$X_{RCVMF} = X_{VMF}, \text{ if } R_c > M_\theta$$

$$= X_C \text{ otherwise}$$

Where R_c is a rank of the central vector pixel and $c=5$ for the window length of $w = 3$ and so on and M_θ is the predefined healthy vector pixel rank inside the window, where X_C is the center vector pixel of the kernel.

Image details are preserved better if the rank chosen is large. However this is at the cost of passing more impulses are removed to the maximum extent with a smaller value of the rank but blurring effect is more pronounced in the restored image.

Rank Conditioned Threshold Vector Median Filter

The rank-conditioned and threshold vector median filter aims to further enhance the RCVMF by incorporating an additional test – a distance threshold for the detection of impulses. In RCVMF a central vector having greater than the predefined rank implies a corrupt vector. However, it may not be true always, because the vectors may be close as per the distance measure. Hence another criterion Θ , is taken into account. It is the distance between the central vector pixel and the vector pixel corresponding to the predefined rank. To find out the value of this pre-determined distance threshold Θ , the code simulating RCTVMF is executed on a noiseless image. Then the mean of the obtained Θ values is calculated and used for the simulations at various noise percentages. This value is used in the program to help select only the corrupt central vector pixels.

The distance threshold Θ is calculated as follows

$$IM(x+i, y+j) \sum_{s=1}^{n^2} L_p = \left(\left(\sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{j=-\frac{w-1}{2}}^{\frac{w-1}{2}} \left(\left(\sum_{x=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{y=-\frac{w-1}{2}}^{\frac{w-1}{2}} a_A \right) \right) \right) \right)$$

Where $A = 1$ when $i = j = w - \frac{w-1}{2}$
 $A = 1+A$ $x + y = -2$
 Where $L_Q = 0$ when $S = 1$
 $L_Q = L_p$ else
 Where $p = 1$ when $i = j = w - \frac{w-1}{2}$
 $p = p + 1$ else

$$L_p = \left((m \times n) - \frac{w-1}{2} \right)$$

where $\Theta =$
 The rank threshold value is calculated as

$$M_\theta = \left(\sum_{i=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{j=-\frac{w-1}{2}}^{\frac{w-1}{2}} \left(R_c = \left(\text{rank} \left(\sum_{x=-\frac{w-1}{2}}^{\frac{w-1}{2}} \sum_{y=-\frac{w-1}{2}}^{\frac{w-1}{2}} a_A = im(x+i, y+j) \right) + R_c \right) \right) \right)$$

Where $R_c = 0$ when $i = j = w - \frac{w-1}{2}$
 On the basis of the above information, the filter has the following form:

$$X_{RCTVMF} = X_{VMF}, \text{ if } R_c > M_\theta \text{ and } L_p > \Theta$$

$$= X_c \text{ otherwise}$$

The distance L_p is usually very big if impulses are present at the center of the window. If the value of threshold is reduced, more and more number of the central vector pixels will be replaced by the vector median and the filter will resemble the RCVMF.

Center Weighted Vector Median Filter

In the case of center weighted median filter the kernel vector pixels are assigned some non negative values called weights. The central vector pixel is assigned a non negative weight while the weight of the neighboring pixels is kept unity. The weights denote the number of copies is obtained. The output Y (say), of a weighted median filter of span N (where N generally denotes the kernel size, $N=9$) associated with N integer weights,

$$W = [W_1, W_2, \dots, W_N]$$

is given by,
 $Y = \text{vectormedian} [W_1 * X_1, W_2 * X_2, \dots, W_9 * X_9]$

Where the $\text{vectormedian}[\cdot]$ denotes the vector median operation.

The center weight is kept odd so that a central element is always obtained. If the center weight has value of one then the present filter becomes a vector median filter. If the center weight is given a value greater than the kernel size then the filter performs as an identity filter. Larger central vector weights imply superior detail preservation and the inferior noise removal capability as compared to smaller central weights.

