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Restoration Analysis of Various Type of MRI Brain Tumor Using Blind De-Convolution Pre-Processing Technique

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Abstract

In radiology department, original patient images may have poor quality, blurriness and noisiness, due to this problem doctor can suffer from the initial processing of diagnosing. We proposed blind deconvolution based PSF estimation using EM technique with an estimated parameter for reducing blurry, noisy in MRI brain tumor degraded images. The brain tumor MRI patient images are used for the experimental work. These images include- (Astrocytoma, Ganglioglioma, Glioblastoma, Epidermoid, Mixed Glioma and Meningnet) (5type of tumors) were used for the experiment. Brain tumor image restored using BD methodology based PSF estimation using EM methodology. The experimental result shows that proposed methodology was found to be 0.98 sec with 10 iterations and regularized lucy method [5] found to be 1.524 sec with 103iteration to complete the restoration process. The image quality measurement value is better than regularized lucy method. The proposed methodology measures the image quality assessment PSNR value is higher with higher value and higher SSIM.

Keywords: Magnetic Resonance Imaging (MRI), Brain tumor, Blind deconvolution, Point Spread function (PSF), Expectation maximization (EM), Regularized Lucy method

INTRODUCTION

The importance of medical image pre-processing is very impotent to deal with the patient-related problem. The imaging technologies are very efficient for treatment planning, diagnosing and identification of the problem with a large variety of disease [6, 7, 8]. The preprocessing of brain imaging analysis is the initial stage to improve and understand of original images and smoothness of the image. Imaging techniques like CT, MRI is very are used to diagnosis. During this stage radiologist need to analysis the visual effects, patient treatment [3] of these medical images According to these requirements, we need to take care of all noisy effects blurriness and distortion in the image. All these impacts of the images are not perfectly performed just because of Occurrence of blur, noise, and other degradations in the images are needed to restore or improve. Image restoration is basically used to improve an original image from the degraded images [9]. Many researchers have been done for image restoration that was based on previously many types of filter and currently used deconvolution methods. For example filtered based normal medical image suggested by [4] Studied Edge Finding filter for reducing noise and Prewitt filter for improving the MRI 3T image quality. Author suggested an analysis filtering techniques with Gabor filters for noise reduction the MRI image [12]. Author presented the noise removal technique using wavelets and curvelets [13]. Author reduced the noise of lungs images in the preprocessing stage [2]. Where wavelet domain method used to remove noise based on discrete wavelet packets transform (WPT) and adaptive Wiener filter. All these filters are used to accurate the normal medical and synthetic image. After this, currently, researchers work on the de-convolution method in the field of electronics and image quality. Many works done by authors, for example, kundur suggested a blind deconvolution technique for the restoration of linearly degraded images of original image or the point spread function. The technique experimented of LIT letter [1]. Peter Hall and Peihua Qiu suggested Blind deconvolution method for blur and noisy image. This technique experimented on human face restoration must be performed from the observed noisy blurred image [10]. The technique experimented on human faces. The idea of synthetic image restoration is to minimize the noise. There are following researchers suggested [1, 11] blind deconvolution for image restoration output. Currently, deconvolution based methods are more beneficial for enhancing image quality and restoration process. In this paper, we have to focus on blind de-convolution method for restoration of MRI brain tumor images. BD represents a tool that can be used to improve the image quality without any need of processing system [9]. Aim of this paper is to work on pre-processing stage for removing blurred and noisy effect on MRI brain tumor images. Currently, many types of research on Blind De-convolution were done with normal synthetic images. But in this paper, we develop a blind deconvolution method with estimated parameters for MRI brain tumor class images. BD method has never been used before as a pre-processing of MRI brain tumors. We work on blind de-convolution as a pre-processing stage.

