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Image Fusion Technique for Impulse Noise Removal in Digital Images Using Empirical Mode Decomposition

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Abstract

This paper introduces the concept of image fusion technique for impulse noise reduction in digital images. Image fusion is the process of combining two or more images into a single image while retaining the important features of each image. Multiple image fusion is an important technique used in military, remote sensing and medical applications. The images captured by two different sensors undergo filtering using vector median or spatial median filter based on the noise density in the image. The filtered images are fused into a single image, which combines the uncorrupted pixels from each one of the filtered image. The fusion algorithm is based on Bi-dimensional Empirical Mode Decomposition (BEMD), which decomposes an image into residue and IMF components. Different fusion rules are used to combine IMFs and Residual components. Finally, the image is recovered using inverse BEMD. The performance evaluation of the fusion algorithm is evaluated using structural similarity index (SSIM) between original and fused image. Experimental results show that this fusion algorithm produce a high quality image than individually filtered image.

Keywords: *Image fusion, Empirical Mode Decomposition, Impulse Noise, Image Processing.*

1. Introduction

Digital images are often corrupted during acquisition, transmission or due to faulty memory locations in hardware [1]. The impulse noise can be caused by a camera due to the faulty nature of the sensor or during transmission of coded images in a noisy communication channel [2]. Consequently, some pixel intensities are altered while others remain noise free. The noise density (severity of the noise) varies depending on various factors namely reflective surfaces, atmospheric variations, noisy communication channels and so on.

In most image processing applications the images captured by different sensors are combined into a single image, which retains the important features of the images from the individual sensors, this process is known as image fusion[3][4]. In this paper, the images captured by two sensors are differently noised depending on the proximity to the object, environmental disturbances and sensor features. These noise images are filtered using two different filtering algorithms based on the noise density. If the noise density is less than 40%, we are using Vector Median filter and if the Noise density is greater than 40%, we are using spatial median filter. The filtered images are fused into a single image using Bi-dimensional Empirical Mode Decomposition (BEMD), thus producing a high quality image. The entire process of our technique is shown in figure 1. The performance evaluation of the image fusion is evaluated using SSIM [5] index between the original and fused image.

This paper is organized as follows: Section II present the impulse noise in images, Section III present the method for noise density calculation in an image, Section IV present the two different filtering algorithms Section V present the image fusion algorithm using BEMD, Section VI present experimental results and finally Section VII reports conclusion.

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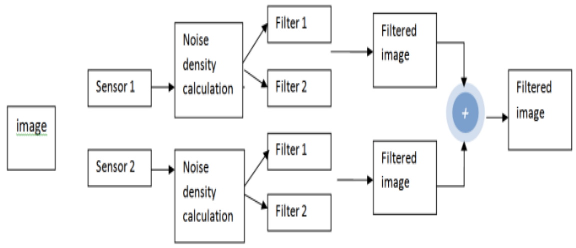

Fig 1: Image Fusion Using BEMD

2. Impulse Noise in Images

Impulse noise [6] corruption is very common in digital images. Impulse noise is always independent and uncorrelated to the image pixels and is randomly distributed over the image. Hence unlike Gaussian noise, for an impulse noise corrupted image all the image pixels are not noisy, a number of image pixels will be noisy and the rest of pixels will be noise free. There are different types of impulse noise namely salt and pepper type of noise and random valued impulse noise.

In salt and pepper type of noise the noisy pixels takes either salt value (gray level -225) or pepper value (gray level -0) and it appears as black and white spots on the images. If p is the total noise density then salt noise and pepper noise will have a noise density of p/2.This can be mathematically represented by (1)

$$y_{ij} = \begin{cases} \text{zero or 255 with probability p} \\ x_{ij} \text{ with probability 1-p} \end{cases} \quad (1)$$

Where y_{ij} represents the noisy image pixel, p is the total noise density of impulse noise and x_{ij} is the uncorrupted image pixel. At times the salt noise and pepper noise may have different noise densities p_1 and p_2 and the total noise density will be $p=p_1+p_2$.

In case of random valued impulse noise, noise can take any gray level value from zero to 225. In this case also noise is randomly distributed over the entire image and probability of occurrence of any gray level value as noise will be same. We can mathematically represent random valued impulse noise as in (2).

$$y_{ij} = \begin{cases} n_{ij} \text{ with probability p} \\ x_{ij} \text{ with probability 1-p} \end{cases} \quad (2)$$

where n_{ij} is the gray level value of the noisy pixel.

3. Noise Density in an Image

[1] Let I be the noisy image of size NXN of an object or scene captured by sensor.

[2] The noise boundaries of noisy image I are computed by spike detection technique [7]. Let L_1 and L_2 be the lower and upper noise boundaries for the noisy image.

