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Blurred Image Restoration with Unknown Point Spread Function

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Abstract
Blurring image caused by a number of factors such as de focus, motion, and limited sensor resolution. Most of existing blind deconvolution research concentrates at recovering a single blurring kernel for the entire image. We proposed adaptive blind- non reference image quality assessment method for estimation the blur function (i.e. point spread function PSF) from the image acquired under low-lighting conditions and defocus images using Bayesian Blind Deconvolution. It is based on predicting a sharp version of a blurry inter image and uses the two images to solve a PSF. The estimation down by trial and error experimentation, until an acceptable restored image quality is obtained. Assessments the qualities of images have done through the applications of a set of quality metrics. Our method is fast and produces accurate results.

Keywords: Image Blur, PSF, Bayesian Parameter Estimation, Blind Deconvolution.

الخلاصة
ان اسباب الضبابية في الصورة تعتمد على عدد من العوامل نذكر منها الخطأ البؤري، الحركة, و قدرة تحليل واطئة . تركز معظم الابحاث في مجال استعادة الصورة على طريقة blind deconvolution على اعتماد نواة واحدة للصورة المصدر. في هذا البحث اعتمدنا طريقة مطورة لتقييم جودة الصورة غير المرجعية لتخمين دالة الضبابية (دالة الانتشار النقطية PSF) من الصورة المكتسبة في ظل ظروف اضاءة منخفضة ووجود خطأ بؤري باستخدام طريقة بايسون الاحصائية. ان اساس هذه الطريقة هو الحصول على نسخة عالية الوضوحية واستخدامها في تخمين دالة الانتشار النقطية PSF. ان عملية التخمين تم بمراحل عديدة وصولا الى نسخة الصورة المستعادة .تم اعتماد عدد من معايير الجودة لتقييم جودة الصور الناتجة. أعطت الدراسة الحالية طريقة سريعة لحل مشكلة عدم وضوح الصورة وبنتائج جيدة.

Introduction
Biomedical images are used to detect the diseases which cannot be detected otherwise. These images may be contaminated with noise or blur which makes the detection of diseases difficult, so the restoration of such images is necessary for the well-being of human [1]. Image restoration is one of the integral components of many image processing applications; the goal of image restoration is to recover the original image from degraded image. The degraded image can be a result of a known or unknown degradation [2]. Common sources of image degradation are the blur which is caused by defocus, motion, and sensor resolution [3][4]. Image deblur is down using deconvolution techniques, in this process noise and blur is removed and we get an estimate of the original image as a result of restoration. Image deconvolution techniques are classified into two categories: Blind technique which both the original sharp image and PSF are unknown and non-Blind technique (PSF is known). In image processing the deconvolution methods recover two convolved images W and H from their convolved version:

$$H = W \times S \dots\dots\dots\dots\dots..(1)$$

W represent the original sharp image, where S represents the PSF, which is responsible for blurring W [5][6]. In this paper we proposed iterative blind deconvolution technique to estimate both the PSF which is unknown and the original image using the Bayesian framework. Solution starts by choosing the blured image as an initial guess of W, then obtain S. Iteration is reversed and we seek to estimate W using the estimated S [7].

The problem of blur kernel (PSF) estimation and more generally Blind deconvolution is longstanding problem in image processing and computer vision. Fergus *et.al* [8]. use the statistics of natural images to estimate the blurring kernel, they address more than Box filters, and present impressing reconstructions of complex blurring kernel. H. Y. Lin *et.al*. [9] propose alternate double iteration algorithm known as the Richards-Lucy algorithm, and characterized with robustness to either Gaussian or Poisson noise. R. Jirik [10] propose 2D-Blind deconvolution of clinical images namely Van Cittert algorithm. Liviu-teodor C. *et.al*. [11] presents a Blind noniverse deconvolution algorithm to eliminate the blurring effect. The algorithm is nonlinear Blind devconvolution which works as a greedy algorithm. Aristidis *et.al.* [12] present three algorithm that solve the Bayesian problem in closed form and can be implemented in the Discrete Fourier domain. O. Michailovich. *et.al.* [13] propose two popular restoration techniques LRA and BID to analyze the recovery of medical ultrasound images.