Absolute Deviation Vector Median Filter

In this filter, the impulse noise detection mechanism does not require the distance calculation and subsequent ordering of the vectors of a kernel. The algorithm deals with the difference values of the red (R) and the green (G) intensities denoted by Ω_{RGi} (say), and the difference values of the green (G) and blue (B) intensities denoted by Ω_{GBi} (say), (where $1 \leq i \leq N, N=9$).

In a 3×3 kernel, it has been observed empirically that Ω_{RGi} and Ω_{GBi} values closely correspond to each other. Thus the mean absolute deviation D'_{RG} and D'_{GB} i.e. the mean of D_{RGj} and D_{GBj} (where $1 \leq j \leq N$, and $j \neq c, c = (N+1)/2, N = 9$) has small values. D_{RGj} and D_{GBj} are the absolute deviation values of Ω_{RGj} and Ω_{GBj} from Ω'_{RG} and Ω'_{GB} respectively. Ω'_{RG} and Ω'_{GB} denote the mean of Ω_{RGj} and Ω_{GBj} (where $1 \leq j \leq N$, and $j \neq c, c = (N+1)/2, N = 9$). The absolute deviation of the central vector Ω_{RGc} and Ω_{GBc} values from Ω'_{RG} and Ω'_{GB} is obtained respectively as D_{RGc} and D_{GBc} .

If the absolute deviation D_{RGc} and D_{GBc} of the central vector pixel exceeds the value of D'_{RG} or D'_{GB} respectively for a 3X3 kernel, the central vector pixel is to be replaced by the vector median of the kernel. The algorithm is represented as follows.

In a 3X3 kernel,

Step 1: Find the difference values of red(R) and the green(G) intensities denoted by Δ_{RGi} and the difference values of the green(G) and blue(B) intensities denoted by Δ_{GBi} .

$$\Delta_{RGi} = X(i, R) - X(i, G)$$

$$\Delta_{GBi} = X(i, G) - X(i, B) \quad \text{Where } i=1 \dots 9$$

Step 2: Calculate the mean of Δ_{RGi} and Δ_{GBi} denoted by Δ^1_{RGi} and Δ^1_{GBi} . Where $i=1,2 \dots 9$ and $i \neq 5$.

Step 3: Calculate the absolute deviation between Δ and Δ^1 .

$$D_{RGi} = |\Delta_{RGi} - \Delta^1_{RGi}|$$

$$D_{GBi} = |\Delta_{GBi} - \Delta^1_{GBi}| \quad \text{where } i=1,2 \dots 9$$

Step 4: Calculate the mean of D_{RGi} and D_{GBi} denoted as D^1_{RGi} and D^1_{GBi} . where $i=1,2 \dots 9$ and $i \neq 5$.

Step 5: Now

$$D_{RGc} = |\Delta_{RGc} - \Delta^1_{RGi}|$$

$$D_{GBc} = |\Delta_{GBc} - \Delta^1_{GBi}| \quad \text{where } i=1,2 \dots 9, i \neq 5 \text{ and } c \text{ is the central vector.}$$

Step 6: If $D_{RGc} > D^1_{RGi}$ OR $D_{GBc} > D^1_{GBi}$ where $i=1,2 \dots 9$ and $i \neq 5$. central vector is corrupted, hence central vector is replaced by Vector Median of kernel.

III. IMAGE FUSION

With the availability of multi-sensor data in many fields such as remote sensing, medical imaging, machine vision and military applications, sensor fusion has emerged as a new and promising research area. The current definition of sensor fusion is very broad and the fusion can take place at the signal, pixel, and feature and symbol level. Multisensor data often presents complementary information about the region surveyed, so image fusion provides an effective method to enable comparison and analysis of such data. The goal of image fusion is to create new images that are more suitable for the purposes of human visual perception, object detection and target recognition. The use of multi-sensor data such as visible and infrared images has lead to increased recognition rate in applications such as automatic target recognition.

