Architecture solution of the non blind iterative Lucy-Richardson deconvolution algorithm

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Abstract—**This paper addresses the problem of blind image restoration. The non blind iterative Lucy-Richardson (LR) algorithm is considered. The proposed architecture solution consists of making the LR algorithm totally blind and fully automatic. For this aim, first a proposed point spread function estimation method is used to estimate the blur kernel and make the LR algorithm blind. Moreover in order to make the LR algorithm automatic, the iterative deconvolution process is controlled by a proposed stopping criterion based on a no reference blurred image quality metric that suggested in [1]. Computer simulations using the Gblur LIVE database [2] are provided in order to illustrate the proposed architecture effectiveness. A comparative study with the shock filter blind deblurring method [3] is performed, emphasizing the good proposed architecture solution behavior.**

Keywords-blur; deblurring; multiplicative multiresolution decomposition (MMD); inverse problem; blur quality assessment.

I. INTRODUCTION

Blur is a common problem in many applications, among which the astronomy, remote sensing as well as in biomedical imaging. In this kind of situations, deblurring is fundamental in making pictures sharper and more useful for analysis and interpretation. Deblurring is considered as an ill-posed inverse problem [6], usually kept at bay by mean of regularization following the classical works of Tikhonov [7]. The success in solving the deblurring image problem depends specially on the amount of the available prior information. This information is generally relying on the original image and the degradation system (Point spread function: PSF). It exists in the literature two kinds of deblurring methods blind and non blind. The non blind ones, such as Wiener filtering [8], Lucy-Richardson [9, 10], least-squares filtering [7] and recursive Kalman filtering [11], assume a known Point Spread Function (PSF), which is not always possible in many real image processing situations. However the blind case, no information about the PSF is supposed known [12]. In this case two approaches could be adopted. The first one consists of propose a blur kernel estimation approach and use a non blind deblurring algorithm [13-15]. The second one turns on the association of a blur kernel estimation method and a deconvolution process [14]. Authors in [13-15] propose a blur kernel estimation method and then the non blind Lucy Richardson (LR) deconvolution algorithm is applied for the deblurring process.

In image deblurring, we seek to recover an original sharp image using a mathematical model of the blurring process. We assume that the image formation could be adequately described by a linear spatially invariant relation and that the noise is additive. A common model for the image formation corresponds to filtering the image f through a two-dimensional (2D) linear system whose impulse response, h, is a Gaussian function. At each pixel (k, l) , the blurred version f_b is then defined as follows:

$$f_b(k,l) = (h * f)(k,l) + n(k,l) \qquad (1)$$

where $'n'$ is an additive random noise.

Blurring affects especially edges [16], which represent discontinuities and high frequency components in images. It was shown in [17] that the MMD is well adapted to blurring analysis. The main contribution of this work is to propose an automatic blind deblurring method for optical blurred images. The proposed approach consists of associate a proposed blur PSF estimation method to the iterative LR deconvolution algorithm. Moreover, the iterative LR algorithm is controlled by a recently proposed stopping criterion [18]. The main advantage of the proposed solution is that, it is totally blind and fully automatic.

In the experiment part, blurred images from the Live database have been considered [2] and the Shock filters blind deblurring method [3] is used for a comparative study.

The rest of the paper is organized as follows. Section 3 details the proposed algorithm architecture for blur effect reduction. Experimental settings, methodology, results and discussions are presented in section 3. We finally conclude the paper with some perspectives for future work.

II. PROPOSED DEBLURRING ARCHITECTURE

In this paper, the Bayesian reasoning based Lucy-Richardson deconvolution algorithm is considered. The LR algorithm is widely used in the literature for blur image restoration [4], [5]. However it presents two disadvantages. It is not blind and it has to be manually stopped. In fact, it is iterative with non explicit stopping criteria. The aim here is to propose solutions for the LR algorithm drawbacks. First, a proposed approach for the blur PSF estimation approach is used to make the algorithm blind. And then to automate the iterative process, a proposed stopping criterion is used. The proposed architecture solution is shown schematically on figure 3. Fist the test image quality score is computed using the quality metric defined in [1]. The study on the Live database images quality revealed

that if the quality score is upper than 0.9, the blur degradation is not perceived. So if the quality note is less than 0.9. The blur kernel (PSF) is then estimated using a proposed method detailed in the section II.1. Finally, the non blind LR deconvolution algorithm is applied. The restored image quality score is computed. While the quality score value is improved, the LR deconvolution algorithm is iterated until no more improvement in the image quality is noticed. Experimentally, *"ξ"* is set to 0.01 [18].