Framework of blind deconvolution based PSF estimation using expectation maximization

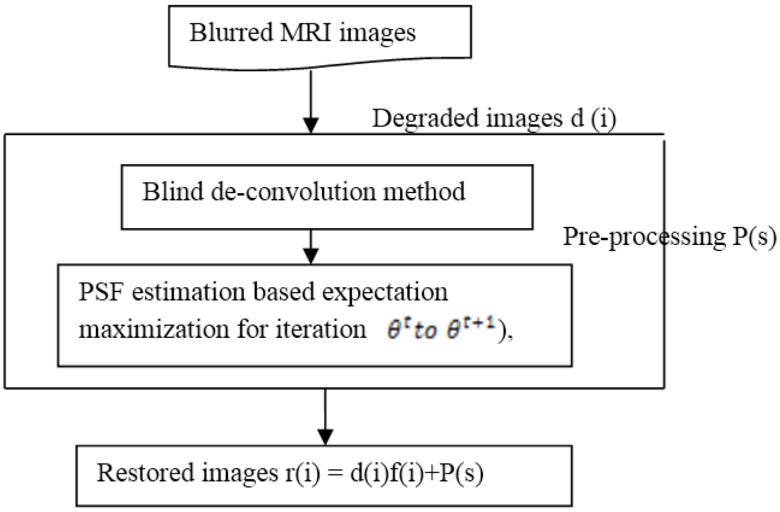


Figure 1 Framework of blind deconvolution based PSF estimation using expectation maximization

The paper is organized as follows: In Section II introducing a Blind de-convolution method and proposed BD algorithm for the restoration of MRI brain tumor image. In Section III experimental results are given. Discussions including comparative analysis with the earlier method are given and Section IV respectively. The paper is concluded in Section V.

BLIND DE-CONVOLUTION

Image pre-processing is the starting stage for the restoration. The framework of the proposed blind deconvolution based PSF estimation using EM shown in *Figure1*. In image processing, blind de-convolution is a de-convolution technique that can recover or restore the blurred image which is poorly determined. The blind de-convolution is an algorithm that produces useful restored images. This proposed technique used to develop for the reduction of blurry, noisy in medical imaging techniques. The degraded image into restored image through blind de-convolution shown in *Figure 2*

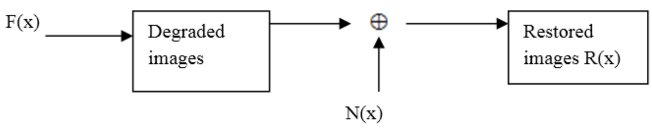


Figure 2 general diagram of blind deconvolution method

The blind de-convolution can recover the poorly determined blurriness image where PSF allow estimation of the image for performance. Many types of research have been proposed blind deconvolution methods for image restoration [1]. In this paper, we have to propose blind de-convolution PSF estimation based EM for MRI brain tumor.

The main objective of blind deconvolution is to estimate f(i, j) and D(i,j). The following equation for the degradation system:

$$g(i,j) = [f(i,j) * D(i,j) + N(i,j)] \qquad (1)$$

Where: (i) is the discrete pixel coordinates of the MRI brain tumor image, g(i, j) is a blurred image, f(i, j)true image, D(i, j) is called point spread function, N(i, j) is noisiness [1]. The following working steps of blind deconvolution are:

1. **Input:** MRI brain tumor images
2. **Degraded image:** in this step, blurred and noisy image is used to simulate for the next step restoration.
3. **Restoration of blurred image:** this step is very important for the conversion of a blurred and noisy image into a restored image.
4. **PSF estimation based on EM:** measure the quality of a counted the set of pixels area with minimum no of iteration
5. **Output:** finally we can get Restored MRI brain tumor images

PSF estimation based Expectation minimization

PSF is used to count the imaging system to a point source or object or region.

$$\text{PSF (Object (u, v),} \qquad (2)$$

$$\text{PSF } (x_i/M - u, y_i/M - v)) \qquad (3)$$

Where M is image is linearly related to object or region plane coordinate. PSF estimation improves the no of iteration based on blind deconvolution. These Iterative methods include expectation-maximization algorithms. This estimation gives the best quality of the restored image. For the initial size of PSF is written as:

$$I(x_i y_i) = \iint O(u,v)\, PSF(xi/M - u, yi/M - v)) \qquad (4)$$

Where o(u,v) is a weighted function of object or region plane.