Bayesian Framework for Blind Deconvolution of image

Bayesian framework is a powerful and flexible methodology for estimation and detection problems because it provides a structured way to include prior knowledge concerning the quantities to be estimated [7]. The fundamental principle of the Bayesian philosophy is to regard all parameters and observable variables as unknown stochastic quantities, assigning probability distributions based on subjective beliefs [6][14]. Thus in Blind deconvolution, the original image W, the point spread function S in Equation (1) are all treated as samples of random fields, with corresponding prior Probability Density Functions (PDF) that model our knowledge about the imaging process and the nature of images. In the notation of this problem the usual form of the Bayes's theorem' may be stated as the conditional probability of an event at W_i given an event at H_k:

$$P(w_i \backslash H_k)= \frac{P(H_k \backslash w_i)P(w_i)}{\sum_j P(H_k \backslash w_i)P(w_i)} \ldots (2)$$

where k={1,K), j={1,J},i={1,I}, H_k is for the moment an arbitrary cell of H.

By considering all the H_k and their dependence on all W_i in accordance with S, so we can say:

$$P(W_i) =\sum_k p(w_i H_k) = \sum_k p(w_i \backslash H_k) P(H_k) \ldots (3)$$

Substituting Equation (2) in Equation (3) gives:

$$P(w_i)=\sum_k \frac{P(H_k \backslash w_i)P(w_i)P(H_k)}{\sum_j P(H_k \backslash w_i)P(w_i)} \quad \ldots (4)$$

use an estimate of the $P(w_i)$function to obtain from equation (2), an approximation of $P(w_i \backslash H_k)$.When this practice is applied here, Eq. (4) becomes:

$$p_{r+1}(w_i)= p_r(w_i) \sum_k \frac{P(H_k \backslash w_i)P(H_k)}{\sum_j P(H_k \backslash w_j)p_r(wj)} \ldots (5)$$

Where r={ 0,1… }

This results in an iterative procedure where the initial $P_o(W_i)$ is estimated. Equation (5) can be reduced to a more easily workable form by $P(W_i)=W_i /W$ and $P(H_k)=H_k /H = H_k /W$, since the restoration is a conservative process and W = H, also $P(H_k \backslash W_i)=P(S_i, k)=S_{i,k} /S$, $S=\sum_j Sj$, j ={1,J}. Then equation (5) becomes:

$$w_{i,,r+1} /w=(w_{i,,r} /w) \sum_k \frac{(Si,k /S).(H_k/w)}{\sum_j (Si,k /S)(wi,r/w)} \ldots (6)$$

Materies and Methodology

In the following section, we present our methods for predicting the deblur image. The blurring process is formulated as an invertible system, which models the blurry image as the convolution of a sharp image with the imaging system's PSF. Thus, if we know the original sharp image, recovering the kernel is straightforward. The key contribution of our work is widely applicable method for predicting a sharp image from a single blurry image. Once the sharp image is predicted, we estimate the PSF as the kernel that, when convolved with the original sharp image, produces the blurred input image. We formulate the estimation using a Bayesian framework. We try to find the most likely estimate for the blur kernel given the sharp image and the observed blurred image, using the known image formation model. We express by using the probability distribution of the posterior using Bayes' rule. The algorithm of proposed method summarized as:

❖ **Algorithms of BM metric**

Input: blur image (g)
Output: blurring metric BM
1. Input image I(x, y)
3. Apply Sobel operator for I(x, y) to detect edges to get $I_e(x_e, y_e)$
4. Isolate each region for the origin image to get $I_e(x_e, y_e)$
5. Compute blurring metric for $I_e(x_e, y_e)$ by finding mean value:
$BM = mean(I_e(x_e, y_e))$

❖ **ABD (adaptive blind deconvlotion) algorithm**

The general steps for the proposed system is as follows

Input: blur image (g)
Output: deblur image (restored) u
1. Input g(x,y) blur image
2. deblurring image by using (BD) blind deconvolution for each radius with r_i for r = 1:14.
3. Specifying different radius for PSF where $h_i = \frac{1}{\pi r^2}$ to get g_{dbi} where g_{dbi} is the images deblur at the different radius End for.
4. Finding the blurring metric for g_{dbi} to get BM_i.
5. Finding the maximum value of BM_i to get BM_{max} that corresponding the PSF_{max}.
6. Apply PSF_{max} in step 2 to get deblurring image (restored) $\hat{f}$.

Results and Discussions

In this section, we demonstrate the performance of the proposed method with experiments real images. Images of Colon tissue were acquired using CCD camera by optical microscope for 400x (magnification). The captured images were saved as (24 bit), the distorted images were divided into 2 datasets (the 1st.set for images with different brightness) Figure 1a, the 2nd.set for out of focus images, figure 2a.