[3] The binary map (BM) of the noisy image is developed using the noise boundaries L_1 and L_2. If the image pixel 'y' lies within the noise boundaries, then it is uncorrupted and represented by a '0' in the binary map. The corrupted pixel is represented by a '1'in binary map.

$$BM = \begin{cases} \text{'0' if } L_1 < y < L_2 \\ \text{'1' if } y < L_1 \text{ or } y > L_2 \end{cases} \quad (3)$$

[4] Compute the noise density ND of the noisy image.

$$ND = \frac{\text{sum of '1's in BM}}{N * N} \quad (4)$$

The value of ND ranges from 0 to 1.

4. Filtering Algorithms

Vector Median Filter:

In the **Vector Median Filter** (VMF) [8] for the ordering of the 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 the distances between each vector pixel and the other vector pixels in the window. The sum of the distances is arranged in the ascending order and then the same ordering is associated with the vector pixels. The vector pixel with the smallest sum of distances is the vector median pixel. The vector median filter is represented as

$$X_{VMF} = \text{VectorMedian(window)} \quad (5)$$

If δ_i is the sum of the distances of the i^{th} vector pixel with all the other vectors in the kernel, then

$$\delta_i = \sum_{j=1}^{N} \Delta(X_i, X_j) \quad (6)$$

where $(1 \le i \le N)$ and X_i and X_j are the vectors, N=9.

$\Delta(X_i, X_j)$ is the distance measure given by the L_1 norm or the city block distance which is more suited to non correlated noise. The ordering may be illustrated as

$$\delta_1 \le \delta_2 \le \delta_3 \le, \ldots, \le \delta_9 \quad (7)$$

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

$$X_{(1)} \le X_{(2)} \le, \ldots, \le X_{(9)} \quad (8)$$

where the subscripts are the ranks. 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,

$$X_{VMF} = X_{(1)} \tag{9}$$

Spatial Median Filter:

The **Spatial Median Filter** (SMF) [8] is a uniform smoothing algorithm with the purpose of removing noise and fine points of image data while maintaining edges around larger shapes. The SMF is based on the spatial median quantile function which is a L_1 norm metric that measures the difference between two vectors. The spatial depth between a point and a set of points is defined by

$$S_{depth}(X,x_1,x_2,\ldots\ldots x_N)=1 - \frac{1}{N-1}\left\|\sum_{i=1}^{N}\frac{X-xi}{\|X - xi\|}\right\| \tag{10}$$

Let $r_1,r_2,\ldots r_N$ represent $x_1,x_2,\ldots.x_N$ in rank order such that

$$\begin{aligned} & S_{depth}(r_1,x_1,x_2,\ldots\ldots x_N) \\ \geq\ & S_{depth}(r_2,x_1,x_2,\ldots\ldots x_N) \\ \geq\ & \\ \geq\ & S_{depth}(r_N,x_1,x_2,\ldots\ldots x_N) \end{aligned} \tag{11}$$

and let r_c represent the center pixel under the mask . Then

$$SMF(x_1,x_2,\ldots\ldots x_N) = r_1 \tag{12}$$

5. Image Fusion Using BEMD

Bi-Dimensional Empirical Mode Decomposition Process:

Empirical mode decomposition (EMD) [9], which has been recently introduced in signal processing by Huang et al. in 1998, is adaptive for analyzing nonlinear and non-stationary data. EMD is a nonparametric data-driven analysis tool that decomposes signals into a series of intrinsic mode functions (IMFs) and one residue. BEMD is an extension of the one dimensional EMD applied to two-dimensional images and has its unique priorities for adaptively extracting image components satisfying human's perception.

The BEMD process (Fig. 2) that generates the residue and IMFs is summarized as follows:

(1) Initialization: j=1(index number of IMF), $I=I_{original}$ and Res=I (the residue);
(2) Identify all local extrema (both maxima and minima) of Res;
(3)Interpolate between maxima and minima to generate upper envelope E_u and lower envelope E_l;
(4) Compute envelope mean plane E_m by averaging the two envelopes
(5) Extract the details: Res= Res–E_m;
(6) Repeat steps (2)-(5) until Res can be considered as an IMF. An IMF is characterized by two specific properties: the number of zero crossing and the number of extrema points is equal or differs only by one; it has a zero local mean;
(7) IMF (j) =Res, j=j+1, I=I–Res, Res=I;
(8) Repeat (2)-(7) until the stopping condition is satisfied or all the set decomposition layers have been processed.