Expectation minimization

PSF estimation based EM algorithm is used to count no of iterative to implement maximum Likelihood (ML) estimate in the presence of hidden data. Each iteration of the EM algorithm consists of two estimate model parameter shown in *Table 1[A].* The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) = to calculate iteration algorithm for parameter, $initial\ starting\ parameter\ with\ t\ point\ \theta^t to\ \theta^{t+1}$, set x of observed data and missing values

$$Y = (\theta^t to\ \theta^{t+1}) = argmax_\theta(exp_{Y|x(\theta^t)}[\log(\theta; x, Y)]) \quad (5)$$

Table 1 Parameter for blind de-convolution [A]

Parameter	Value
Max ROI size	[1024 1024];
MS levels	4
PAR. verbose	0
PAR. gamma	1e2
PAR. Lp	0.3
PAR. beta_h	1e4*PAR. gamma
PAR. alpha_h	1e1*PAR. gamma
PAR. centering_threshold	20/255;
PAR. beta_u	1e0*PAR. gamma
PAR. alpha_u	1e-2*PAR. gamma
PAR. gamma_nonblind	2e1*PAR. gamma
PAR. beta_u_nonblind	1e-2*PAR. gamma_nonblind
PAR. Lp_nonblind	1
PAR. maximum iteration_u	10
PAR. maximum iteration_h	10

Proposed blind deconvolution based PSF estimation using EM algorithm

1. Let, the PSF parameters like object, PSF, filter type, h_size, sigma Where: PSF (Object (u, v), PSF ($x_i /M - u, y_i /M - v$))

h_size=(size of the estimated PSF (upper bound of the expected PSF)

Calculates the Blurred Noisy MRI tumor image= (im_filter, Image, PSF, noise type, mean μ, variance v);

2. Let, start with initial size of PSF

3. Calculate Blind deconvolution= (Blurred Noisy, INITPSF, iterations ι)

$I(x_i y_i)$

$$=\iint O(u,v)\,PSF(xi\ /M\ - u, yi\ /M\ - v))$$

ω = e(I, e, 0.01);

se1 = strel('disk',1);

se2 = strel('line', hsize, sigma);

ω = ~I length (ω,[se1 se2]);

ω = 1(I length (ω,se1));

ω ([1:3 end-(0:2)],:) = 0;

ω (:,[1:3 end-(0:2)]) = 0;

4. Introduce new PSF = P;

5. newPSF(find(new PSF < 0.1))=0;

6. The EM algorithm is an efficient iterative procedure to compute the Maximum Likelihood (ML) = to calculate iteration algorithm for parameter Table 1[A] $ial\ starting\ parameter\ with\ t\ point\ \theta^t to\ \theta^{t+1}$,

set X of observed data and missing values

Y =$(\theta^t to\ \theta^{t+1})$=$argmax_\theta(exp_{Y|x(\theta^t)}[\log(\theta; x, Y)])$

7. [Function I, PSF) = deconvblind (Blurred Noisy, newpsf I($x_i y_i$),iterations($\theta^t to\ \theta^{t+1}$), ω);

MSE_ = MSE (Blurred Noisy, FI);

PSNR_ = PSNR (Blurred Noisy, FI);

SSIM_ = ssim (Blurred Noisy, FI)

Display Input representation of degraded blur and noisy Brain tumor MRI image

1. Measure the original brain tumor MRI image quality with respect to blurred, noisy, mean error, signal noise ratio and similarity measurement.
2. Find degrade brain MRI image with respect to (I,hsize,sigma,mean,variance,filtertype,noisetype)
3. Input brain tumor MRI Image
4. Set stream value with 0 seeds
5. Apply PSF for filtertype, h size, sigma and V = variance;
6. Calculate Blurred Noisy brain tumor MRI image using filter (I,PSF), noise type, mean, variance);
7. Find image quality measures with respect to MSE, PSNR and SSIM (I,BlurredNoisy);