IV. QUALITY ASSESSMENT OF SPATIAL DOMAIN

Quality assessment of images has been successfully employed in the authentication area, such as iris and fingerprint verification, which is used to evaluate the quality of the captured images. Fingerprint quality is usually defined as a measure of the clarity of the ridge and valley structures. In the multi-focus image fusion, it is the first step to investigate whether the region of the image is clarity or not, so we incorporate the quality

assessment into multi-focus image fusion algorithm. Generally speaking, the quality assessment can be classified into two ways, namely the frequency domain assessment and the spatial domain assessment. We incorporate the latter one into this algorithm.

In order to assess the image quality in a local region, we partition a given image into a lattice of blocks

of size $b \times b$. For each block B, let $g_s = (g_s^x, g_s^y)$ denote the gradient of the gray level intensity at site $s \in B$. The covariance matrix of the gradient vectors for all b^2 sites in this block is given by

$$J = \frac{1}{b^2} \sum_{s \in B} g_s^T g_s = \begin{bmatrix} j_{11} & j_{12} \\ j_{21} & j_{22} \end{bmatrix}$$

The above symmetric matrix is positive semi definite with Eigen values

$$\lambda_1 = \frac{1}{2} \left(\text{trace}(J) + \sqrt{\text{trace}(J)^2 - 4 \det(J)} \right)$$

$$\lambda_2 = \frac{1}{2} \left(\text{trace}(J) - \sqrt{\text{trace}(J)^2 - 4 \det(J)} \right)$$

Where $\text{trace}(J) = j_{11} + j_{22}$, $\det(J) = j_{11}j_{22} - j_{12}^2$ and $\lambda_1 \geq \lambda_2$. The quality assessment defined as

$$\lambda = \lambda_1 - \lambda_2$$

This measure reflects the clarity of the local region. The clearer the local region is, the bigger the measure is.

Multi-Sensor Image Fusion using quality assessment

The block diagram for multisensor image fusion is shown in figure 2. The algorithm for the multisensor image fusion using quality assesment is as follows:

- [1] Let I^1, I^2, \dots, I^5 be the noisy images of an object or scene captured by sensors S^1, S^2, \dots, S^5 respectively. Let I^i be of size $N \times N$ where $i = 1, 2, \dots, 5$.
- [2] Filter the noisy images using five different filtering algorithms. The filtered images are denoted as R^i .
- [3] The recovered images R^i for $i = 1, 2, \dots, 5$ are divided into non-overlapping rectangular blocks (or regions) with size of $m \times n$. The j^{th} image blocks of R^i are referred by R^i_j .
- [4] Quality assessment value (λ) of R^i_j is calculated and the results of R^i_j are denoted by λ^i_j .

In order to determine the sharper image block, the quality assessment value of image blocks from 5 recovered images are sorted in descending order and the same ordering is associated with image blocks. The block with the maximum quality Assessment is kept in the fused image. The fusion mechanism is represented as follows:

If λ_j^i is the quality assessment value of block R_j^i , the ordering of assessment values is given by

$$\lambda_{(1)} > \lambda_{(2)} > \dots > \lambda_{(5)}$$

and this implies the same ordering to the corresponding blocks

$$R_{(1)} > R_{(2)} > \dots > R_{(5)}$$

Where the subscripts are the ranks of the image blocks. Since the block with the largest quality assessment value is in the fused image, it will correspond to rank 1 of the ordered blocks i.e;

$$\text{Fused Block} = R_{(1)}$$

In this paper, five noisy images are captured by sensors are filtered using Vector Median Filter (VMF), Rank Conditioned VMF, Rank conditioned and Threshold VMF, Center Weighted VMF and Absolute Deviation VMF. These filtered images are fused into a single image while retaining the important features of each image which is called image fusion. This is represented in figure 1.

