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Restoration of Noisy Microarray Images using Filtering Techniques

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ABSTRACT

Gene expression in large scale analysis is performed by microarray imaging and its accuracy is based on the experiments performed and processing the image further. It is known well that the noise produced during the gene expression analysis will affect the accuracy significantly. The quality of microarray image is affected by several errors particularly noise. Various noise types are present in an image that generates different influence on image processing as well as it is not essential to eliminate every noise, this noise elimination of noise effects establishes difficult issue in the analysis of microarray images. Conventionally several mathematical approaches are utilized for the noise estimation when processing the microarray images. The restoration model was developed in this paper. Noise image is provided as an input and the noise type is estimated by the probability density function (PDF) utilizing appropriate filter for image denoising and restored microarray images are produced. Image sharpening is performed by Blind deconvolution and the image with noise mixture are restored by bilateral filter. Therefore, good restored images are produced from the simulation results with increased Peak Signal to Noise Ratio (PSNR) values and decreased Mean Squared Error (MSE) values.

INTRODUCTION

In modern biomedical research, microarray technology is a powerful tool used for simultaneous measurement of levels of expression with thousands of genes [1]. In 1995 microarray technology was invented, and many approaches of microarray image processing, mathematical models and techniques of data mining are developed for particular types in the analysis of DNA microarray imaging [2]. The microarray image processing was categorized into 3 steps, they are gridding, segmenting and extraction of intensity [3]. These steps are continuous gridding step efficiency and strength are significant for the process of segmentation. In the process of gene expression profiling, the analysis is mainly performed by microarray imaging because of its efficiency. The technology of DNA microarray is often utilized for monitoring the alterations in gene expression in thousand number of genes at the same time. The restoration of image is essential for the information interpretability enhancement in images for providing increased input for further stages of processing image. The quality of image was improved by restoration of images through image refining as per the content of structure, content of statistics, texters, edges and noise presence for perfect gene expression profiling expression [4].

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RELATED WORKS

Microarray images of an automatic segmentation are present in the abounds of existing literature approaches. Markov random field (MRF) and active-contour-based methods are presented by the authors in [5]. The technique based on the order-statistics was presented in [6]. In [7] correlation-statistics-based approach is presented. The enhancement of microarray images with the wavelet denoising method was presented in [8]. Noise-reconstruction-dependent approach was introduced in [9]. In [10] microarray image-segmentation approach dependent on k-means clustering was described. The major limitations of the previously mentioned approaches are performed well for increased SNR images. Global subgrid gridding are integrated with the spot's local gridding in the algorithm of fully automated gridding algorithm in [11]. The information of the structure was extracted by this technique like inter-subgrid spacing, inter-spot spacing and spot center position for achieving effective gridding. Low level image pre-processing is an alternative method received by the BeadChip microarray technology was developed in [12]. In [13] an autoencoder dependent image denoising to enhance DNA MAI was proposed. Classic autoencoder is used for the stochastic extension. By this method there is a noticeable decrement in noise as compared to other current related approaches. Impulse noises are removed by several image filters from the images of testing are presented in [14,17]. The output of filter are utilized for the generation of rules. GSA are used for the selection of optimal rules and the system of fuzzy logic was provided for the noise pixel detection. The process of microarray image processing is noise inherent is developed by the authors in [15-23]. Noise present in the image are denoise by succeeding processing of images through stationary wavelet transform (SWT). SWT's time invariant characteristics are specifically used in image denoise. Reduction of noise are introduced in [16, 19] including two divisions: reduction of edge noise and reduction of highly fluorescence noise.

I. Proposed Technique for microarray image restoration

A. Proposed restoration system model

Restoration system prototype deliberates around the techniques of image restoration which are used for noisy microarray images restoration as represented in Figure 1.