Table 2. Parameters to estimates the brain tumor MRI image quality [B]

Parameters	value
Noise type	Gaussian
Filter type	Gaussian
edgealgo	Sobel
Iteration	Less
Edge method	sobel

Representation of degraded image into restored image in mathematical form

1. **Input:** degraded brain tumor MRI image in h size, sigma, mean, variance, noise type, filter type [B].
2. Apply blind deconvolution for restoration of brain tumor MRI image
3. Find blind deconvolution PSF (4)
4. Apply expectation maximization (5) with respect to (MSE, PSNR, SSIM, PSF (4))
5. Representation of blind deconvolution restoration for brain tumor MRI image deconvemblind(I,hsize,sigma,mean,variance,noisetype,noisetype,iterations,edgealgo,threshold [B])
6. **Output**: restored brain tumor MRI images.

EXPERIMENTAL RESULTS

The different types of brain tumor MRI image dataset are used in this work. These brain tumor MRI images are taken from MRI division lab, Sawai Mansingh SMS hospital Jaipur, India and Kamaljeet MRI division lab, Punjab, India are used for the CAD system like pre-processing, segmentation and classification. To collect the brain tumor image total November 2015 to December 2016 duration are taken. These images include- (Astrocytoma, Ganglioglioma, Glioblastoma, Epidermoid, Mixed Glioma and Meningnet) grading from I to II with lower to a higher percentage of malignant tumor (5type of tumors) were used for the experiment.

Image learning

Initially, the image learning phase is very important for pre-processing image analysis. In this learning phase, MRI brain tumor image dataset collects from radiology department. In many hospitals, machine equipment techniques scan the digital medical MRI images in an original row and DICOM format. DICOM format images are copied in CAD system and prepared to analyze the image. These images are converted into several file formats: JPEG, TIFF, GIF, and PNG. In this research work, JPEG file format with 256*256 pixel form is used to analyze the brain tumor MRI images. Figure 3 shows the.DCM to jpg conversion

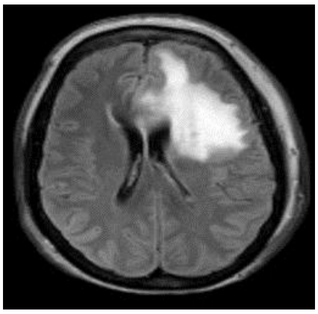


Figure 3. DCM to jpg conversion

The example of Meningnet tumor, female was used to restore through Blind de-convolution based PSF estimation using EM shown in *Figure 4*. Where implemented parameter values for MRI brain tumor shown in *Table 3*

Table 3: The resultant blind de-convolution parameter values for MRI brain tumor

Parameters	values
Sigma value	1
PSF estimation method	EM
Image s	mcg16807 random stream (Meningnet tumor, female)
seed	0
Normal Transform	Polar
Iteration	10
threshold	0.01

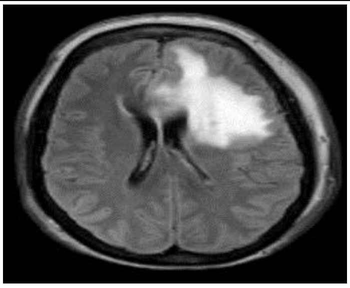
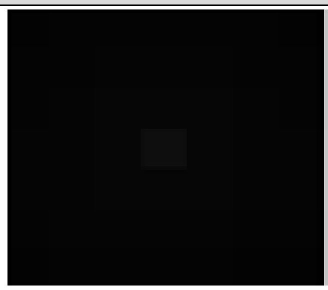
Image type	Restoration image quality process	PSF estimated no. of iteration 10
		