V. RESULTS

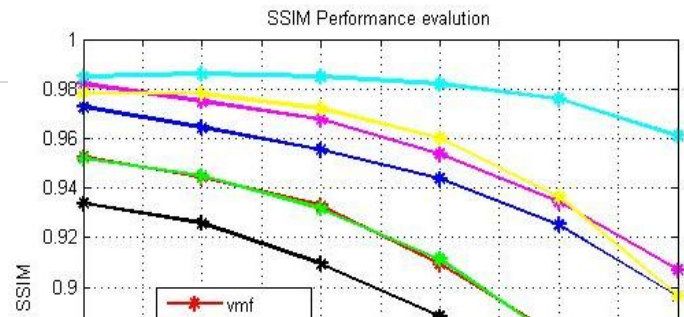
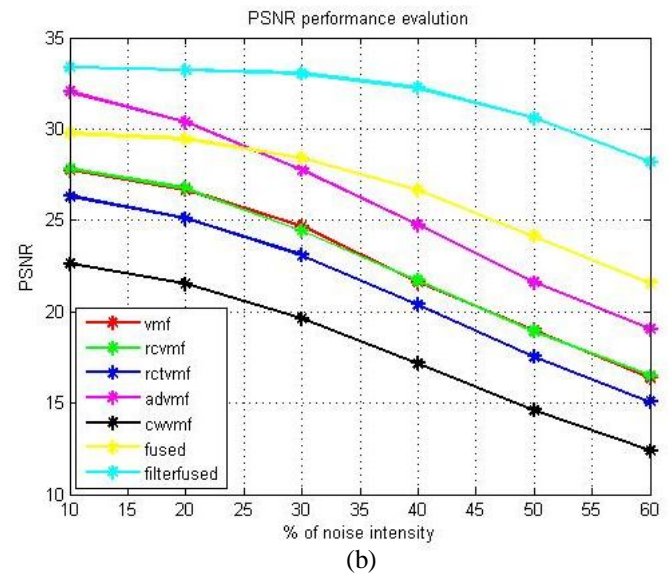
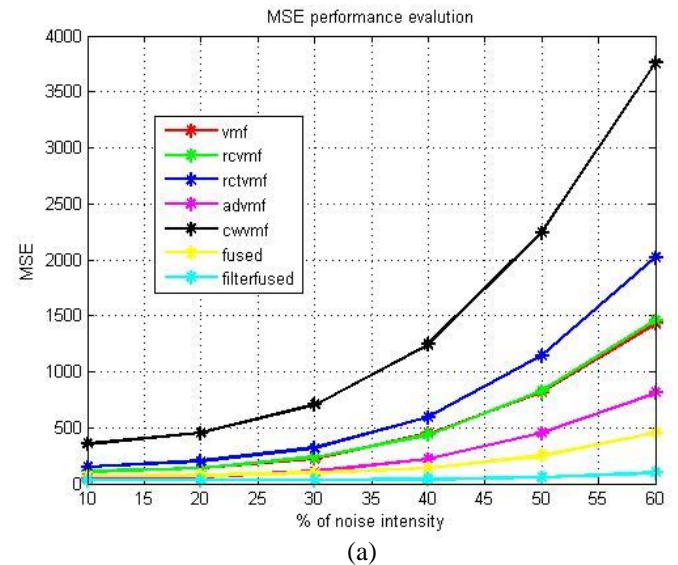
In general the images captured by different sensors are corrupted with noise. The noise from these images must be removed for further processing. Once noise removed from the images, these images are combined into a single image. Because, individual sensor cannot provide all the information. Especially in case of remote sensing applications it is necessary to combine the information from all sensors. This is done by image fusion technique. The image fusion technique enables the combination of all individual images into a single image without losing any original information.

In this paper images captured by different sensors are considered. It is assumed that all different images are contaminated with impulse noise with different noise density (10%-60%). The images are filtered individually using different filtering algorithms namely, Vector Median Filter (VMF), Rank Conditioned Vector Median Filter (RCVMF), Rank conditioned and Threshold Vector Median Filter (RCTVMF), Center Weighted Vector Median Filter (CWVMF) and Absolute Deviation Vector Median Filter (ADVMF). Each filter removes the impulse noise and these filtered images are fused for further processing.

