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Vector Filtering Techniques for Impulse Noise Reduction with Application to Microarray Images

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ABSTRACT

Microarray technology allows the simultaneous monitoring of thousands of genes. Based on the gene expression measurements, microarray technology have proven powerful in gene expression profiling for discovering new types of diseases and for predicting the type of a disease. Gridding, segmentation and intensity extraction are the three important steps in microarray image analysis. A high level of noise has been introduced in microarray images due to large number of error-prone steps in microarray experiment, leading difficult in extraction of accurate log-intensity ratios. This paper, presents a comparative study of different vector filtering techniques that are used for removal of impulse noise. These algorithms are applied for denoising the microarray images. The performance of these filters is evaluated through the commonly used objective criteria such as Mean Absolute Error (MAE) and Mean Square Error (MSE). Experimental results show that Adaptive Center Weighted Vector Filters are best for removal of impulse noise in microarray images providing better spot localization and the estimation of their intensity.

Keywords: Microarray Image Analysis, Impulse Noise, Vector Filters, Image Processing

INTRODUCTION

Microarrays widely recognized as the next revolution in molecular biology that enable scientists to monitor the expression levels of thousands of genes in parallel [1]. A microarray is a collection of blocks, each of which contains a number of rows and columns of spots. Each of the spot contains multiple copies of single DNA sequence [2]. The intensity of each spot indicates the expression level of the particular gene [3]. The processing of the microarray images [4] [5] usually consists of the following three steps: (i) gridding, which is the process of segmenting the microarray image into compartments, each compartment having only one spot and background (ii) Segmentation, which is the process of segmenting each compartment into one spot and its background area (iii) Intensity extraction, which calculates red and green foreground intensity pairs and background intensities.

The quality of microarrays is not always perfect due to large number of electrical, optical, chemical procedures such as slide fabrication, dye labeling, scanning, blur and dust etc, which lead to a high level of noise from different sources and in different forms. Detection of spot and getting accurate intensities through automatic spot localization is a difficult tack as the noises blur the edge information and vary the grid geometry. Several filtering techniques have been developed to filter the microarray images. This paper presents a comparative study of the different vector filtering techniques for removal of impulse noise in microarray images. Denoising of image decreases the noise contamination and increases the robustness of the microarray analysis ie., gridding and segmentation steps with minimal reduction of spot edge information.

This paper is organized as follows: Section 1 presents Impulse noise models in digital images, Section 2 presents different vector filtering techniques, Section 3 presents Experimental results and Section 4 report conclusions.

1. 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. 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 (grey 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).

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

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

2. VECTOR FILTERING TECHNIQUES

Vector filters are nonlinear filters [9] whose output is based on ranking the pixels contained in the image area encompassed by the mask, and then replacing the value of the center pixel with the value determined by the ranking result.

VECTOR MEDIAN FILTER

In the Vector Median Filter (VMF) [7] a suitable distance measure is chosen for the ordering of the vectors in a particular kernel or mask. The most widely used distance measures are L_1 (Manhattan distance) and L_2 (Euclidean distance). Calculate 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 in the window. The vector pixel with the smallest sum of distances is the vector median pixel. The vector median filter is represented as

$$\text{VMF} = \text{vectormedian (window)} \quad (3)$$

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

$$\lambda_i = \sum_{j=1}^{9} \Delta(X_i, X_j) \quad (4)$$

where $(1 \le i \le 9)$ 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 L_2. The ordering may be illustrated as

$$\lambda_1 \leq \lambda_2 \leq \lambda_3 \leq, ..., \leq \lambda_9 \quad (5)$$

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

$$X_{(1)} \leq X_{(2)} \leq, ..., \leq X_{(9)} \quad (6)$$

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.,

$$VMF = X_{(1)} \quad (7)$$

BASIC VECTOR DIRECTIONAL FILTER

In the Basic Vector Directional Filter (BVDF) [8], the vector angels are incorporated instead of vector distances. Let W be the processing window of size n and f_i, {i=1,2,…n} be the pixels in W and let α_i correspond to f_i. Then