Original MRI image	Restored PSNR 69.09, SSIM 0.98 and MSE 46.09	PSF estimation based EM with no. of iteration 10 and threshold 0.01
(a)	(b)	(c)

Figure 4: shows the preprocessing Blind de-convolution based PSF estimation using EM results with respect to MRI brain tumor (Meningnet tumor, female image) fig (a) shows the original Meningnet tumor. In fig (b) image restored using BD methodology based PSF estimation. We can see that PSNR image quality is higher with higher value and higher SSIM. In fig (c) pixels tumor estimated with PSF estimation based EM with no. of iteration 10.

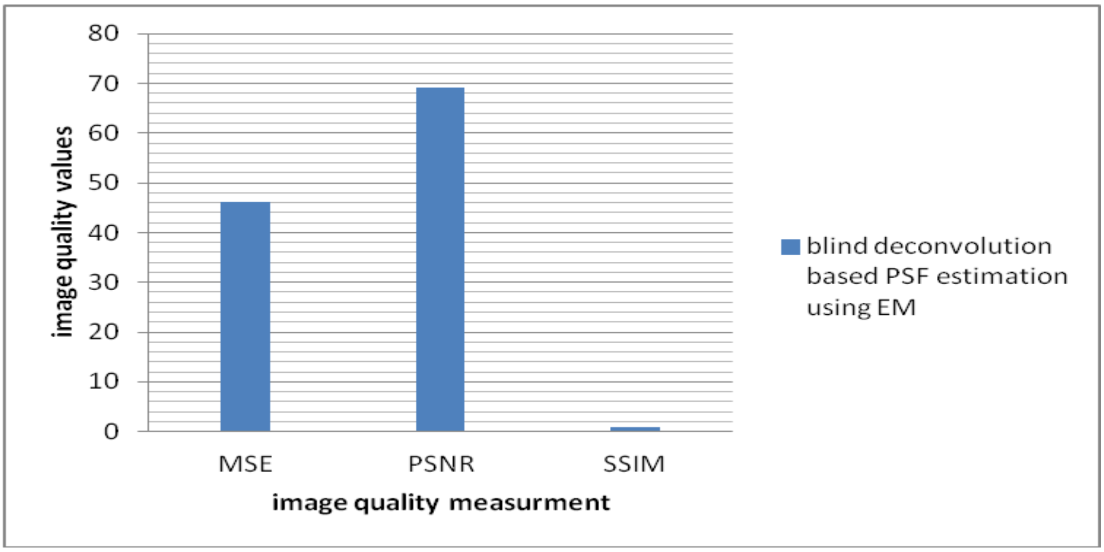


Figure 5 blind deconvolution based PSF estimation using EM method for restored image (mcg16807 random stream (Meningnet tumor, female) quality measurement values

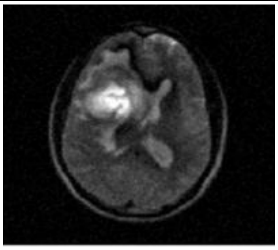
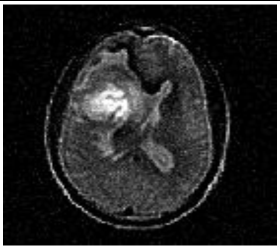
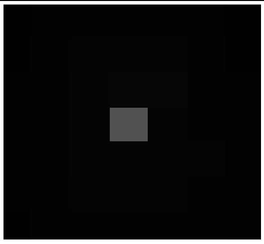
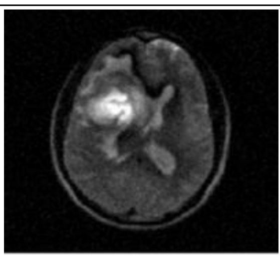
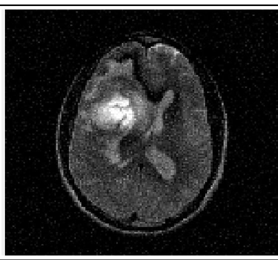
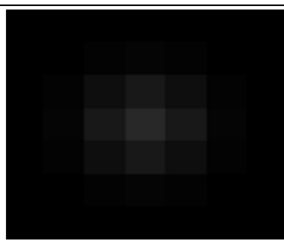
De-convolution method	**MRI brain Tumor classes (example of Astrocytoma tumor – age 30 male)**		
	Original image	**Pre-processed Restored image**	**Estimated PSF**
Blind de-convolution based PSF estimation using EM			
Regularized Lucy de-convolution [Laasmaa, M et al. 2011]			