The performance of each filter can be evaluated by using image quality measures. The common image quality measures are mean square error, peak signal to noise ratio and structural similarity index. The fused image is compared with original image using these image quality measures.

The performance of each filter and fusion of these images can be evaluated by image quality measures. The figure 2 (a) shows the Mean Square Error of each

filter and fused image at different noise densities. The figure 2 (a) shows the peak signal to noise ratio of each filter and fused image at different noise densities. The figure 2 (b) shows the structural similarity index of each filter and fused image at different noise densities. Each filter specified with different colors in figures. The resultant images of VMF, RCVMF, RCTVMF, CWVMF, ADVMF. Here images for 60% of noise are represented in Figure 3.



using single sensor and single filtering technique, we are using different sensors for capturing the image of object and different filtering techniques are applied simultaneously for removal of noise. By considering quality assessment of each filtered image captured by different sensors, the images are fused which results in more noise free image than any individual filtered image. The filtered images are fused based on the quality assessment in spatial domain for removal of impulse noise. Now this fused image is again filtered using absolute deviation VMF which performs better than fused image. The performance evaluation of each filter and fusing technique is done by using image quality measures like mean square error, peak signal to noise ratio and structural similarity index.

Figure 2 image quality measures for river image. (a) MSE vs Noise percentage (b) PSNR vs Noise percentage (c) SSIM vs Noise percentage

VI. CONCLUSION

Digital images are often corrupted by impulse noise captured by sensors. The impulse noise in an image captured by sensor depends on the combination of an illumination source and the reflection or absorption of energy from that source. This noise should be removed from image for further processing. There are different algorithms for the removal of impulse noise in images. For impulse noise, median filter is the best choice. The different filtering techniques for removal of impulse noise are presented. In this paper vector median filter, rank conditioned vector median filter, rank conditioned & threshold vector median filter, center weighted vector median filter and absolute deviation vector median filter are analyzed by applying to remote sensing images for removal of impulse Noise. But in some applications only removal of noise from image is not sufficient. Instead of

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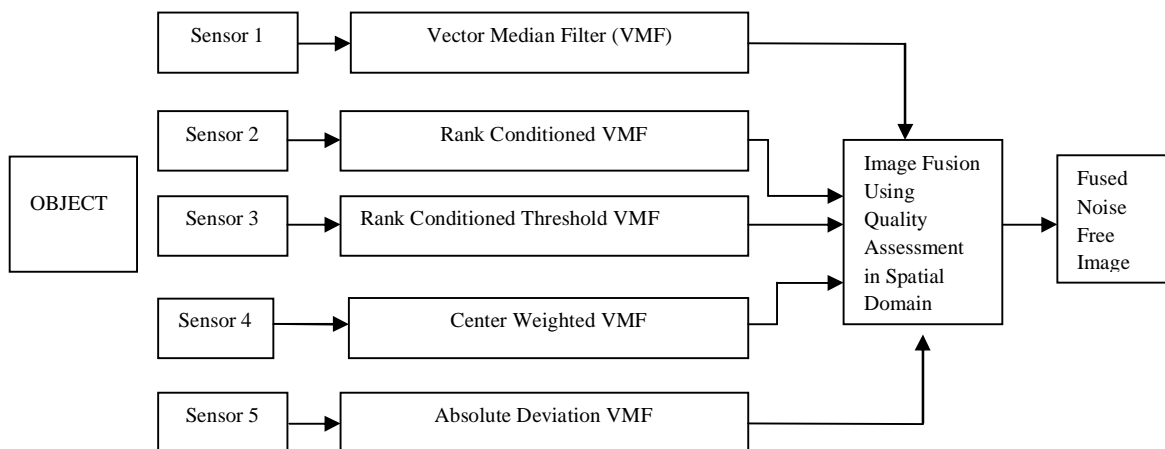