$$\alpha_i = \sum_{j=1}^{9} A(f_i, f_j) \quad (8)$$

where $A(f_i, f_j)$ denotes the angle between f_i and f_j. An ordering of the α_i's

$$\alpha_{(1)} \leq \alpha_{(2)} \leq …….. \leq \alpha_{(9)} \quad (9)$$

implies the same ordering to the corresponding f_i's

$$f_{(1)} \leq f_{(2)} \leq …….. \leq f_{(9)} \quad (10)$$

The first term in (10) constitutes the output of the BVDF

$$BVDF\ [f_1, f_2, ……f_9] = f_{(1)} \quad (11)$$

DIRECTIONAL DISTANCE FILTER

The VMF and BVDF differ only in the quantity that is minimized. The VMF Minimizes the distance sum metric, while the BVDF minimizes the angle sum metric. To incorporate the properties of both VMF and BVDF, the distance sum criterion and the angle sum criterion is combined in the minimization formula, leading to Directional Distance Filter (DDF) [8, 9]. Let W be the processing window of size n (n=9) and f_i, {i=1,2,…n, } be the pixels in W and let σ_i correspond to f_i, then

$$\sigma_i = \lambda_i * \alpha_i = \sum_{j=1}^{9} \Delta(f_i, f_j) * \sum_{j=1}^{9} A(f_i, f_j) \quad (12)$$

An ordering of the σ_i's

$$\sigma_{(1)} \leq \sigma_{(2)} \leq \ldots\ldots.. \leq \sigma_{(9)} \quad (13)$$

implies the same ordering to the corresponding f_i's

$$f_{(1)} \leq f_{(2)} \leq \ldots\ldots.. \leq f_{(9)} \quad (14)$$

The first term in (14) constitutes the output of the DDF

$$DDF\,[f_1, f_2, \ldots\ldots f_9] = f_{(1)} \quad (15)$$

SPATIAL MEDIAN FILTER

The **Spatial Median Filter** (SMF) [10] 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

$$S_{depth}(X, x_1, x_2, \ldots\ldots x_N) = 1 - \frac{1}{N-1}\left\| \sum_{i=1}^{N} \frac{X - x_i}{\|X - x_i\|} \right\| \ (N=9) \quad (16)$$

Let $r_1, r_2, \ldots. r_9$ represent $x_1, x_2, \ldots.. x_9$ in rank order such that

$$S_{depth}(r_1, x_1, x_2, \ldots\ldots x_9) \geq S_{depth}(r_2, x_1, x_2, \ldots\ldots x_9) \geq \ldots\ldots \geq S_{depth}(r_9, x_1, x_2, \ldots\ldots x_9) \quad (17)$$

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

$$SMF(x_1, x_2, \ldots\ldots x_9) = r_1 \quad (18)$$

CONTENT BASED RANK FILTER

The Content Based Rank Filter (CBRF) [11], ranks the vectors according to a metric that incorporates more information between two vectors as a whole than the measures used in VMF and BVDF. The metric considers the similarity between two vectors which is expressed as the ratio of commonality and totality of two vectors. Let W be the processing window of size n (n=9) and f_i, {i=1,2,…n} be the pixels in W and let C_i correspond to f_i, then

$$C_i = \sum_{j=1}^{9} G(f_i, f_j) \quad (19)$$

Where $G(f_i, f_j) = \sqrt{\dfrac{\|f_i\|^2 + \|f_j\|^2 - 2.\|f_i\|.\|f_j\|.\cos\theta}{\|f_i\|^2 + \|f_j\|^2 + 2.\|f_i\|.\|f_j\|.\cos\theta}}$