II.1. Point Spread Function (PSF) Estimation method

As blurring affects especially edges and makes transitions larger, the proposed PSF estimation approach is based on computing edge pixels spreading through a multiresolution analysis using a Multiplication Multiresolution Decomposition MMD [19, 20]. The MMD is a nonlinear multiplicative decomposition using filter banks with critical sub-sampling and perfect reconstruction. Herein, the MMD is used to extract all edges and singularities. The proposed approach for PSF estimation could be explained in three main steps. First, edge pixels are extracted at each resolution level using the MMD, and then the spreading out of each detected edge pixel is estimated. Finally an analysis and an interpretation of the obtained values are performed.

A. Edge detection

Apply the MMD at three resolutions to extract detail images (Figure 1). To reduce the noise effect and for a better edge pixel extraction, an adequate threshold is applied at each resolution level "j", on the detail images as follows:

$$y'_{2c}(k,l) = \begin{cases} y_{2c}(k,l) & if\ y_{2c}(k,l) > Th_j\ , \\ \beta & otherwise\ . \end{cases} \qquad (2)$$

$with\ \ Th_j = \beta \times j + m_j.$

The subscript 'c' denotes the horizontal, 'h', vertical 'v', or diagonal 'd' details obtained from the MMD. β is set to 0.5.
By studying the MMD's detail coefficients at different resolutions, we found that it is useful to define a set of threshold Th_j relying on the resolution level j and m_j the mean value of the obtained details at each resolution level defined as follows.

$$m_j = \frac{1}{N_j \times M_j} \sum_{k=1}^{k=N_j} \sum_{l=1}^{l=Mj} y_{2c}^{(j)}\,(k,l) \qquad (3)$$

here N_j *and* M_j, represents the number of rows and columns of the MMD's image detail at each resolution level j.

B. Estimate the detected edge pixels spreading out values

Figure 2 represents the obtained MMD's coefficients when applied on a 1D signal (continuous and step edge). Accordingly, one could notice that if the signal does not contain any transition the corresponding MMD's values are equal to β =0.5. However if the signal contains transitions the MMD's coefficients values are different from β (figure 2). Based on this analysis, the edge spreading value is computed in the MMD's domain by counting the number of pixels around the edge pixel that different from β*=0.5* (figure 2). The spreading out of each detected edge pixel is computed following the orthogonal direction. The spread is then computed as the sum of both counts excluding the edge pixel. Computing the edge spread is done for all detected edge pixels at each direction (horizontal, vertical and diagonal).

C. An analysis step

Having information about the total number of edge pixels and their spreading values, the aim now is to analyze the obtained information. For this aim, only the maximum spreading value in the three directions (horizontal, vertical and diagonal) is considered. The histogram of the detected edge pixels spreading values at each resolution level is then constructed. Finally the spreading mean value of all the detected edge pixels is chosen as the considered image blur kernel.
The advantage of this method lies in the fact that it could be adapted to the local blur problem. In fact, the information about the blur kernel is estimated at each edge pixel.

III. EXPERIMENTS AND RESULTS

The proposed architecture performance has been evaluated on blurred images from the Gblur LIVE database. This database comprises a set of twenty-nine original images, high-resolution (24 bits/pixel) in RGB colors (Figure 4). All these original images are filtered using a circular-symmetric 2-D Gaussian kernel of standard deviation ranging from 0.42 to 15 pixels, which results in a set of 174 stimuli [2].
Before testing the proposed deblurring method performance, we first evaluate the proposed PSF estimation method, then the non blind Lucy-Richardson algorithm efficiency is tested and finally we evaluate the proposed blind automatic deblurring architecture.

