Selective Median Switching Filter for Noise Suppression in Microstructure Images of Material

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Abstract

The image pre-processing is very critical and important task in any digital image analysis system. The eventual success and failure of image analysis depends on the performance of pre-processing techniques applied on the image to be analyzed. In digital images, different noise types are noticed and to attenuate each type of noise, different pre-processing methods have been proposed in literature. The main focus of this paper is on pre-processing the microstructure images. Among many types of noise, impulse noise is the one which is generally noticed in microstructure images. This paper is to present a novel, efficient and suitable pre-processing method for negotiating the impulse noise that is generally present in microstructure images. Through this paper, a new filtering method, selective median switching filter (SMSF) has been proposed. The proposed method is compared with filtering methods those belong to median filter family for their efficiency in negotiating with impulse noise. The efficiency of proposed method is compared with other methods by computing the three image quality assessment methods, namely, mean square error (MSE), peak signal-to-noise ratio (PSNR) and correlation coefficient. The experimental results confirm that the proposed SMSF method is efficient in handling the impulse noise present in microstructure images of material. Also, the proposed SMSF method is quite efficient in preserving the edge information in images.

Keywords: Pre-processing, SMSF, Median Filter, MSE, PSNR, Correlation Coefficient, Microstructure.

1. INTRODUCTION

In general, the images to be processed are not in process-ready condition. Therefore, in any digital image processing application, one or the other pre-processing method is a mandatory first step. In this paper, the microstructure images of cast iron material are considered for study. Some of the sample microstructure images are shown in the Figure 1. There is direct relationship between the microstructure of material and the properties of the material [1]. Therefore, for the analysis of microstructure images, the quality of microstructure image matters. It is generally observed that the microstructure images of material suffer from impulse noise. The amount of noise varies from one material sample to another. Accurate analytical reports can be expected only from good quality microstructure images.

FIGURE 1: Sample Microstructure Images of Cast Iron.

2. IMPULSE NOISE

Impulse noise 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 the 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. The 'salt and pepper' and random valued impulse noise are the two different types of impulse noise types. 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. The presence of impulse noise affects the segmentation results [2,5-8]. False regions are made by considering isolated noisy pixels present in the image and these false contours affect the qualitative and quantitative analysis results.

2.1 De-Noising Methods

The noise usually corrupts images by replacing some of the pixels of the original image with new pixels having luminance values near or equal to the minimum or maximum of the allowable dynamic luminance range. In most of the applications, it is very important to remove impulse noise from image data, since the performances of subsequent image processing tasks are strictly dependent on the success of image noise removal operation. However, this is a difficult problem in any image processing system because the restoration filter must not distort the useful information in the image and preserve image details and texture while removing the noise.

Many methods have been proposed in the literature to deal with impulse noise [3,9,12,18]. Median filtering methods are the general choice to deal with impulse noise. There are many variants of median filtering methods, for experimentation, we have considered most commonly preferred median filtering methods, namely, median filter [9], weighted median filter [11,12,14,20], switching median filter [19]. Each one of the median filter variant has inherent merits and drawbacks. The basic median filter is a simple rank selection filter that attempts to remove impulse noise by changing the luminance value of the center pixel of the filtering window with the median of the luminance values of the pixels contained within the window. Although the median filter is simple and provides a reasonable noise removal performance, it removes thin lines and blurs image details even at low noise densities. The weighted median filter [12,17,19] and the center-weighted median filter (CWM) [10,14] are modified median filters[13,16] that give more weight to the appropriate pixels of the filtering window. These filters have been proposed to avoid the inherent drawbacks of the basic median filter by controlling the tradeoff between the noise suppression and detail preservation. The switching median filter is composed of the median filter with an impulse detector. In this approach, the impulse detector aims to determine whether the center pixel of a given filtering window is corrupted or not. If the center pixel is identified by the detector as a corrupted pixel, then it is replaced with the output of the median filter, otherwise, it is left unchanged. Some extensions of the basic switching median filter including multiple median-based filters in the structure have also been proposed. Adaptive center weighted median (ACWM) [11,15] filter that avoids the drawbacks of the CWM filters and switching median filters and input data will be clustered by scalar quantization (SQ) method, that is resulted in fix threshold for all of images, but modified adaptive center weighted median (MACWM) filter will be used from FCM method, then bound between clusters for any image achieved by information of same image, as a result, clustering of input data to M block would be done better. This study has motivated to test their performance on microstructure images and forced to propose a modified method of median filtering, which is reliable, computationally light and preserve the edge information to a greater extent.
Having known that the microstructure images have the impulse noise, the median filters have been experimented for their optimum performance. The median filters experimented are, basic median filter, weighted median filter, center weighted median filter, switching median filter.