An ordering of the C_i's

$$C_{(1)} \leq C_{(2)} \leq \ldots\ldots.. \leq C_{(9)} \tag{20}$$

implies the same ordering to the corresponding f_i's

$$f_{(1)} \leq f_{(2)} \leq \ldots\ldots.. \leq f_{(9)} \tag{21}$$

The first term in (21) constitutes the output of the CBRF

$$CBRF\ [f_1, f_2, \ldots\ldots, f_9] = f_{(1)} \tag{22}$$

WEIGHTED VECTOR MEDIAN FILTER

Let W be the processing window of size n (n=9) and f_i, {i=1,2,…,n} be the pixels in W. Let us assume that $w_1, w_2, \ldots, w_9$ represent a set of nonnegative integer weights so that weight w_i for i=1,2,…,9 is associated with the input sample f_i. Thus the weighted vector distance is defined as

$$V_i = \sum_{j=1}^{9} w_j \,.\, \Delta(f_i, f_j) \text{ for } i=1,2,\ldots.9.$$

An ordering of the V_i's

$$V_{(1)} \leq V_{(2)} \leq \ldots\ldots.. \leq V_{(9)} \tag{23}$$

implies the same ordering to the corresponding f_i's

$$f_{(1)} \leq f_{(2)} \leq \ldots\ldots.. \leq f_{(9)} \tag{24}$$

The first term in (24) constitutes the output of the WVMF [12], it is the sample with minimum aggregated weighted distance.

$$WVMF\ [f_1, f_2, \ldots\ldots, f_9] = f_{(1)} \tag{25}$$

Depending on the weight coefficients $w_1, w_2, \ldots, w_9$ the WVMF can perform a wide range of smoothing operations so that the optimal weight vector may be practically found for each filtering operation.

CENTER WEIGHTED VECTOR FILTERS

The Center Weighted Vector Median Filter [13] is same as WVMF, in which the center pixel weight is varied while the other pixels weights are fixed. Let W be the processing window of size n (n=9) and f_i, {i=1, 2,…, n} be the pixels in W. Let us assume that $w_1, w_2, \ldots, w_9$ (except w_5) represent a set of nonnegative integer fixed weights (normally 1) so that weight w_i for i=1,2,3,4,6,7,8,9 is associated with the input sample f_i. The central pixel weight w_i is given by

$$w_i = \begin{cases} n-2k+2 & \text{for } i=(n+1)/2 \\ 1 & \text{otherwise} \end{cases} \quad (26)$$

where k is the smoothing parameter with values ranging from 1,2,…., (n+1)/2. If k=1, the CWVMF is equivalent to the identity operation and no smoothing is performed. If k= (n+1)/2, the maximum amount of smoothing is performed and the CWVMF is equivalent to WVMF.

Thus the center weighted vector distance is defined as

$$CV_i = \sum_{j=1}^{9} w_j \cdot \Delta(f_i, f_j) \text{ for } i=1, 2, \ldots 9 \quad (27)$$

and the center weight w_j (j=5) is given in equation 26.

An ordering of the CV_i's

$$CV_{(1)} \leq CV_{(2)} \leq \ldots\ldots \leq CV_{(9)} \quad (28)$$

implies the same ordering to the corresponding f_i's

$$f_{(1)} \leq f_{(2)} \leq \ldots\ldots \leq f_{(9)} \quad (29)$$

The first term in (29) constitutes the output of the CWVMF, it is the sample with minimum aggregated weighted distance.

$$CWVMF[f_1, f_2, \ldots, f_9] = f_{(1)} \quad (30)$$

ADAPTIVE CENTERWEIGHTED VECTOR FILTERS

The Adaptive Center Weighted Vector Filters [11] ie; ACWVMF, ACWVDF and ACWDDF is based on dividing the pixels into two classes, namely corrupted and noise-free pixels. The central pixel is examined according to the following rule.

If Value > T Then center pixel is noisy

Else center pixel is noise free

Where T is the threshold parameter set to 80, 0.19, 10.8 for VMF, VDF and DDF respectively. The parameter λ =2. If the central pixel is noisy, it is replaced by the output of three basic vector filters, ie VMF, VDF and DDF. Otherwise it remains unchanged. The mathematical expressions for the three adaptive center weighted vector filters is given below

$$f_{ACWVMF} = \begin{cases} f_{VMF} & \text{if } \sum_{k=\lambda}^{\lambda+2} \Delta\,(f_{CWVMF}, f_c) > T \\ f_c & \text{Otherwise (center pixel value)} \end{cases} \quad (31)$$

$$f_{ACWVDF} = \begin{cases} f_{VDF} & \text{if } \sum_{k=\lambda}^{\lambda+2} A\,(f_{CWVDF}, f_c) > T \\ f_c & \text{Otherwise (center pixel value)} \end{cases} \quad (32)$$

$$f_{ACWDDF} = \begin{cases} f_{DDF} & \text{if } \sum_{k=\lambda}^{\lambda+2} \sigma\,(f_{CWDDF}, f_c) > T \\ f_c & \text{Otherwise (center pixel value)} \end{cases} \quad (33)$$