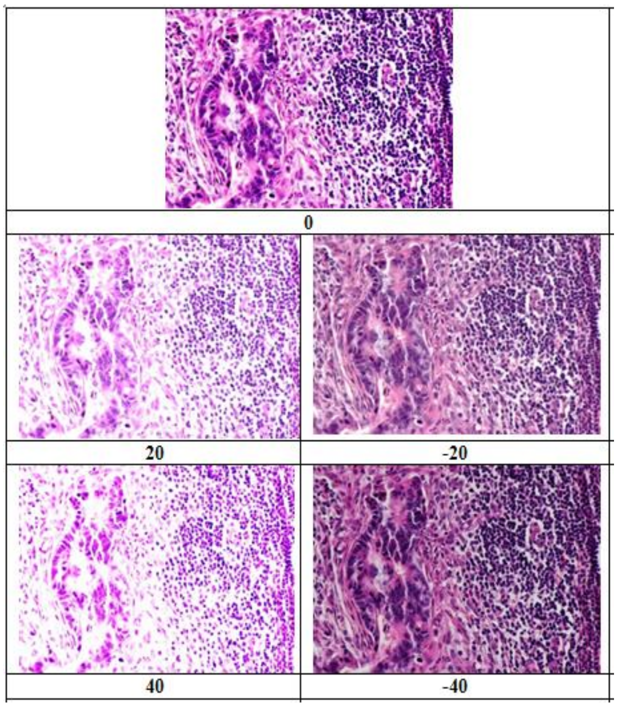

Figure 1a: Colon tissue images under different brightness

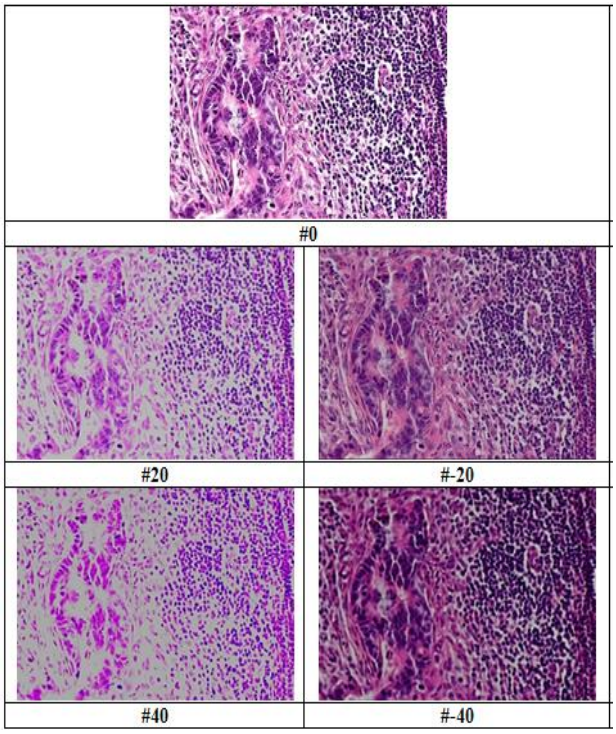

Figure 1b: deconvolved output using our recovered PSF.

