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Multi Sensor Image Fusion using Bi-Dimensional Empirical Mode Decomposition for Noise Removal in Digital Images

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Abstract: The digital images are corrupted by impulse noise due to errors generated in camera sensors, analog-to-digital conversion and communication channels. Therefore it is necessary to remove impulse noise in-order to provide further processing such as edge detection, segmentation, pattern recognition etc. Filtering a noisy image, while preserving the image details is one of the most important issues in image processing. In this paper, introduces an image fusion technique for impulse noise reduction, where the fused image will combine the uncorrupted pixels of the noisy images obtained from different sensors. The image captured by different sensors undergoes iterative filtering algorithm, search for the noise-free pixels within a small neighborhood. The noisy pixel is then replaced with the value estimated from the noise-free pixels. The process continues iteratively until all noisy-pixels of the noisy image are filtered. The filtered images are fused in to a single image using a fusion algorithm by the Bi-dimensional Empirical Mode Decomposition (BEMD). The experimental results show the proposed algorithm can perform significantly better in terms of noise suppression and detail preservation in images than a number of existing nonlinear techniques.

Keywords: Impulse Noise, Empirical Mode Decomposition, Noise Removal, Image Processing.

I. 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 'n' sensors are differently noised depending on the proximity to the object, environmental disturbances and sensor features. The noisy images are filtered using an iterative filtering algorithm, and finally the filtered images are fused into a single image using the Bi-Dimensional Empirical Mode Decomposition. The entire process of fusion is shown in figure 2.

Non-linear filters exhibit better performance as compared to linear filters [5] when restoring images corrupted by impulse noise. Filtering techniques such as Adaptive Median Filter (AMF) [7], Progressive Switching Median Filter (PSMF) [8], Decision Based Algorithm (DBA) [10] etc., have been developed for removal of impulse noise. These techniques estimate noisy pixels taking into account all pixels within the window, without considering the status of (noisy/ noise-free) pixels. Consequently, the estimated noisy pixel value will not be accurate, degrading the quality of restored image.

In this paper, we use a new iterative filtering algorithm for removal of impulse noise in noisy images. The algorithm emphasis on the noise-free pixels within small neighborhood. First the pixels affected with noise are detected. If we did not find certain number of noise-free pixels within neighborhood, then the central pixel is left unchanged. Otherwise the noisy pixel is replaced with the value estimated form the noise-free pixels within neighborhood. The process iterates until all noisy pixels are estimated in the image. After that, the filtered images are fused into a single image. The main steps of the proposed filtering algorithm are shown in figure 1.

The rest of the paper is organized as follows: Section 2 presents the impulse noise models in digital images, Section 3 presents the proposed iterative filtering algorithm, Section 4 presents BEMD, Section 5 presents the experimental results and finally Section 6 reports conclusion.

II. IMPULSE NOISE IN DIGITAL IMAGES

Impulse noise is independent and uncorrelated to the image pixels and is randomly distributed over the image. 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 two types of impulse noise namely fixed value impulse noise and random valued impulse noise.

In this paper, we focus on the detection and de-noising of fixed valued impulse noise, namely salt and pepper noise. In salt and pepper type of noise the noisy pixels takes either salt value (gray level -225) or pepper value (grey level -0) and it appears as black and white spots on the images [5]. Consider a corrupted image Y of size NxM, which containing the salt and pepper noise with probability p is mathematically represented in the form:

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

Where i=1,2,….,M and j=1,2,…..N and 0<p<1. y_{ij} represents the intensity of the pixel located at position (i, j). x_{ij} and n_{ij} denote the intensity of the pixel (i, j) in the original image and the noisy image respectively.

III. THE FILTERING ALGORITHM

The filtering algorithm is divided into three stages.

Stage 1: CONSTRUCTION OF BINARY IMAGE

In this step, a binary image is constructed for the noisy image Y. When the gray level images is contaminated with salt-and-pepper noise, a noisy pixel takes either a maximum intensity value (I_{max}= 255) or a minimum intensity value (I_{min}= 0). This dynamic range [I_{max} I_{min}] provide information about the noisy pixels in the image. The binary image b_{ij} is constructed by assigning a binary value 1, if the intensity of the pixel located at position (i, j) in the noisy image is Imax or Imin, otherwise assign a binary value 0.

The binary image B is computed from the noisy image Y as follows:

$$b_{ij}=\begin{cases} 1, \text{ if } y_{ij}=I_{max} \\ 1, \text{ if } y_{ij}=I_{min} \\ 0, \text{ otherwise} \end{cases} \quad (2)$$

where i=1,2,……N and j=1,2,……M.

The entries of "1" and "0" in the binary image B represent the noisy and noise-free pixels, respectively. This binary image provides information about the noisy density in the corrupted image, which is used in the filtering process.