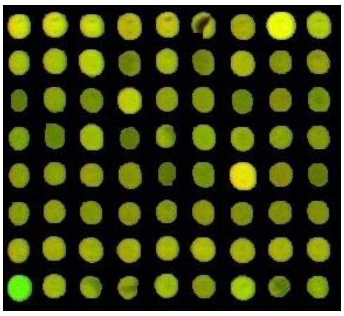
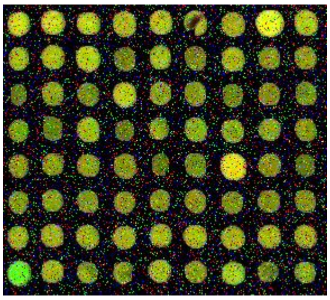
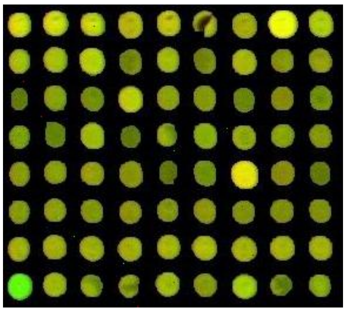
3. EXPERIMENTAL RESULTS

In order to compare the performances of the vector filtering techniques, we used two real cDNA microarray images drawn from the standard microarray database corresponds to breast category aCGH tumor tissue. The first microarray image is a 261*289 pixel image that consists of a total of 75429 pixels. The second microarray image is a 559*489 pixel image that consists of total 273351 pixels. Impulse noise with densities 10, 15 and 20 are added to microarray image. Presented Vector Filtering algorithms are applied on the noisy images in order to reduce the noise. For qualitative evaluation, only the output of ACWVMF for different noise densities is shown in figure 3. To evaluate the achieved results, objective criteria such as mean absolute error (MAE) and mean square error (MSE) are used to reflect the noise suppression and signal-detail preservation in the image. Table 1 and Table 2 shows the MAE and MSE values of the microarray images filtered by different filtering algorithms with different noise densities. Over all the filtering algorithms, Adaptive Center Weighted Vector Filtering algorithms outperform the other noise reduction techniques.

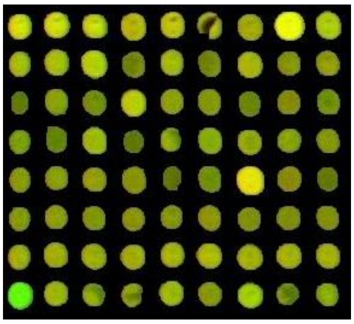
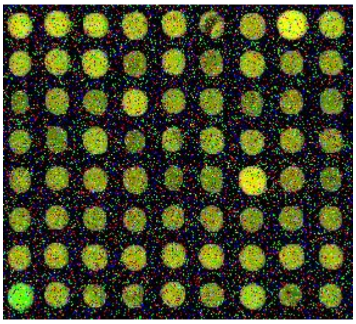
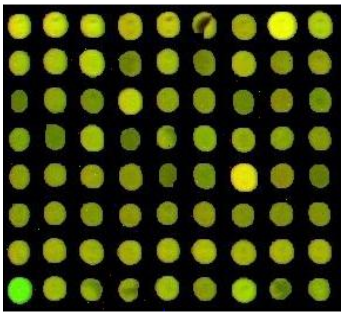
4. CONCLUSION

In this paper, different vector filtering techniques has been used for noise removal in microarray images. The output results reveal that adaptive center weighted filtering techniques outperforms the other filtering techniques used for noise suppression. During the filtering, the impulse noise in microarray images has been removed, while the edges of the spot remain well preserved, leading to better microarray analysis ie., gridding, segmentation and intensity extraction. These smoothing algorithms can play a key role in improvement of microarray image analysis.