Figure 6. Comparison of different convolution method with respect to MRI brain tumor images

The Blind de-convolution based PSF estimation using EM gives the best restoration result as compare to other methods shown in *figure 6 and Table 4*. Previously Regularized lucy deconvolution method experimented on microscopy images for the analysis of image qualities [5]. In this work, we use brain tumor class images for restoration image based on Regularized lucy de-convolution method [5].

Table 4. Comparison of different de-convolution method with image quality assessment values measurements

De-convolution method	**PSF estimation method based expectation maximization**		
	MSE	**PSNR**	**SSIM**
Blind de-convolution based PSF estimation using EM	10.9899	87.5324	0.9921
Regularized Lucy de-convolution [Laasmaa, M. 2011]	12.80	81.8765	0.8478

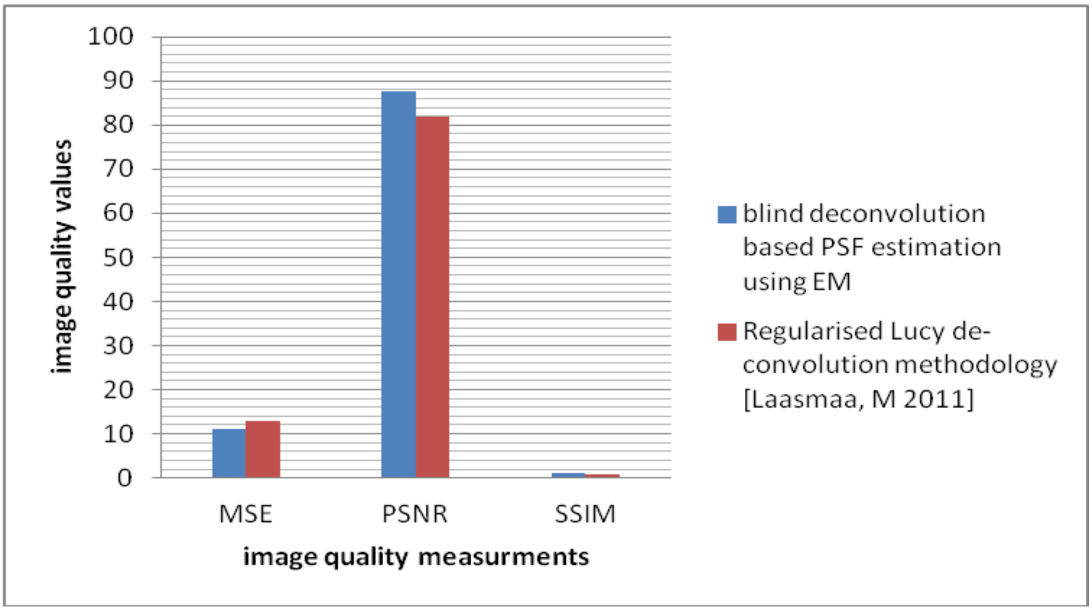


Figure 7. Comparison analysis between Blind de-convolution based PSF estimation using EM method and regularized lucy deconvolution [5] using image quality measurements

Table 5 comparison analysis between Blind de-convolution based PSF estimation using EM and regularized lucy deconvolution [5] with respect to iterations and timestamp values