The proposed method includes systematic analysis of performance of each of the noise suppressing filters mentioned in Section 2 in presence of impulse noise of different distributions. Each time after applying the noise suppression filter, means square error (MSE), peak signal-to-noise ratio (PSNR) and correlation coefficient (CC) are determined. The MSE and PSNR are computed by using the Eqs. (1) and (2), respectively:

$$MSE = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}(I_2(x,y)-I_3(x,y))^2 \tag{1}$$

$$PSNR = 10\log_{10}\left(\frac{255^2}{MSE}\right)dB \tag{2}$$

where 255 is the peak gray-level of the grayscale image, I_2 represents the grayscale image, and I_3 represents the filtered image; each of dimension MxN. The summation in Eq.(1) is over all the pixels (x,y) of the images. The PSNR value computed for the filtered image indicates the performance of the filtering method.

The correlation coefficient (CC) is a measure that determines the degree to which two variable's (images) variations are associated. The CC is computed by using the Eq. (3).

$$CC = \frac{\sum_{y=1}^{M}\sum_{x=1}^{N}(I_2(x,y)-\overline{I_2})(I_3(x,y)-\overline{I_3})}{\sqrt{\sum_{y=1}^{M}\sum_{x=1}^{N}(I_2(x,y)-\overline{I_2})^2}\sqrt{\sum_{y=1}^{M}\sum_{x=1}^{N}(I_3(x,y)-\overline{I_3})^2}}$$

(3)

where $\overline{I_2}$ is the mean intensity of image I_2 and $\overline{I_3}$ is the mean intensity of image I_3. The correlation coefficient is a number between 0 and 1. If there is no relationship between the two variables the correlation coefficient is 0 or very low. As the strength of the relationship between the two variables increases so does the correlation coefficient. A perfect fit gives a correlation coefficient of 1.

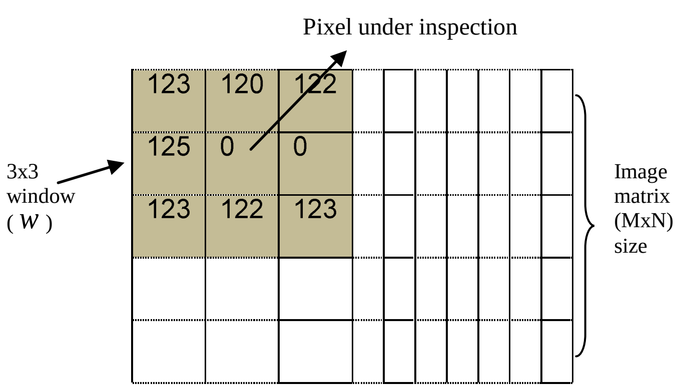


FIGURE 2: Image Matrix With Intensity Values.

2.2 Proposed Selective Median Switching Filter (SMSF)

The SMSF method is a modified method of basic switching median filter. The SMSF is a point-wise linear operation, it operates on a 3x3 neighborhood pixel window (w) around the pixel under inspection (Figure 2). Each pixel undergoes a noise-check process and it is replaced by new intensity value when it is found to be a noise pixel.

The proposed method is given in the following algorithm.

Algorithm: Selective median switching filter

Step 1: Input RGB microstructure image I_1 and convert to grayscale image I_2.

Step 2: Consider 3x3 window W at top-left corner.

Step 3: Find the median, W_{median}, of window elements of W.

Step 4: Determine the difference (D_i) of each element of window W from the central pixel element of window W.

Step 5: Determine the mean, D_{mean}, of D_i.

