# An Enhanced Adaptive Vector Median Filtering Technique to Remove High Density Salt-and-Pepper Noise from Microarray Image

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## ABSTRACT

In this paper, an efficient technique has been proposed to reduce high density salt-and-pepper noise from microarray images. This technique introduces an enhanced vector median filtering technique, that differentiates between corrupted and uncorrupted pixels and every corrupted pixel is replaced with the value estimated from the neighborhood noise-free pixels in the window size. Moreover, based on the local noise density, the proposed filter shows adaptive behavior by adjusting the current filtering window size. In case of extreme high density noise, last processed pixel is used to replace the corrupted pixel. Different experimental results show that, the proposed algorithm can perform significantly better than other existing non-linear techniques in terms of noise suppression, while preserving fine details of the microarray images.

#### **General Terms**

Image Processing.

## **Keywords**

Salt-and-pepper noise, noise removal, vector median filter, adaptive vector median filter, microarray.

## **1. INTRODUCTION**

Microarray technology has led the way from studies of the individual biological functions of a few related genes, proteins or, at best, pathways towards more global investigations of cellular activity [1]. A microarray is a collection of spots containing DNA deposited on the solid surface of glass slide. Each of the spot contains multiple copies of single DNA sequence [2]. In microarrays, thousands of probes are fixed to a surface, and RNA samples (the targets) are labeled with fluorescent dyes for hybridization. After hybridization, laser light is used to excite the fluorescent dye; the hybridization intensity is represented by the amount of fluorescent emission, which gives an estimate of the relative amounts of the different transcripts that are represented. There are many microarray platforms that are different in array fabrication and dye selection.

In cDNA microarrays, both the probes and the targets are cDNAs. mRNA from biological samples is reverse transcribed and simultaneously labeled with Cy3 and Cy5. After hybridization, Cy3 and Cy5 fluorescence is measured separately, and captured in two images. These are merged to produce a composite image, which goes though preprocessing before expression values are analyzed. Long-oligonucleotide microarrays are similar to cDNA microarrays, but the probes are derived from genomic or EST sequences. High-density oligonucleotide microarrays involve probe pairs that each

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consist of 25-nt oligonucleotides. Each probe pair has a perfect-match (PM) probe and a mismatch (MM) probe. The MM probe has identical sequence to the PM probe, except at the central base and functions as an internal control. Unlike cDNA microarrays, the mRNA sample is converted to biotinylated cRNA and only one target is hybridized to each array — therefore, only a single color of fluorescence is used [3].

The evaluation of microarray images is a difficult task as the fluorescence of the glass slide adds noise floor to the microarray image. The processing of the microarray image requires noise suppression with minimal reduction of spot edge information that derives the segmentation process. Thus the task of microarray image enhancement is of paramount importance [4]. Here, Figure 1 shows examples of grayscale Microarray image.

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#### Figure 1 : Examples of grayscale Microarray Images

Salt-and-pepper noise is a type of noise that corrupts microarray images very often. In this type of noise, a certain amount of original pixels of a digital image are randomly corrupted by either maximum (255) or minimum (0) intensities of the dynamic gray level range at a different level of density. So, image corrupted by salt-and-pepper noise appears as black and white spots on it.

Several non-linear filtering techniques have been proposed which exhibit better result in reducing noise. In the technique of Vector Median Filter (VMF) [5], sum of the distances between each vector pixel and the other vector pixels in the window is calculated. Then 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 and is chosen to replace the centre pixel of the window. Besides, Progressive Switching Median Filter (PSMF) [6], Decision Based Algorithm (DBA) [7] etc. have been also developed for the removal of impulse noise. These techniques estimate noisy pixels considering all pixels within the window, without differentiating between corrupted and uncorrupted pixels, which ultimately degrades the image quality. Recently, in order to remove impulse noise in microarray images, Improved Vector Median Filtering Algorithm (IVMF) [4] has been proposed where corrupted and uncorrupted pixels are differentiated and only corrupted pixels are taken into account. In this algorithm, noise free pixels are stored in an array R. A constraint of minimum three noise-free pixels within the window (the minimum length of the array  $\mathbf{R}$  should be three) is implied. If this condition is satisfied, then it replaces the central noisy pixel with the estimated value. Now the estimated value is found by ordering the elements in the array  $\mathbf{R}$  based of the sum of distances between each element and other elements in the array R. Then 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 [4]. A major limitation of this approach is the constraint of minimum three noise free pixel within the window because minimum number of noise free pixels might be less than three within a fixed window in case of high density noise.