The Noise Density of the corrupted image is calculated as follows:

$$ND=\frac{\text{Number of } 1'\text{s in binary image}}{\text{Total number of pixels (NxM)}} \quad (3)$$

The value of the noise density (ND) ranges between 0 and 1.

Stage 2: NOISE FILTERING METHOD

Consider a window of size q x q at each pixel location (i, j) of the noisy image Y and the binary image B. We prefer to use the value of q (=3), because the larger size window may not be too efficient and effective. Larger window may also remove the edges and fine image details. By applying small window of size 3x3, we obtain the noisy image patch $Y_{i,j}$ and the binary image path $B_{i,j}$.

For each iteration, we count the number of noisy pixels in the binary map B. If the value of count K is a positive integer and the central pixel y_{ij} within the 3X3 window is noisy, then the array R is populated with noise-free pixels. The maximum length of the array R is eight, indicating all the pixels are noise free. The minimum length is zero, shows that all the pixels in the window are noisy. Depending upon the noisy density in the window, the length of the array varies from zero to eight. We emphasize a constraint of minimum three noise-free pixels within the window, ie., the minimum length of the array R should be three. If this condition is satisfied, then we replace the central noisy pixel with the estimated value ie.,

$$g_{ij}=\begin{cases} e_s, \text{ if } b_{ij}=1 \text{ \&\& Length(R)} \geq 3 \\ y_{ij}\text{ , otherwise.} \end{cases} \quad (4)$$

Where e_s is the estimated value of the noisy pixel.

Currently, we estimated the value of noisy pixels by using a suitable distance measure. The elements (noise-free pixels) in the array R are ordered on the basis of the sum of distances between each element and other elements in the array R. The sum of distances is arranged in ascending order and the same ordering is associated with the elements in the array R. The element in the array with the smallest sum of distances is the estimated value of the noisy pixel.

If d_i is the sum of distances of the i^{th} element in the array R with all other elements, then

$$d_i=\sum_{j=1}^{N} \Delta(X_i, X_j) \quad (5)$$

Where $1 \leq i \leq N$, X_i, X_j are the elements in the array, N is the length of the array R, and $\Delta(X_i, X_j)$, is the distance measure given by L_1 norm.

The ordering may be illustrated as

$$d_1 \leq d_2 \leq d_3, \ldots, d_N \quad (6)$$

And this implies the same ordering to the corresponding elements in the array R.

$$X_{(1)} \leq X_{(2)} \leq, \ldots, \leq X_{(N)}. \quad (7)$$

Where the subscripts are the ranks. Since the element with the smallest distance is the estimated noisy pixel, it will correspond to rank 1 of the ordered elements ie., $X_{(1)}$. Figure 1 shows the main steps of the proposed algorithm.

Stage 3: UPDATE NOISY IMAGE AND BINARY IMAGE.

If the noisy pixel is estimated from the noise-free pixels within the window, the binary image B is also updated by changing the entries at the corresponding location of the image from "1" to "0". At the end of each iteration, we obtain a refined image G and updated binary image B. After a few iterations, depending upon the intensity of the salt-and-pepper noise, all entries in the binary image becomes zeros. The updating process terminated and we obtain a restored image G.

1. Take the intial noisy image Y.
2. Computation of binary map B
3. Compute the value of K that represent the noise-free pixels in B and assign $Y \rightarrow X$
4. Check: If K=0, output resorted image X and stop. else
   - i) Check if y_{ij} is noisy, then do
   - ii) Fill the array R with noise-free pixels
   - iii) Check if length of array R >3 , do
   - iv) Update b_{ij} and x_{ij} using the value estimated from noise-free pixels in R.
   - v) Process each y_{ij} and get updated X and B
   - vi) For the next iteration; assign $X \rightarrow Y$ and go to step 3.

Figure 1: Proposed Algorithm

IV. IMAGE FUSION USING BEMD

A. 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 4) that generates the residue and IMFs is summarized as follows:

a. Initialization: j=1(index number of IMF), $I=I_{original}$ and Res=I (the residue);
b. Identify all local extrema (both maxima and minima) of Res;
c. Interpolate between maxima and minima to generate upper envelope E_u and lower envelope E_l;
d. Compute envelope mean plane E_m by averaging the two envelopes
e. Extract the details: Res= Res–E_m;
f. 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;
g. MF (j) =Res, j=j+1, I=I–Res, Res=I;
h. Repeat (2)-(7) until the stopping condition is satisfied or all the set decomposition layers have been processed.

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.

B. 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 principal component analysis 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. 5 is the schematic flowchart of the proposed method using two images.