Step 6: Determine the mean, W_{mean}, of elements of W.

Step 7: If $D_{mean} >= W_{mean}$, then replace the central pixel value of window W by W_{median} value; otherwise, leave central pixel value of window W unchanged.

Step 8: Repeat Steps 2 to 7 by moving the window left to right row-wise over the entire image I_2 to yield the filtered image I_3.

Step 9: Output the filtered image I_3.

3. EXPERIMENTAL RESULTS AND DISCUSSION

For experimentation, we have used microstructure images of various compositions of cast iron drawn from the microstructures library [4]. Each image is added with 'salt and pepper' noise in the range 5% to 60% and then subjected to proposed SMSF method for noise suppression. The performance of the proposed filter and other filtering methods is assessed by determining the peak signal-to-noise ratio (PSNR), mean square error (MSE) and correlation coefficients (CC) for the filtered images. The comparison of performance of proposed filter SMSF with other filters is shown in the Figure 3. For better image quality, the PSNR and CC values are higher and MSE values are lower. The value of D_{mean} gives the dispersion of window elements around the central pixel value in eight orientations, while the W_{mean} gives the dispersion around the average pixel values of the window elements.

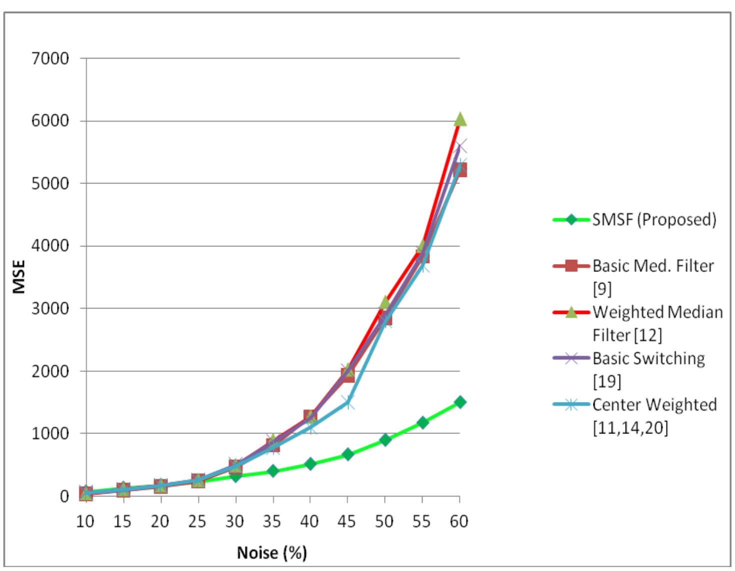


FIGURE 3 (a): Performance Comparison of Proposed Method SMSF And Other Filters In Terms of MSE.

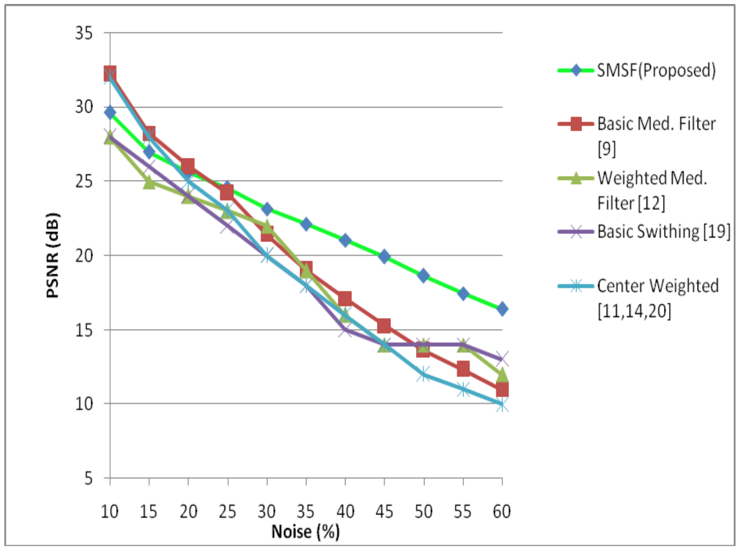


FIGURE 3 (b): Performance Comparison of Proposed Method SMSF And Other Filters In Terms of PSNR.