In this paper, we present an enhanced algorithm for removing salt-and-pepper noise from microarray images. Here, the drawbacks of IVMF [4] in implying the constraint of minimum three noise free pixels has become quite relaxed by using adaptive behavior of filtering window based on local features of the image. Moreover, in case of higher density of noise, last processed pixel is used to replace the corrupted pixel.

#### 2. PROPOSED TECHNIQUE

Consider an image *X* corrupted with salt-and-pepper noise. A sliding window  $W_m$  of size  $(2m+1) \times (2m+1)$  centered at X(i,j) is used for detecting noisy and noise free pixels. The algorithm starts with m=1 and checks whether X(i,j) is noisy

(0 or 255) or not. If it is noise free, then  $W_m$  slides to next pixel and starts processing again. If X(i,j) is noisy then the values in  $W_m$  are checked and among them only the noise-free values (which are not 0 and 255) are stored in an array  $R_m$ .

If the number of elements in  $R_m$  is more than or equal to three, then the sum of the distances between each elements and other elements in  $R_m$  is calculated as follows,

$$Di = \sum_{K=1}^{N} difference(X_i, X_k)$$
(1)

Where *N* is the length of  $\mathbf{R}_m$ .  $X_i$  and  $X_k$  are the elements in  $\mathbf{R}_m$ , and  $1 \le i \le N$ .

After measuring the distances, they are arranged in ascending order. This can be illustrated as,

$$D_1 \le D_2 \le D_3, \dots, \dots, \le D_N \tag{2}$$

Now same ordering is implied to the corresponding elements in the array  $R_m$ .

$$X_{(i)} \le X_{(2)} \le X_{(3)}, \dots, \dots, \le X_{(N)}$$
(3)

The element in the array with the smallest sum of the distance is the estimated value for replacing the centre pixel X(i,j).

On the other hand, if the number of elements in  $\mathbf{R}_m$  is less than three, then  $W_m$  is expanded by incrementing the value m by Iand the algorithm again stores the noise free pixel values in  $\mathbf{R}_m$  and checks for at least three noise free elements in that array. This process is repeated until at least three noise free elements are found in  $\mathbf{R}_m$  or the size of the processing window  $W_m$  reaches a pre-defined maximum size (m = 4). As like as the previous steps, if the number of elements in  $\mathbf{R}_m$  is more than or equal to three within the maximum size, then the estimated value is calculated using equations (1),(2) and (3) and X(i,j) will be replaced with the estimated value. Otherwise, the last processed pixel from the previous iteration will be chosen to replace the centre pixel X(i,j). Figure 1 illustrates a flowchart of the proposed algorithm.



Figure 2: Flowchart of the proposed filtering technique

## 3. EXPERIMENTAL RESULTS

The performance analysis of the proposed technique is tested with a simple  $283 \times 283$  grayscale Microarray image. Peak-Signal-to-Noise ratio (PSNR) and Mean Square Error (MSE) are calculated to measure the quality of the restored image, where,

$$MSE = \frac{1}{MN} \sum_{ij} (y_{ij} - x_{ij})^2$$
(4)

$$PSNR = 10 \log_{10} \frac{(255)^2}{MSE}$$
(5)

Here, x denoted the original image, y denoted the corrupted image.