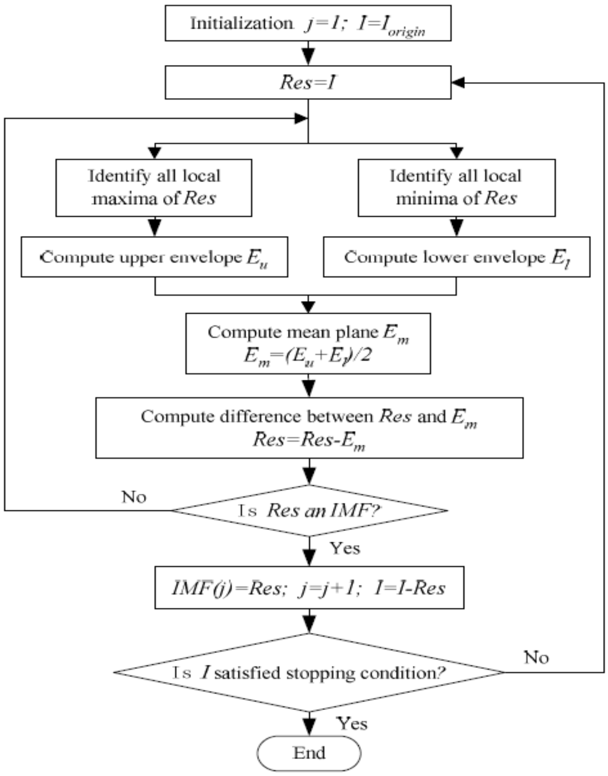

Figure 2: BEMD Process

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

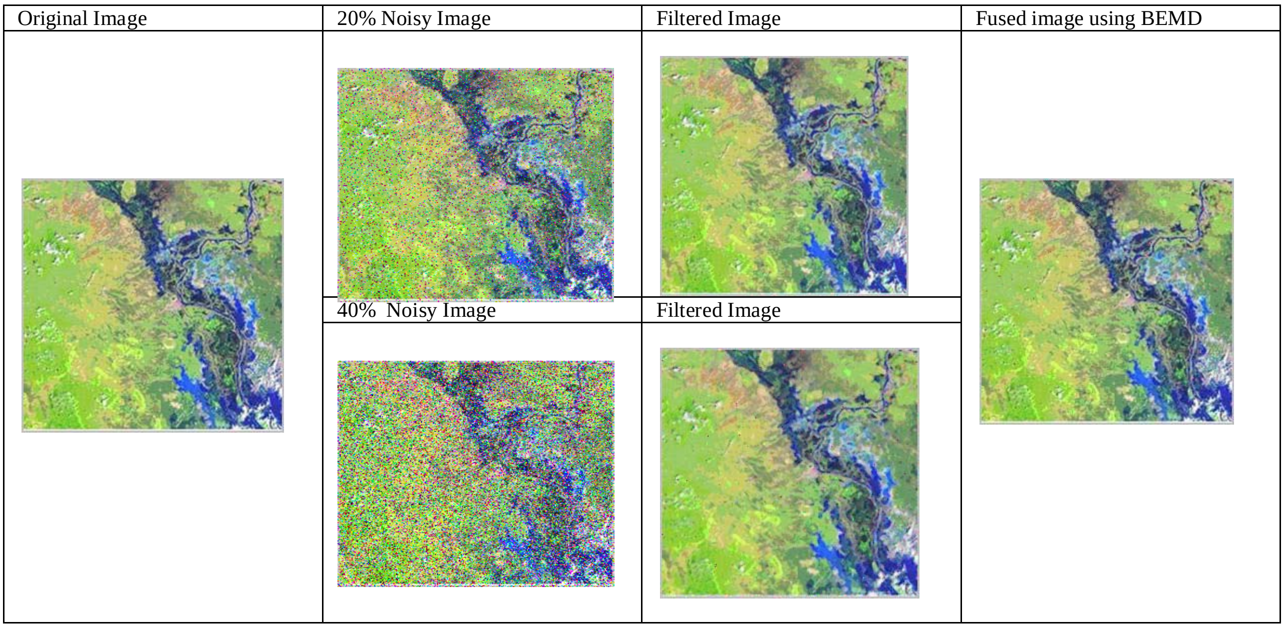

Figure 3: Experimental results of proposed Image Fusion algorithm

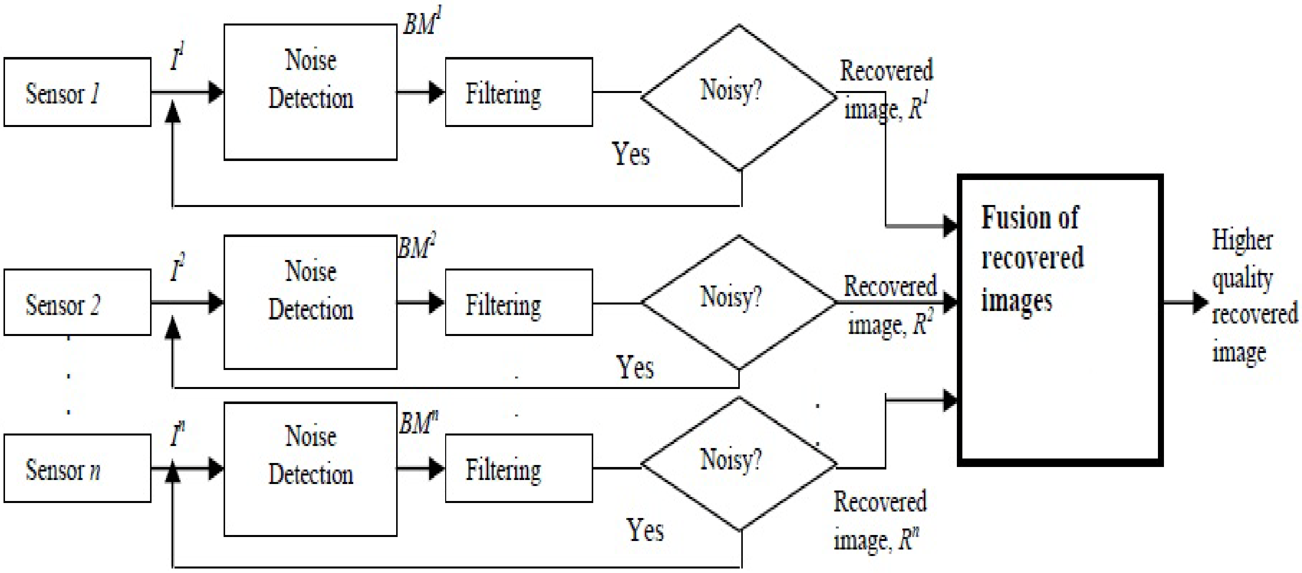

Figure: 4 Bloch Diagram of Impulse Denoising

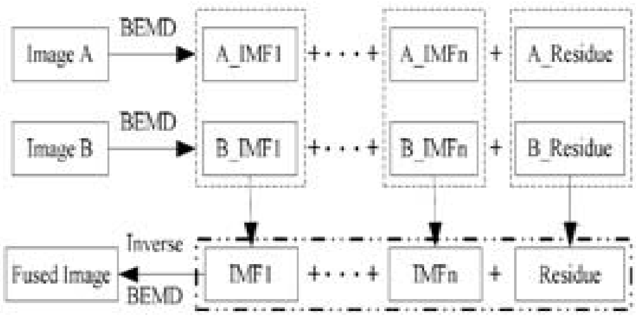

Figure 5: Fusion rules between IMFs

V. 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. Here we are assuming, n=2, ie; 2 sensors. The noisy image is processed using a iterative filtering algorithm based on the noise density in the image. These filtered images are fused into a single image using Bi-dimensional Empirical Mode Decomposition. The experimental results are shown in Figure 3. Table (1) shows the results of PSNR values of filtered images with different noise densities.

Table 1: Performance Comparison Corrupted With Various Noise Densities

ND(in percentage)	AMF	PSMF	DBA	Filtering and Fusion
10%	33.74	36.41	38.24	43.64
20%	28.47	30.27	32.44	37.47
30%	23.03	26.23	29.03	33.83
40%	18.15	20.25	21.15	26.62
50%	14.36	15.21	17.36	24.36
60%	11.61	13.06	15.61	21.61
70%	9.08	11.06	13.48	19.28
80%	7.16	9.46	12.06	13.16

First the remote sensing image is corrupted with varying levels of noise density from 10 to 90 using the salt-and-pepper noise. The simulation results obtained from the proposed scheme are compared with the well known salt-and-pepper filtering algorithms: AMF, PSMF and DBA. Figure 3 shows the results.

We used the image quality metric, peak signal-to-noise ratio (PSNR), to measure the quality of the restored image. The PSNR measure is defined as

PSNR=$10\log 10\frac{(255)^2}{\mathrm{MSE}}$, Where MSE is the mean squared error between the original noise-free image and the restored image.

Table 1 shows the simulation results, in terms of the PSNR measure, for the remote sensing image. In table 1, our proposed algorithm provided the best PSNR value. Among other restoration algorithms, our proposed scheme highlights the best visible quality of the restored microarray image.

VI. CONCLUSION

In this work, we propose a fusion algorithm for removal of impulse noise in digital images. The noisy images captured by 'n' sensors undergo filtering iteratively by replacing the noisy pixel with the value estimated from the noise-free pixels within the small neighborhood for the entire image. The filtered images are fused into a single image using the quality assessment of spatial domain .This scheme provides superior performance in removing the noise, while preserving the fine image details and edges.

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