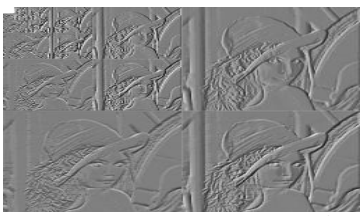


Figure 1. MMD multiresolution analysis for J=5

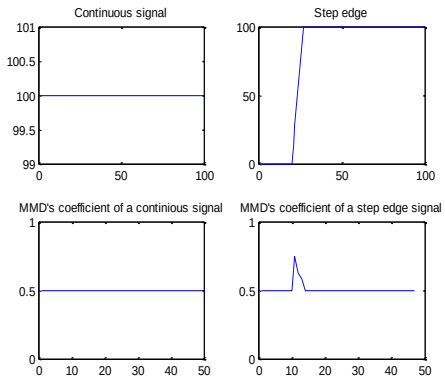


Figure 2. MMD multiresolution application on 1D signal

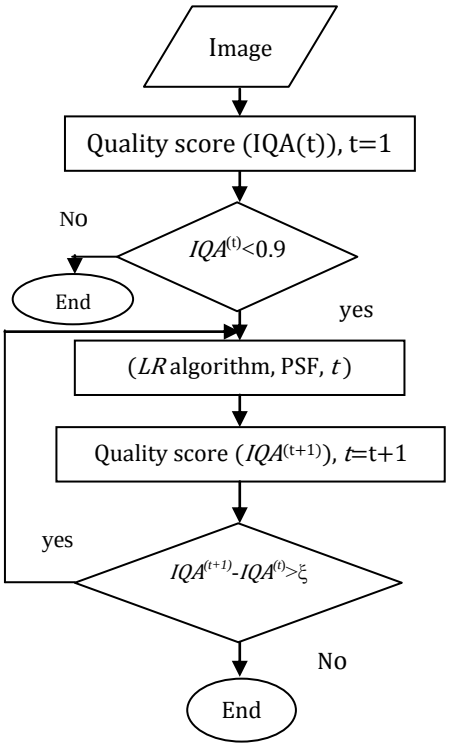


Figure 3. Flow-chart of the proposed solution.

A. *Proposed blur PSF estimation method evaluation*

To illustrate the proposed PSF estimation method effectiveness, let us consider from the LIVE database one original image and its blurred version represented in Figure 5. While computing the edge spread of the entire images using the proposed algorithm, obtained results are shown in Figure 6. Accordingly, it could be clearly noticed that the estimated edges spreading values (ESV) are more important in the blurred image compared to the clearest one. Indeed blurring affects especially edges and makes transitions spreading larger. However in clearer images, transitions are sharp and edges spreading values are narrower.

While applying the proposed algorithm on all Live dataset images (174 images), the obtained mean Spreading out value of each image is evaluated against the real spread value representing the Standard Deviation value of the Gaussian function introducing blur in this image available in the Live database. In addition, the estimated blur kernel for each image is tested against its blur quality measure using the no reference blur image quality measure developed in [1]. Obtained results are represented in Figures 7 and 8.

For data fitting a Logistic regression has been considered. It is defined in (eq.4).

$$ESV_i = \frac{\alpha_1 - \alpha_2}{1 + e^{\frac{SD_i - \alpha_3}{|\alpha_4|}}} + \alpha_2 \qquad (4)$$

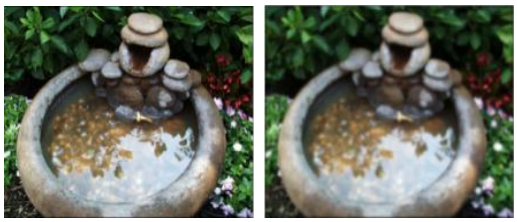
where α_1, α_2 ,α_3 *and* α_4 are the logistic parameters, ESV_{pi} is the predicted Spreading value of the image i, and SD_i is the given Standard Deviation value of the considered image i.

To appreciate the obtained interpolation model, a Spearman Rank Order Correlation Coefficient (SROCC) is used.

$$SROOC = 1 - \frac{\sum D^2}{n^2(n^2-1)} \qquad (5)$$

D is the difference between interpolating model and samples and n is the total number of samples.