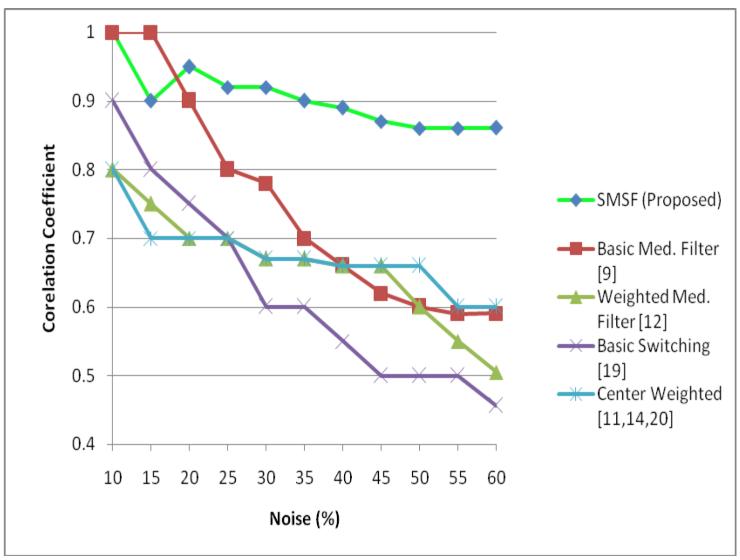


FIGURE 3 (c): Performance Comparison of Proposed Method SMSF And Other Filters In Terms of CC.

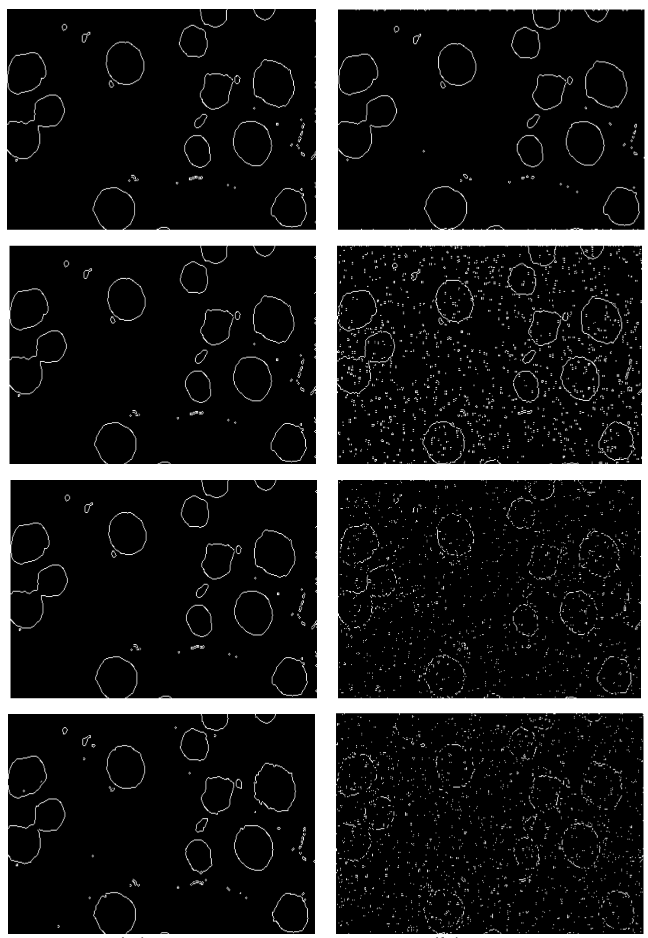
It is observed that the proposed method SMSF is capable of preserving the edges of regions of interest (ROI) present in the images to a greater extent as compared to the basic median filter method. The edge profile of regions present in the filtered image is shown in the Figure 4. In the basic median filter method, the central pixel value of the window is replaced unconditionally by median of window elements and hence the edge information is lost. Whereas in the proposed SMSF method, a selective replacement of central pixel value is done based on the condition $D_{mean}>=W_{mean}$ in the inspecting window (Step 7 in the Algorithm). It is observed that, in case of uniform regions, the D_{mean} value is less than the W_{mean}, and hence, the centre pixel is not replaced. In case of noisy central pixel value, D_{mean} value is much higher than the W_{mean}, and therefore, the central pixel value is replaced by median value. In case of edges, the 3x3 inspection window shows majority of pixel intensity values close to each other, so that

D_{mean}<W_{mean}. Hence, the central pixel is not replaced by median value, and therefore, the edges are not blurred.