Microarray Image 1 | Noise Density 10% | Filtered Image (ACWVMF)

Microarray Image 1 | Noise Density 15% | Filtered Image (ACWVMF)

Microarray Image 1 | Noise Density 20% | Filtered Image (ACWVMF)

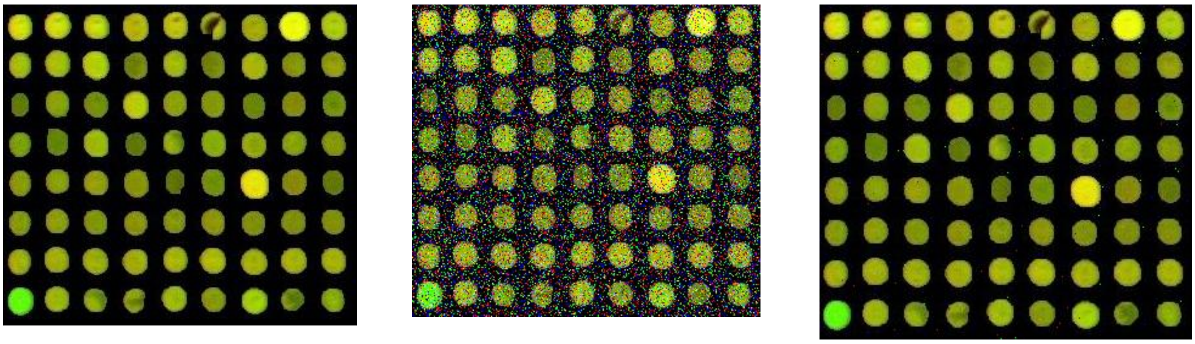
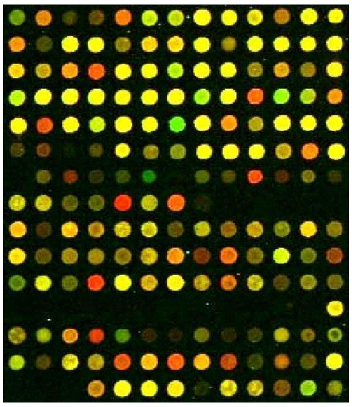
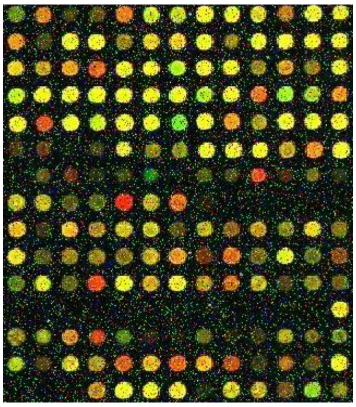


Figure 1: Experimental Results: ACWVMF Output

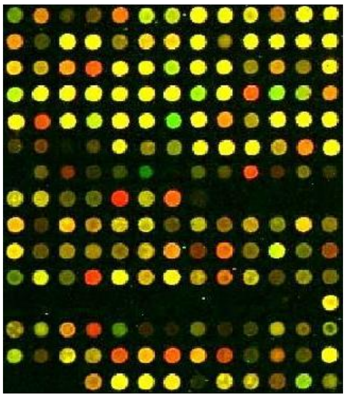
Microarray Image2



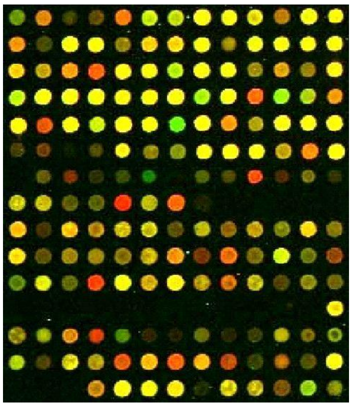
Noise Density 10%



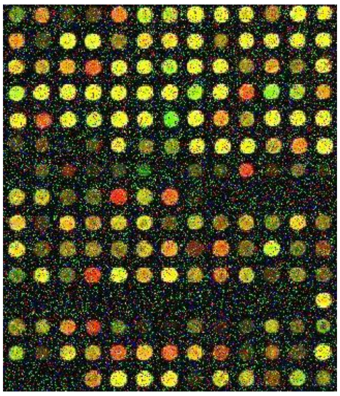
Filtered Image (ACWVMF)