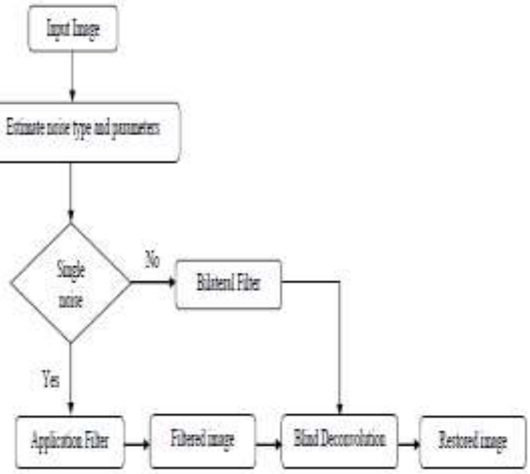

Figure 1. Restoration system model

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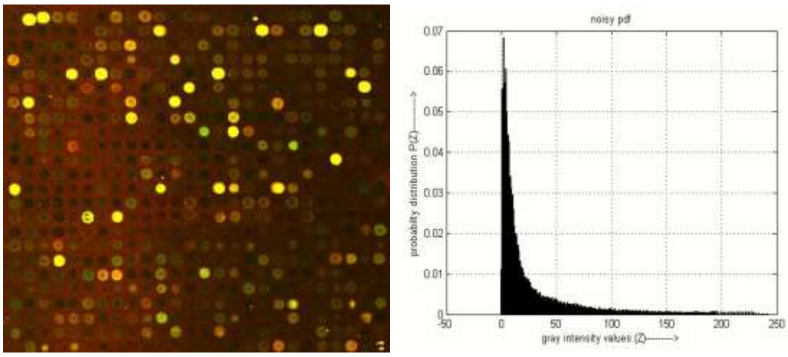
The input to the system model is a noisy microarray image. The model estimates the noise types are exists in the image, by plotting the Probability density function (PDF) of the noisy image. Random variable with Probability distribution is defined by statistical measurement of PDF. The PDF obtained is contrasted with standard noises such as Salt & Pepper, Erlang, Gaussian, Uniform, Log normal, Rayleigh, Exponential etc. Type of noises are from the input images are obtained by this comparison. The parameters of statistics like input image's mean and standard deviation are computed. Noise type is found and suitable parameters are recognized and, suitable filter is put into noise removal. E.g; Gaussian type of noise are identified then Gaussian noise was removed by Gaussian filter as straight. Techniques of Filters are used for edge blurring of the filtered image. Image sharpening, is performed by Blind Deconvolution was used for image sharpening as well as for the unknown source of noise, Blind Deconvolution is used for image denoise. It is suitable for single source of noise. Generally, noise source mixture are present in real images and in for this scenario, comparison of PDF for some images does not produce appropriate noise type estimation. For noise mixture, restoration of degraded images are done by bilateral filter if noise mixture is present in the image. Figure 3 shows a noisy microrray image and in Figure 4 shown is the PDF of the noisy microarray image. Figures 5-6 shows the PDF of Exponential, Gaussian, Erlang and Rayleigh standard noises.



(a) (b)

Figure 2. Noisy microarray image

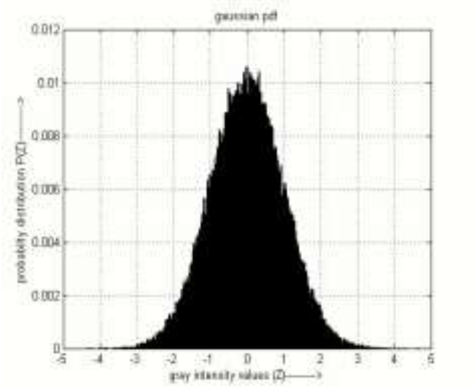


Figure 3. PDF of the Gaussian noise.