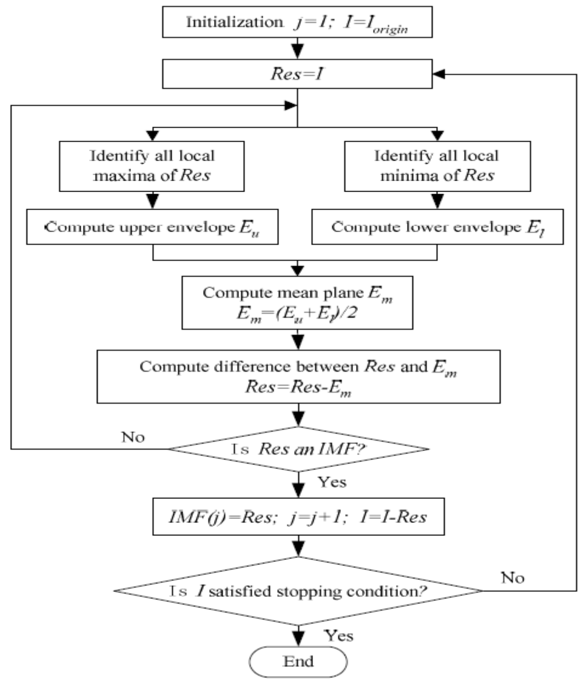

Fig 2: BEMD Process

The first few IMFs obtained from BEMD contain the highest spatial frequencies which correspond to salient features in source image, and the residue represents low frequency information in source image.

Image Fusion:

Each filtered image is firstly decomposed by BEMD into one residue and a series of IMFs. Then different fusion rules are applied to different image components. When fusing the IMF components, fusion using quality assessment of spatial domain [10] is used. When fusing the residual component, the pixel level image fusion method is adopted. In the end, the image is recovered by carrying out the inverse BEMD. Fig. 3 is the schematic flowchart of the proposed method.

Here, the processing of two images A and B is considered, though the algorithm can be extended to handle more than two.

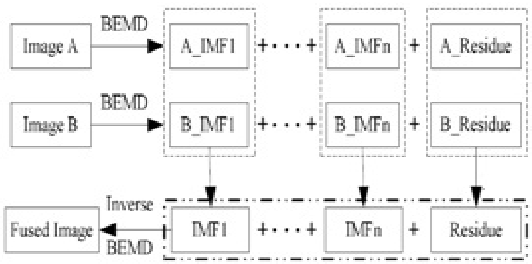

Fig 3: Fusion rules between IMFs

6. Experimental Results

The performance evaluation of filtering using image fusion method is tested on the true color remote sensing image with 290x290 pixels. The impulse noise is added into the image with different noise densities. The noisy image is processed using a filtering algorithm based on the noise density in the image. These filtered images are fused into a single image using BEMD. The performance of algorithm is evaluated by computing SSIM between the filtered (after fusion) image and the original image .The experimental results are shown in Figure 4. Table (1) shows the results of SSIM of filtered images with different noise densities.

The Structural Similarity (SSIM) paradigm hypothesized that the comparison between a reference image and a distorted image consists of three factors. They are luminance comparison, contrast comparison and structural comparison.

Given two real valued sequences $x=\{x_1,\ldots,x_n\}$ and $y=\{y_1,\ldots,y_n\}$, $\bar{x}$ is the mean of x, σ_x^2 is variance of x, σ_y^2 is variance of y and σ_{xy} is the covariance of x,y.

$$\sigma_x^2 = \frac{1}{n-1}\sum (x_i - \bar{x})^2 \qquad (13)$$

$$\sigma_y^2 = \frac{1}{n-1}\sum (y_i - \bar{y})^2 \qquad (14)$$

$$\sigma_{xy} = \frac{1}{n-1}\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \qquad (15)$$

Then, SSIM can be computed as

$$\mathrm{SSIM} = \frac{\sigma_{xy}}{\sigma_x\sigma_y} \cdot \frac{2\,\overline{xy}}{\bar{x}^2 + \bar{y}^2} \cdot \frac{2\sigma_x\sigma_y}{\sigma_x^2+\sigma_y^2} \qquad (16)$$

7. Conclusions

In this paper, an image fusion technique using BEMD for impulse noise reduction in digital images is presented. The proposed technique helps to attain high quality images. Images of an object or scene, captured by sensors undergo filtering using different filtering algorithms individually and these de-noised images are fused by the proposed technique. The Fusion using BEMD provides superior performance in removing the noise, while preserving the fine image details and edges. The proposed method is simple and can be used for real-time imaging applications.

References

[1] Tao Chen, Kai-Kaung Ma and Li-Hui Chen, "Tri-state median filter for image Denoising", IEEE Transactions on Image Processing, Vol 8, no.12, pp.1834-1838, December 1999.

[2] Reihard Berstein," Adaptive nonlinear filters for simultaneous removal of different kinds of noise in images," IEEE Trans on circuits and systems , Vol.cas-34, no 11,pp.127-1291, Nivember 1987.

[3] O.Rockinger," Image sequence fusion using ashift invariant wavelet transform," IEEE transactions on image processing, 3:288-291, 1997.