The performance analysis of the proposed algorithm (PA) is compared with some existing filtering algorithm, namely VMF [5], DBA [7] and IVMF [4] in terms of PSNR and MSE. Table 1 shows the PSNR comparison of different algorithms for Microarray image with varying noise density.

Fable 1. PSNR	comparison for	the Microarray image
corrup	ted with various	noise densities

Noise (%)	PSNR (dB)				
	VMF	IVMF	DBA	PA	
10	34.98	34.7	31.73	34.96	
20	31.25	30.46	29.31	31.25	
30	28.76	24.93	26.55	28.8	
40	26.66	19.34	23.64	26.86	
50	24.66	14.78	21.13	25.09	
60	22.37	11.2	19.2	23.57	
70	19.76	8.3	17.38	21.94	
80	16.75	6.34	15.51	19.75	
90	13.39	5.04	13.82	15.82	

Figure 3-4 shows different graphical representations of the performance comparison for the Microarray image from where it can be observed that, PSNR values are higher for the proposed algorithm and MSE is lower than the other algorithms.



Figure 3: Performance comparison graph of PSNR for Microarray image



Figure 4: MSE comparison for the Microarray image corrupted with various noise densities

Figure 5 shows the visual inspections performed on Microarray image in order to compare the effectiveness of different algorithms in removing salt-and-pepper noise.



Figure 5: Results of applying different filtering methods on Microarray image corrupted with saltand-pepper noise. Here, (a) is the original Microarray image and (b) shows images corrupted with 20%,

40%, 60%, and 80% salt-and-pepper noise, respectively from left to right. Row (c), (d) and (e) show the results obtained by using VMF, IVMF and PA, respectively on the corrupted images of (b)

## 4. CONCLUSION

In this work, we proposed a technique to remove salt-andpepper noise from microarray images. In this approach, only the corrupted pixels are taken into account and those ones are replaced by value estimated from the neighborhood pixels depending on distance measurements. The adaptive behavior of the processing window has been integrated here in order to get more accurate estimated values for noisy pixels. Moreover, in case of high density noise, value estimated from the previous iteration has been used to replace a corrupted pixel in microarray image. This scheme gives superior performance in comparison with different existing noise removal algorithms, such as VMF, DBA and IVMF in terms of PASNR, MSE and visual inspections. Therefore, the proposed technique provides the better result while preserving the visual quality and necessary details of the microarray images.

### 5. REFERENCES

- [1] Hoheisel, D. J. 2006. Microarray technology: beyond transcript profiling and genotype analysis. Nature Reviews, Vol. 7- No. 3, pp- 200-210.
- [2] Chen, W. B., Zhang, C. and Liu, W. L. 2006. An Automated Gridding and Segmentation Method for cDNA Microarray Image Analysis. 19th IEEE

Symposium on Computer-Based Medical Systems (1063-7125), pp. 893 – 898.

- [3] Allison, D. B., Cui, X., Page, G. P. and Sabripour, M. 2006. Microarray data analysis: from disarray to consolidation and consensus. Nature Reviews, Vol. 7-No.1, pp. 55-65.
- [4] AnjiReddy, V. and Vasudevarao, J. 2012. Improved Vector Median Filtering Algorithm for High Density Impulse Noise Removal in Microarray Images. Global Journal of Computer Science and Technology, Vol. 12-No.2, pp. 37-40.
- [5] Laskar, R.H., Bhowmick, B., Biswas, R. and Kar, S. 2009. Removal of impulse noise from color image. TENCON 2009 - 2009 IEEE Region 10 Conference.
- [6] Zhou, W. and Zhang, D. 1999. Progressive Switching median filter for the removal of impulse noise from the highly corrupted images. IEEE transactions on circuits and systems II. Analog and Digital Signal Processing, Vol-46, pp.78-80.
- [7] Srinivasan, K. S. and Ebnezer, D. 2007. A New Fast and Efficient Decision based Algorithm for Removal of High Density Impulse Noises. IEEE Signal Processing Letters, Vol-14 pp.189-192.