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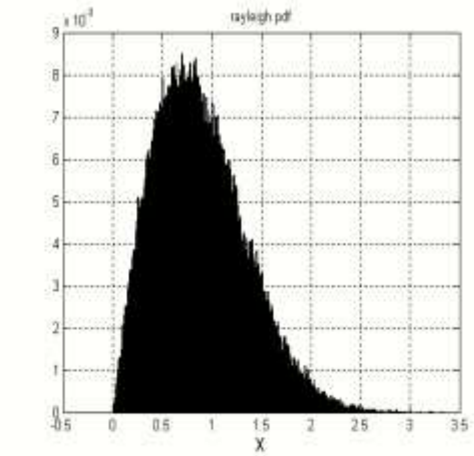

Figure 4. PDF of the Raleigh noise

B. Bilateral Filtering

When noise mixture is present in the image then the system discussed in section will not yield better results. When microarray image contains mixture of noise sources then restoration of that microarray image is done through bilateral filtering process. A bilateral filter is an preservation of edge and noise reduced smoothing filter. In an image, every pixel with intensity is substituted by an intensity value's weighted average from nearer pixels. Gaussian distribution forms the basis of weight. Euclidean distance is not only dependent factor for weights as well as on the radiometric differences (differences in the intensity). Every pixel with systematic looping are used for preservation of sharp edges and weights are assumed for adjacent pixels consequently. Guassian smoothing concept are extended by weighting the coefficients of filter as per the intensity of relative pixel. Intensity different pixels from the central pixel are less weighted, however, with nearer proximity to the pixel at the center. With the non-linear guassian filter, there occurs an effective convolution, with weights depending on intensity of pixel. Spatial domain and intensity domain are the two guassian filters at a localized pixel neighbourhood. Similar to the conventional filters, bilateral filtering is done within in an image range within the domain. Two pixels are nearer to each other in which, it occupies closer spatial location, or these two pixels are closer to each other, that is, with closer values, probably in an understandable manner. In an image, original brightness function is represented as *f* that maps the pixel coordinates (x, y) to a light intensity value and with provided pixel intensity *a* at (x, y) inside a neighbourhood's size n, with centre a_0, and *r(a)* is the range of filter in which the coefficient assigned and are calculated as.

$$r(\alpha_i) = e^{\frac{[f(a_i)-f(a_n)]^2}{2a_0^2}} \quad (1)$$

Likewise, *g(a)* is the domain filter which assigns the coefficient and are obtained by the function of closeness below:

$$g(x, y; t) = e^{-\frac{x^2+y^2}{2t}} \quad (2)$$

where the scale parameter is given by t.

If a_0 is the neighborhood's central pixel, then its value is given by $h(a_0)$

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$$h(a_0) = k^{-1} \sum_{i=0}^{n-1} f(a_i) \times g(a_i) \times r(a_i) \tag{3}$$

Normalization constant for maintaining zero-gain is denoted by k.

Bilateral filtering is nothing but domain and combined range filtering. The value of pixel at *(x,y)* is replaced by same and closer values of pixel. Values of pixels in little neighbourhood are same to all, and the operations of standard domain filter are performed by the bilateral filter, noise causes the weak correlation differences among the values of pixel.

Blind Deconvolution From the characteristics of degraded image, true image are estimated by process of Blind Deconvolution. Image without information or partial information are used for this process. Iterative Constrained algorithm's subset is Blind Deconvolution process which is used for the *h(x,y)* estimation simultaneously with *f(x,y)*. There is no measurement of *h(x,y)* whereas other iterative constrained algorithms needs the measurement of *h(x, y)* through data acquired from the fluorescent bands of sub resolution. The noisy image degradation in spatial domain was demonstrated as,

$$g(x,y) = f(x,y)*h(x,y) + \mathrm{n}(x,y) \tag{4}$$

where

g(x,y): blurred image (measurement)

f(x,y): true image (unknown object)

h(x,y): point spread function (unknown or poorly known PSF)

n*(x,y)*: additive noise (contamination)

* : discrete two dimensional (2-D) linear convolution operator

C. Point Spread Function (PSF)

Light point where the blurring of optical system occurs is Point Spread Function (*PSF*). In the frequency domain, Optical Transfer Function's (*OTF*) inverse Fourier transform is PSF. The linear response is described by *OTF*, position-invariant system to an impulse. *PSF's* Fourier transfer is *OTF*. Image is recovered by using an inverse problem of Image deblurring that is agonized from linear degradation. The degradation of blurring is space-invariant or space sensitive. The approaches of image deblurring was partitioned into two modules, they are blind and non-blind. Unknown blind operator is present in blind class, whereas in non-blind class the blurring operator is known. The algorithm 1 discussed below, is *PSF* produced from information available, inside the data set *g(x,y)*.