Figure 1 Block Diagram of multisensor Image fusion

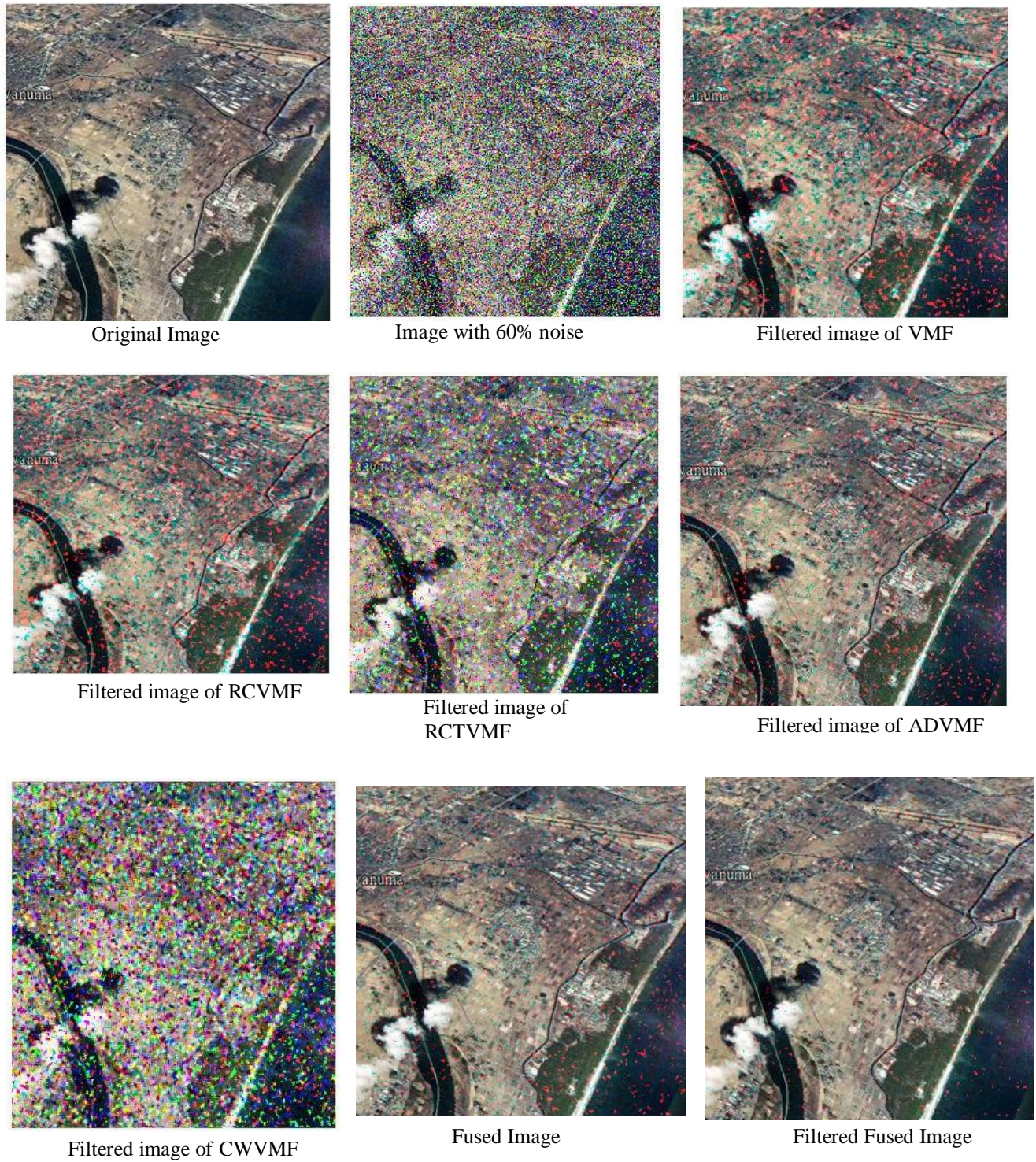


Figure 3 Resultant images after filtering and fusing