De-convolution method	No. of Iterations	Timestamp value
Blind de-convolution based PSF estimation using EM	10	0.98sec
Regularized Lucy de-convolution [Laasmaa, M. 2011]	103	1.524sec

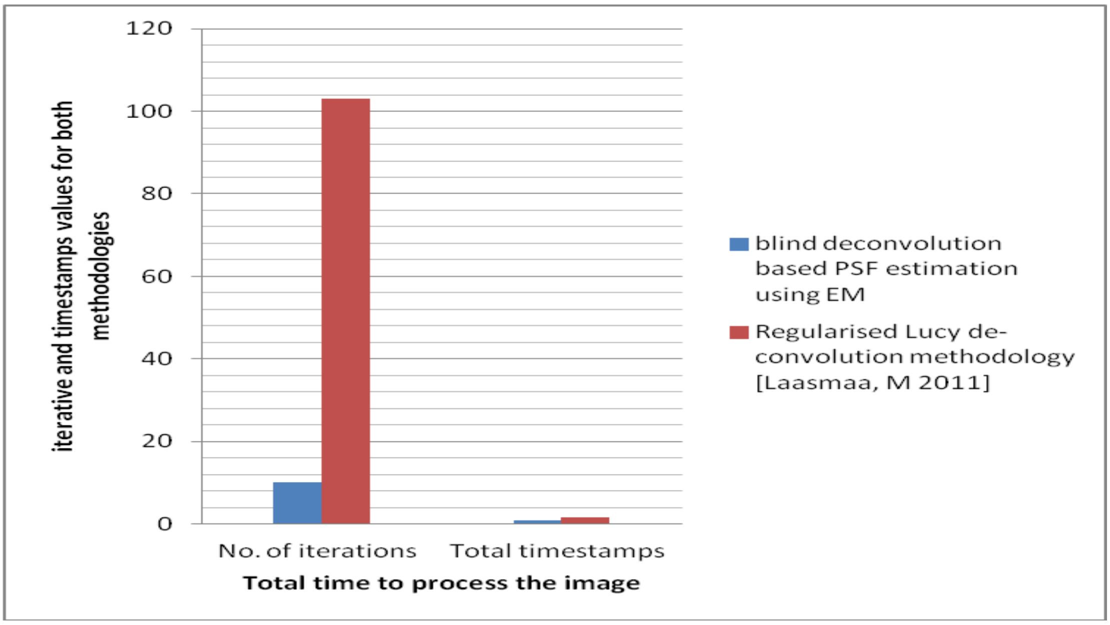


Figure 8. Iteration and timestamps values for between Blind de-convolution based PSF estimation using EM method and regularized lucy deconvolution[5]

CONCLUSIONS

In radiology department, row original patient data images need to diagnose. Images may have poor quality, blurriness and noise due to this problem doctor can suffer from the initial diagnosing process. Pre-processing is the most important step to improve the image quality and reduce the noise effects and blurriness. In this work, we present a blind deconvolution based PSF estimation using EM technique for the restoration or improve the medical images of degraded original medical images. We proposed blind deconvolution based PSF estimation using EM technique for the reduction of blurry, noisy in MRI brain tumor imaging techniques. The brain tumor MRI patient images are used for the experimental work. *Table 5* shows the comparison between blind de-convolution and other methods. We can see that blind deconvolution based PSF estimation using EM technique gives the best performance and provide a good quality improvement of MRI brain tumor images. Comparative analysis of pre-processing technique shows that blind deconvolution based PSF estimation using EM method takes less 0.98 sec to run the process than 1.524 sec time regularized lucy method [5] also blind de-convolution method takes 10 iterations than the regularized lucy method 103 iterations to complete the restoration process shown in *Figure 5* and figure 8 with SSIM value 0.9921, PSNR value 87.5324 and MSE value 10.9899 were calculated through based PSF estimation using EM technique. The image quality of blind de-convolution based PSF estimation using EM is better than regularized lucy method [5].

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