The steps below outlines the sequence of estimation of *f(x,y)* and *h(x,y)*

1. Estimation of *f(x,y)* caused *g(x,y)*.

2. Estimation of *h(x,y)* produced *g(x,y)* from the *f(x,y)* estimated,

The above steps are repeated for predetermined number of iterations**.** The *PSF* information is obtainable from the image.

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Algorithm : Blind Deconvolution

Input : Blurred Image or unknown source image

Output : Restored image F

1: Number of iterations are initialized ‘*n*’, *PSF*, *h*, *weight ‘w’ (no. of pixels to be considered)*

2: For i=1 to n

3: Restored PSF = Blind Deconvolution (*g,h,n,w,a*).

4: Endfor

5: **return.**

EXPERIMENTAL RESULTS

Techniques of filtering are useful for microarray images drawn from various databases (SMD, UNC, TBDB). Filtering methods like Average filter, Laplacian filter, Gaussian filter, Median filter, Rank Order filter, Bilateral filter, Max-Minimum filter, Bypass filter, Lowpass filter, High boost filter, Contraharmonic filter and Alpha-trimmed filter are employed for comparision and found that, proposed filter works better for microarray images. Figure 6 shows a noisy image and in the Figure 7 shown is the filtered image through bilateral filtering.

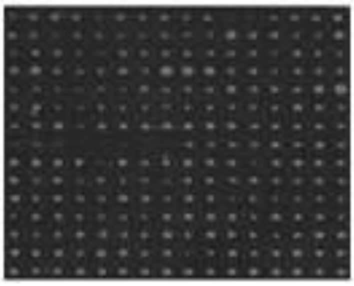

Figure 5. Noisy image

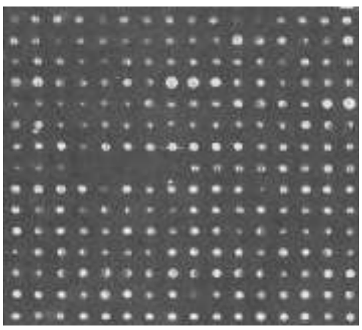

Figure 6. Bilateral filtered image

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Filtering degree was quantified as and also the algorithms of restoration are enhanced, measures of performance like Mean Squared Error (MSE), Peak Signal to Noise Ratio (PSNR) and Structure Similarity Index Measure (SSIM) are used. Image quality is increased by increasing PSNR value and lowering the value of MSE. Various filter's performance are compared. The results infer that, bilateral filter works best in eliminating each and every noise from the image. Analysis of Performance is illustrated in Figure 8 and Figure 9.

Figure 7. PSNR values for different filters

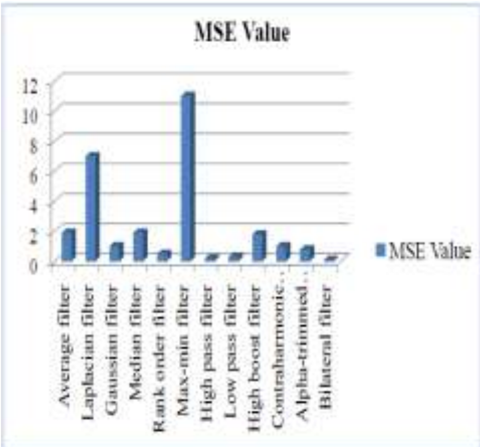

Figure 8. MSE values for different filters

Similarities present in between two images are measured by Structural Similarity Index Measure (SSIM) depending on distortion-free image which is considered as reference. Image quality is measured by viewing SSIM and it is contrasted with some images provided and termed as the best quality. PSNR and MSE in the conventional approaches are improved by SSIM and it proved its human eye perception inconsistency. Equation 1 is used for calculating SSIM. Lower noise is indicated by highest SSIM value in an image and this proposed SSIM is contrasted with state-of-art methods and produces significant improvement.