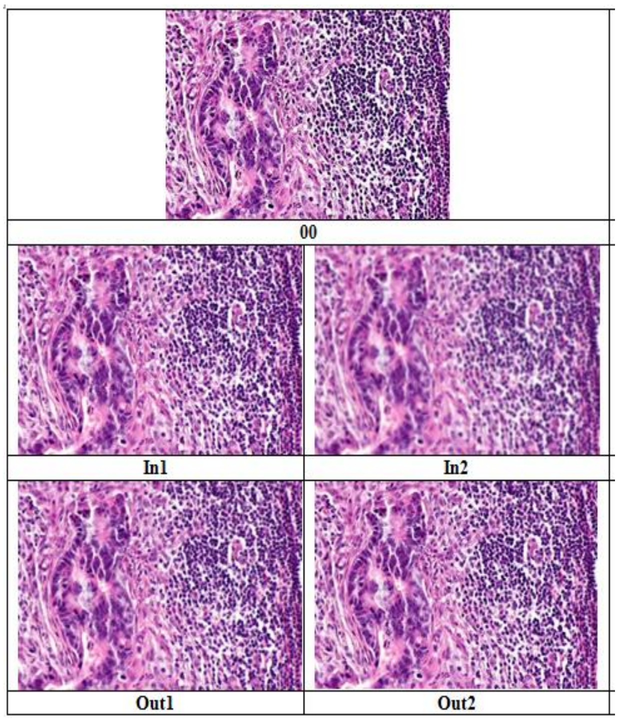

Figure 2a: Colon tissue images with different geometrical miss-focus

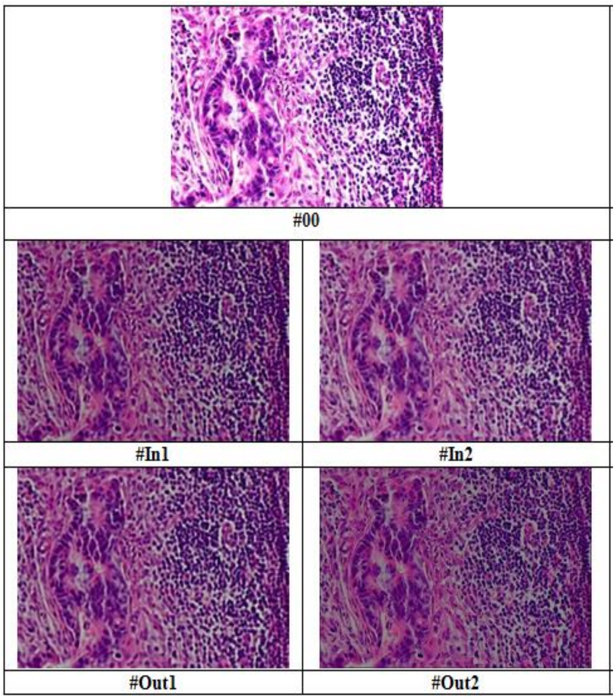

Figure 2b: the deconvolved output using our recovered PSF.

The restored images obtained by the proposed method corresponding to different PSFs are shown in Figure 1b and 2b which presents results for the deblurred images of set 1, and set 2, respectively obtained from the proposed Bayesian algorithm. For each image we show in Figure 3 and Figure 4 the graphical results of histogram and the recovered PSF for the two sets of images respectively. By comparing with the original image in figure 1 and 2. It is evident from these results that the proposed algorithm can not only estimate the actual PSF, but also provides restored images with very high visual quality in all cases.

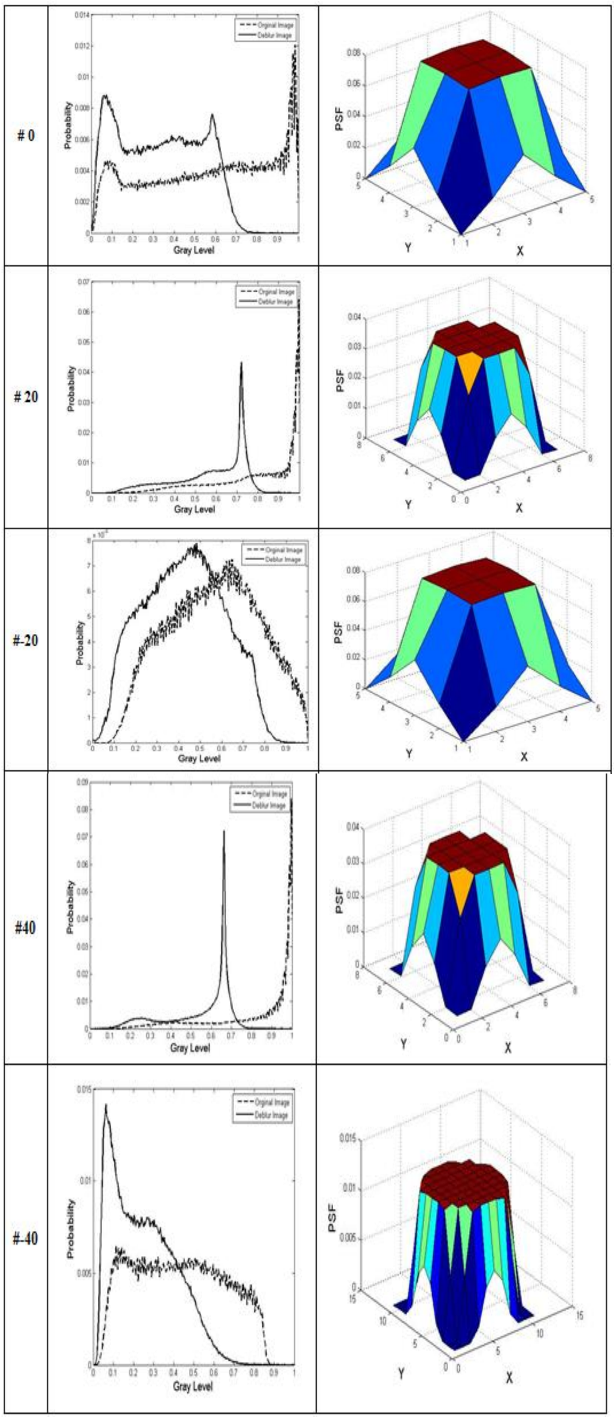

Figure 3: The corresponding recovered PSFs for set 1.