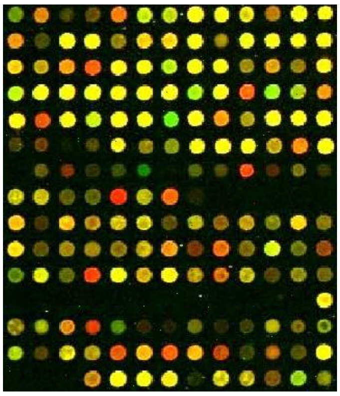
Microarray Image2



Noise Density 15%



Filtered Image (ACWVMF)



Microarray Image2 | Noise Density 20% | Filtered Image (ACWVMF)

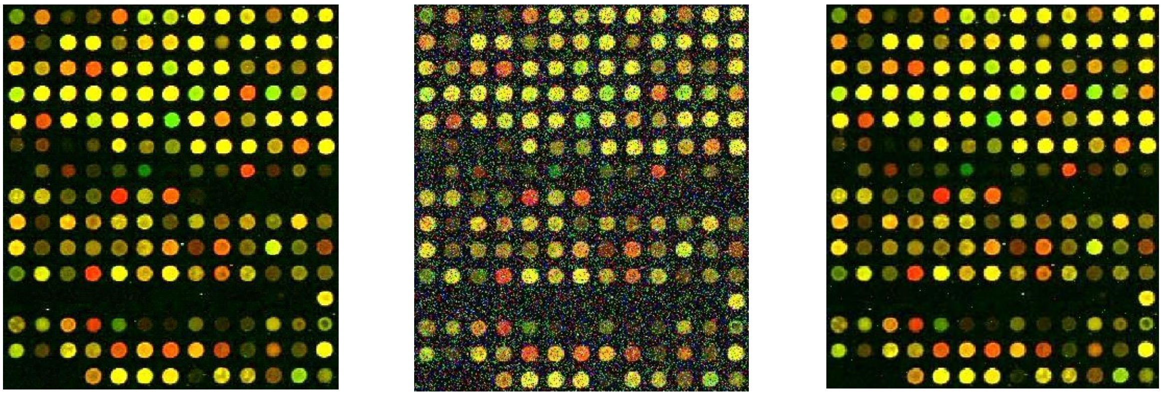


Figure 2: Experimental Results: ACWVMF Output

Table 1: Results achieved using the microarray image1

Noise	10%		15%		20%	
Method	MAE	MSE	MAE	MSE	MAE	MSE
VMF	0.169	20.6	0.179	28.6	0.199	30.6
BVDF	0.214	31.2	0.314	39.2	0.424	41.2
DDF	0.172	19.9	0.192	29.9	0.206	37.9
SMF	0.181	20.01	0.201	27.6	0.389	34.9
WVMF	0.0907	11.6	0.0997	19.6	0.107	24.6
CWVMF	0.0816	8.99	0.0916	13.99	0.0989	16.89
ACWVMF	0.0069	8.23	0.0099	12.23	0.0109	17.23
ACWVDF	0.0098	9.24	0.0118	16.24	0.0132	18.24
ACWDDF	0.0080	8.46	0.0090	13.46	0.0120	18.46

Table 2: Results achieved using the microarray image2

Noise	10%		15%		20%	
Method	MAE	MSE	MAE	MSE	MAE	MSE
VMF	0.259	32.6	0.399	38.6	0.469	42.6
BVDF	0.314	39.2	0.414	44.2	0.524	46.2
DDF	0.272	29.9	0.382	49.9	0.496	49.9
SMF	0.281	30.1	0.401	39.6	0.476	44.9
WVMF	0.0997	24.6	0.1687	34.6	0.198	41.6
CWVMF	0.0896	18.29	0.1321	33.99	0.204	42.89
ACWVMF	0.0129	17.23	0.0189	32.23	0.0219	38.23
ACWVDF	0.0168	19.44	0.0218	33.14	0.0332	37.67
ACWDDF	0.0177	19.96	0.0240	34.46	0.0342	38.66

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