μ_x :- The average of x.

μ_y :- The average of x.

σ_x^2 and σ_y^2:- variance of x and y.

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σ_{xy}:- The covariance of x and y .

$C_1$and C_2:- Two variables to stabilize the division with weak denominator.

Table-1: SSIM comparison of proposed with existing filtering techniques

Image ID	SSIM			
	Median filter	Gaussian	Low pass	Proposed
32070	0.6204	0.9254	0.9219	0.9672
39119	0.3133	0.9133	0.923	0.9723
35964	0.5234	0.8723	0.9121	0.9865
422471	0.4323	0.7652	0.8761	0.9872

Enhancement of the image restored is evaluated by analysing the performance. The highest possible ratio of signal power to the corrupted noise power is defined as PSNR. Denoised image's PSNR is 181.1 dB and 58.81 dB for noisy image. Thus, the image recovered is the noisy image' s improved version with increased PSNR value which is three times higher than the original image. For the noisy image MSE value is 181 and 0.00088676 for the image recovered and this represents that the content of noise is reduced in the image. If the value of PSF is lower than 7, it represents the image is without the effect of blurring and later the image restored is induced by blurring. The value of PSNR is high and it shows that image recovered is good as represented in figure 10 and 11.

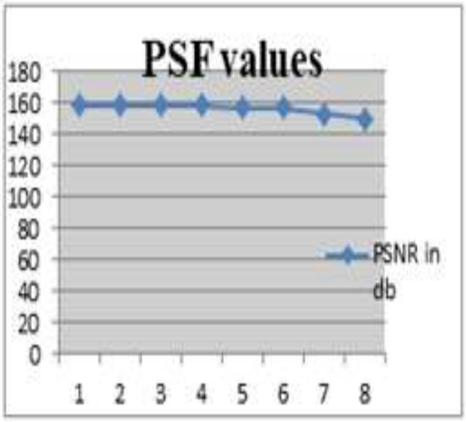

Figure 9. Comparison of variation in PSNR value for different PSF values

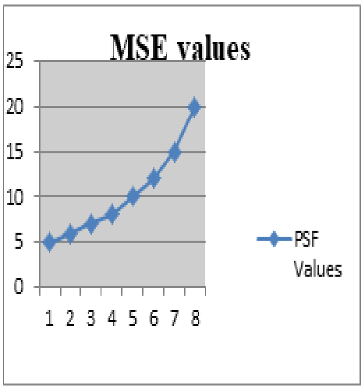

Figure 10. Comparison of variation in MSE value for different PSF values

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In the process of image restoration utilizing Blind Deconvolution is done by Point Spread Function (PSF). For the real microarray images, experiments were carried out by the variation in PSF with 3 conditions, PSF are insisted by 3 conditions, PSF oversized and PSF undersized. At the center PSF maximum true values are located and where the borders are diminished. At the border, signal with high variation restorated using undersized PSF and there is no enhancement in image restored are not shown in blurred image and edges of PSF with oversize are performed and are smoothened with low blurring is leftover with robust effect of ringing in it. Increased enhancement of restored image is obtained by the process of restoration performed by init PSF and the effect of ringing is kept as same. The effect of ringing are removed for image restoration, iteration number are increased and function of weight are defined. Figure 12 shows the noisy image and in Figure 13 shown is the filtered image. The recovered image after Blind Deconvolution is shown in Figure 14. The output of different PSF images are shown in Figure 15. The recovered PSF for different conditions are shown in Figure 16.