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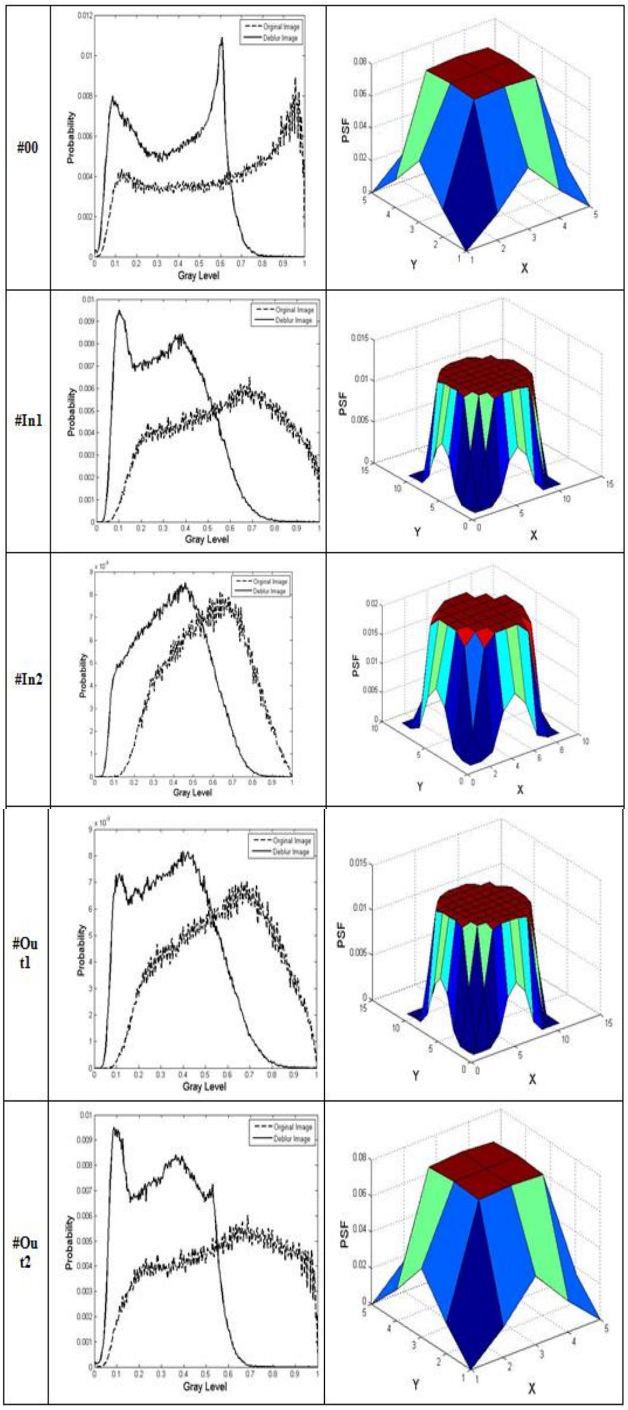

Figure 4: The corresponding recovered PSFs set 2.

As an objective measure of the quality of the restored image, we use the measurement of Mean Square Error (MSE).

$$MSE = \frac{1}{MN}\sum_{i=1}^{N}\sum_{j=1}^{M}[x(i,j) - y(i,j)]^2 \ldots (6)$$

x(i, j) represent the element of the original image in the position, y(i, j) represent the element of the deblurring image in the position [6].

The Mean-Squared Errors (MSE) between the original image and the restored images are given in Table 1. It is clear that the restored images are very close to the original image. Both quantitative MSE results and visual inspection of the recovered PSFs suggest that the algorithm is very successful in estimating the original PSFs.

Table 1: MSES between the original and the restored images

Brightness Image	MSE	Deblur Image	MSE
0-#0	102	00-#00	142
20-#20	115	In1-# In1	132
-20-# -20	85	In2-# In2	78
40-#40	98	Out1-# Out1	45
-40	123	Out2	87

Conclusions

In this paper, we presented the Bayesian formulation for blind deconvolution from Colon image acquired using optical microscope, where there is no priori information about both the sharp image and/or the blurring PSF. The unknown image, blur and all model parameters, including brightness variances, are estimated from the observations without prior knowledge or user intervention. The size of the blurring PSF, can be accurately estimated for both poor intensity and blurred images so that when some prior knowledge about the unknowns is available, it can easily be incorporated into the algorithm. Experimental results demonstrate that the proposed algorithm is very effective in providing high quality restored images. On the other hand, the proposed framework is very flexible so that when some prior knowledge about the unknowns is available, it can easily be incorporated into the algorithm.

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