[4] Chaveli Ramesh and T.ranjith, "Fusion performance measures and a lifting wavelet transform based algorithm for image fusion", In Proc. 5th International conference on image fusion, july 2002,pp 317-320.

[5] Z. Wang and A. C. Bovik, "A universal image quality index," IEEE Signal Processing Letters, vol. 9, pp. 81–84, Mar. 2002.

[6] S.Indu, Chaveli Ramesh, "Image Fusion Algorithm for Impulse Noise Reduction", Proceedings of ARTCom.2009, IEEE.

[7] S.Indu , Chaveli Ramesh, " A noise fading technique for images highly corrupted with impulse noise", Proceedings of the ICCTA07 , IEEE.

[8] James C. Church, Yixin Chen, and Stephen V. Rice, "A Spatial Median Filter for Noise Removal in Digital Images", 2008 IEEE.

[9] N.E.Huang, Z.Shen, S.R.Long, "The empirical mode decomposition and the Hilbert Spectrum for non-linear and non-

stationary time series analysis". Proc. Roy. Soc, London.A, Vol.454, pp.903-995, 1998.

[10] Jingo Zhang, Xue Feng, Baoling Song, Mingjie Li, "Multi-Focus Image Fusion Using Quality Assessment of Spatial Domain and Genetic Algorithm", HIS, IEEE 2008.

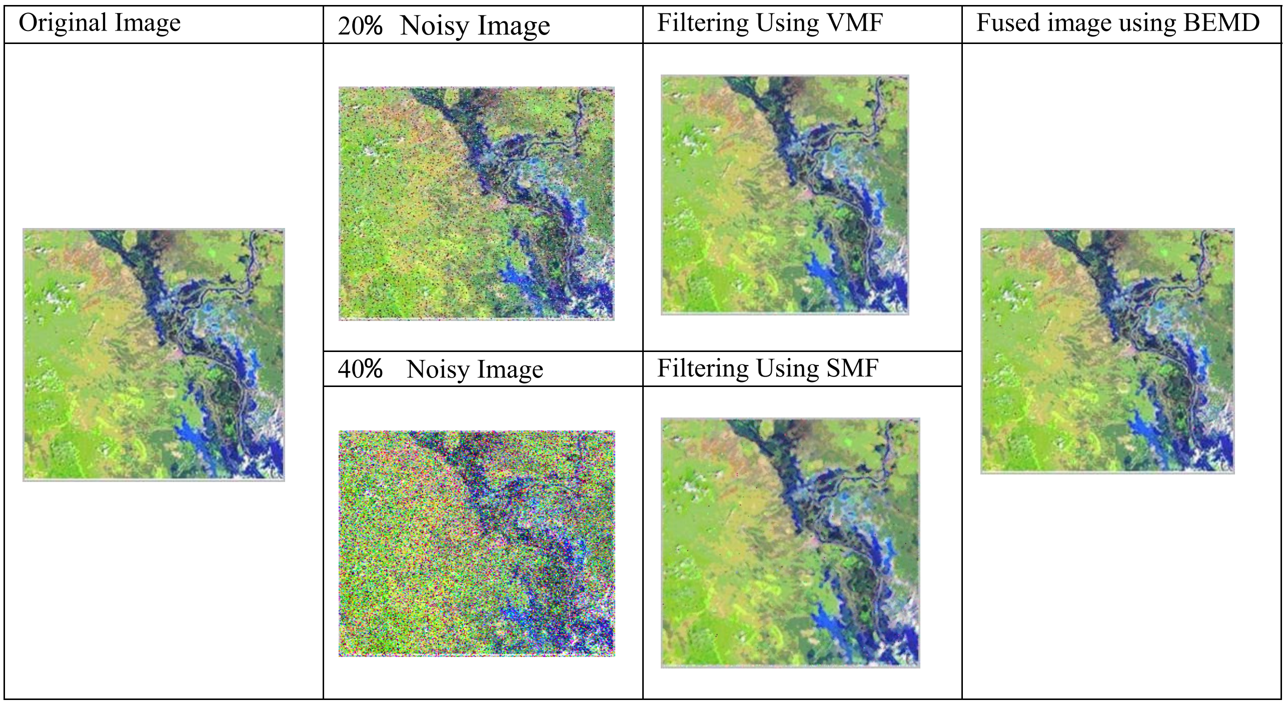

Fig 4 : Experimental Results

Table 1: SSIM Values between original and fused image

Sensor1	Sensor2	Filtered Image (Sensor1) (VMF) SSIM Value	Filtered Image (Sensor2) (VMF/SMF) SSIM Value	Fused Image SSIM Value
20%	40%	0.9247	0.9431	0.9541
30%	45%	0.8973	0.9067	0.9273
35%	50%	0.8611	0.8801	0.8971
39%	55%	0.8211	0.8389	0.8411