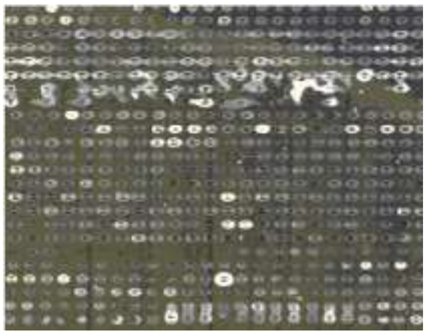

Figure 11. Input noisy image

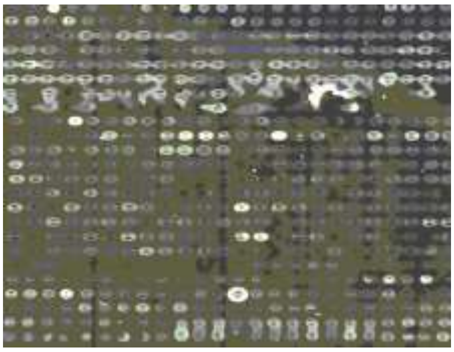

Figure 12. Filtered image

Figure 13. Recovered image after Blind Deconvolution

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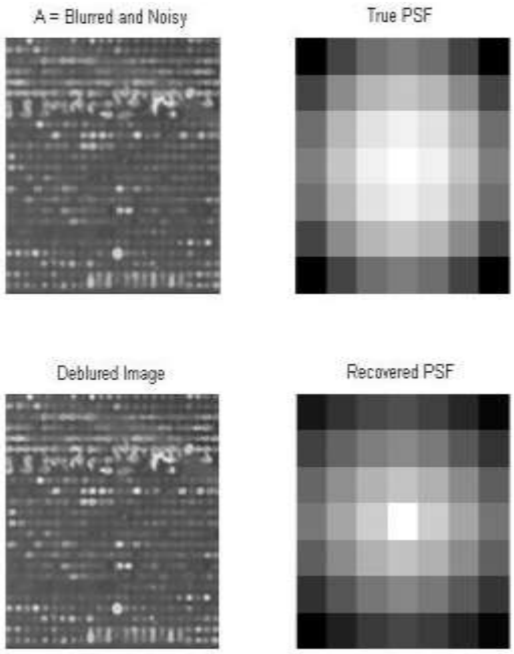

Figure 14. Output of Blind Deconvolution

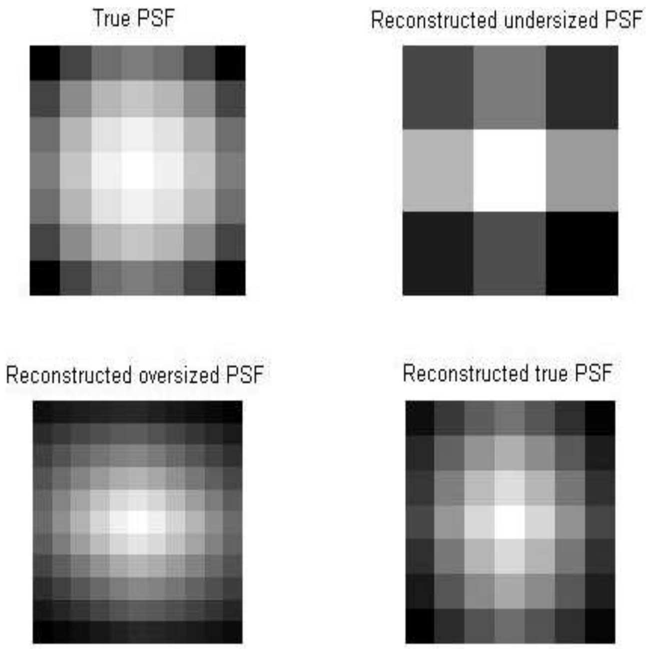

Figure 15. Recovered PSF for different conditions with iterations

CONCLUSION

In this paper, a novel technique for restoration of micro array images are presented. The model of restoration system is developed by the above technique by considering input as the noisy image noise type present in the image was estimated and suitably calls for denoise the image. Source of noise mixture are present in an image, the noisy image are denoised by bilateral filter. Later the application of techniques in filtering, blurring is applied in denoised image as well as blind resolution approach is applied. Both the blurred and true image estimates are calculated by blind convolution approach by utilizing the image without information or partial information. PSNR value is obtained as high and the recovered image is good with lower MSE value. Best results are produced by image restoration approach as contrasted with state-of-art method. Therefore, good recovered image is provided as result with increased PSNR and decreased MSE.

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