The proposed method is tested on 50 microstructure images of materials of various compositions and also 20 standard test images used for denoising experiments, e.g. Lena, pout, coin, rice, etc. The sample test images and corresponding resultant filtered images obtained by the proposed method are shown in the Figure5.

Effect of noise on segmentation
The impulse noise affects image segmentation and quantification results. It is observed that the segmentation time with active contours method is directly proportional to the amount of noise present in the image. In an image with 5% of impulse noise, 700 to 800 numbers of iterations are necessary to segment. When, the same image is corrupted by 10% of impulsive noise, the segmentation process requires 1100 to 1300 iterations.

The enhancement of image quality leads to better segmentation results. This is demonstrated by applying active contour method to the SMSF filtered image. The Figure6 shows the segmentation results obtained by active contour method applied to SMSF filtered microstructure image. The segmented images show that there are no false contours or loss of boundary information in the segmented regions. Therefore, one can expect greater accuracy in quantification results in further image analysis procedures.



(a) (b)

FIGURE 4: Comparison of Edge Preserving Property of Basic Median Filter And Proposed Method At Different Noise Levels, 10%,20%, 30% and 35% (top to bottom). (a) Edge Information After Applying The Proposed Method And (b) Edge Information After Applying The Basic Median Filtering Method.

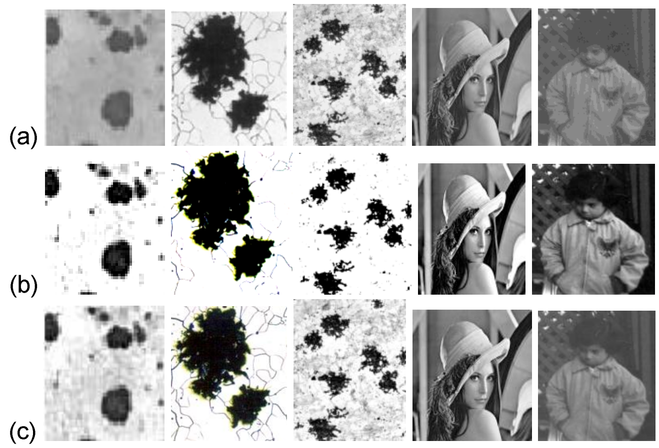


FIGURE 5 (a) Sample Test Images, (b) Resultant Filtered Images Obtained By Proposed SMSF Method And (c) Resultant Filtered Images Obtained by Basic Median Filter Method.

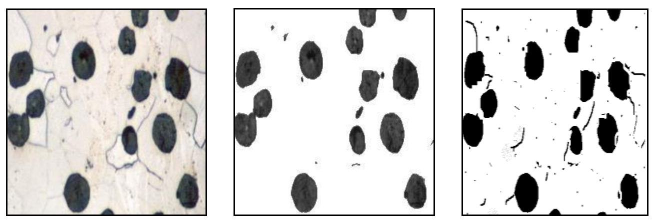


FIGURE 6: (a) Original Microstructure Image, (b) Segmented Image Obtained By Active Contour Method And SMSF Filter and (c) Segmented Image Obtained By Active Contour Method And Basic Median Filter.

4. CONCLUSION

Through this paper, a novel filtering method by name, selective median switching filter for suppressing the impulse noise has been proposed (SMSF). The results of filtering method are quite encouraging and it has proved to be more efficient than the other median filtering methods that are generally preferred to deal with the impulse noise. Unlike other median filtering methods, the proposed method has property of preserving edges while acting on impulse noise quite efficiently. Also, the proposed method plays vital role in quality of the segmentation of images and reduces the amount of time required for segmentation significantly.

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