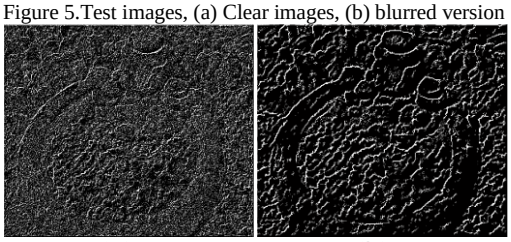
Figure4. Live dataset original images



(a) (b)

IQA(a)=0.9827 IQA(b)=0.6725

Figure 5.Test images, (a) Clear images, (b) blurred version



(a) (b)

Figure 6. The detected edges spreading out of, (a) Clear image, (b) Blurred version

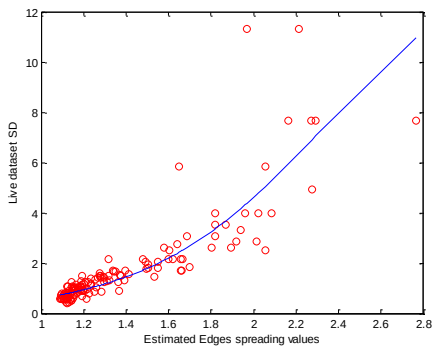


Figure 7. Scatter plot of the Estimated ESV versus SD values

SROOC= 0.9138, RMSE= 0.9595

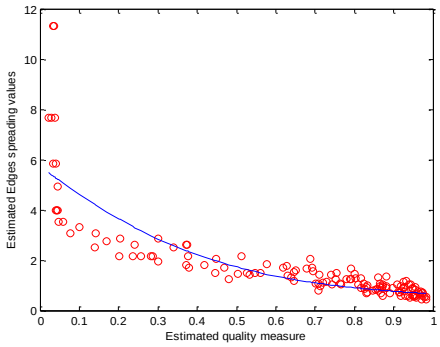


Figure 8. A scatter plot of the Estimated ESV versus the obtained quality measure values.
SROCC = 0.9273, RMSE =0.9590.

The quantitative evaluation of Figures 7 and 8 revealed a high Spearman correlation value (SROOC) between the interpolation model and the obtained samples (more than 90%) for a small Root Mean Square Error (less than 1).
From all obtained results, one could conclude that the proposed algorithm for blur kernel estimation provides a faithful estimation compared to real values.

B. The Lucy Richardson deconvolution algorithm analysis

This experiment part is dedicated to the analysis and the performance evaluation of the non blind Lucy Richardson (LR) algorithm using blurred images from Gblur LIVE database. For this aim, six test images are considered. Three fairly blurred and three heavily blurred. Test images are presented in Figure 9. Their quantitative evaluation in terms of Standard deviation (SD), the Peak Signal to Noise Ratio (PSNR) and quality score (*IQA*) are illustrated in Table 1. The non blind LR deblurring algorithm associated to the proposed stopping criterion is applied on each considered blurred image using the real PSF values available in the LIVE database. Deblurred images are illustrated in Figure 10. Their quantitative evaluation in terms of PSNR, *IQA* and Iteration Number (IN) is represented in Table 2. According to obtained results illustrated in (Figure 10 and Table 2), one could notice that the LR deconvolution algorithm performs well on fairly blurred images however for the heavily blurred images the LR algorithm is less efficient.

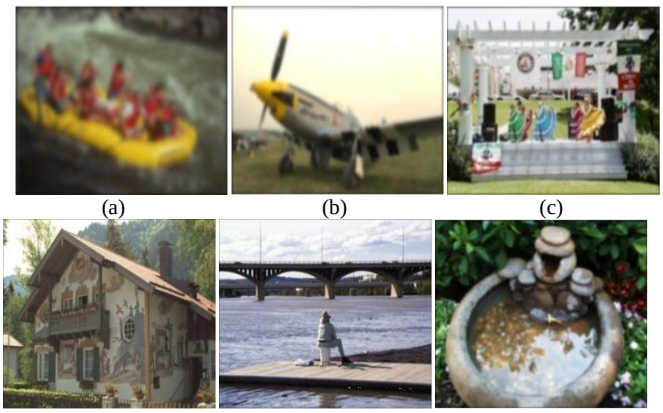


Figure 9. Test images, (a, b, c) heavily blurred, (d, e, f) fairly blurred.

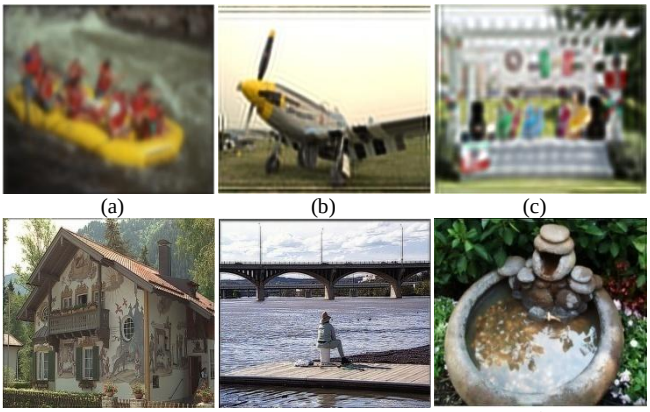


Figure 10. Restored images using the LR algorithm

Table 1: Evaluation of a set of Blurred images.

image	(a)	(b)	(c)	(d)	(e)	(f)
SD (σ)	7.666	4.916	3.16663	1.25	1.1067	2.5104
PSNR	25.10	26.93	24.4535	29.165	30.153	27.983
IQA	0.297	0.356	0.4497	0.8437	0.7958	0.5829

Table 2: Evaluation of the obtained restored images.

image	(a)	(b)	(c)	(d)	(e)	(f)
PSNR	24.68	26.99	24.7260	74.4	74.4	74.4
IN	23	15	18	7	7	8
IQA	0.532	0.507	0.4517	0.9851	0.9856	0.9908

C. The proposed blind automatic deblurring architecture evaluation

Herein we are interested on evaluating of the LR algorithm on fairly blurred images (Figure 9, d, e f) using the estimated PSF values. Moreover for a comparative study, the Shock filter (SF) blind iterative method, based on Partial Differential Equations (PDE), associated with the proposed stopping criterion is considered.
Figure 11 illustrate obtained restored images using the LR algorithm associated to the proposed stopping criterion and using the estimated PSF values. One could notice that the blur effect is considerably reduced compared to blurred images represented in Figure 9. Indeed edges and fine image details are sharper and clearer.

Figure 11. Restored images with LR and ESD

Figure 12. Restored images with SF and ESD

Table 3: Evaluation of the proposed stopping criterion using classical deblurring methods LR and SF.

Images	LR (real SD)			LR (estimated ESD)			SF		
	PSNR	*IQA*	IN	PSNR	*IQA*	IN	PSNR	*IQA*	IN
(d)	74.4	0.9851	7	74.4	0.9849	7	24.7911	0.9186	5
(e)	74.4	0.9856	7	74.4	0.9907	6	26.1012	0.8660	4
(f)	74.4	0.9908	8	74.4	0.9795	8	23.8106	0.8852	8

Figure 12 depicts the restored image using the SF method. Comparing obtained images represented in Figure 10 (images d, e and f) and Figure 11. It could be noticed that there is not any apparent difference between restored images using the real SD values (Figure 10) and the estimated ones (Figure 11). Quantitative evaluation of obtained deblurred images using the LR algorithm with the real PSF values (Figure 10) and the estimated ones (Figure 11) and also the SF method (Figure 12) is illustrated in Table 3.

From all obtained values illustrated in Table 3, we can say that the LR algorithm provides quantitatively the same performance while associated with the real or the estimated PSF values. Compared to the SF blind method, it is clear that the LR blind algorithm provides best results in terms of PSNR and *IQA*.

From all experiments carried out, we conclude that, first the LR non blind algorithm is efficient for fairly blurred images restoration unlike the heavily blurred ones. Secondly the proposed architecture blind and automatic solution for the LR non blind iterative algorithm revealed encouraged results especially on fairly blurred images.

IV. CONCLUSION

This paper addresses the blind iterative deconvolution problem in image restoration. For this study, the non blind iterative LR algorithm is considered. An analysis and an automation of the algorithm are made. For this aim, a new method for blur PSF estimation is proposed to make the algorithm blind. Moreover to control the iterative process and make the algorithm fully automatic, a recently proposed stopping criterion is used. Obtained results revealed that the proposed architecture solution provides interesting results especially for fairly blurred image.

V. REFERNCES

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