# Edge based Blind Single Image Deblurring with Sparse Priors

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Abstract: Blind image deblurring is the estimation of the blur kernel and the latent sharp image from a blurry image. This makes it a significant ill-posed problem with various investigations looking for adequate solutions. The recourse to image priors have been noticed in recent approaches to improve final results. One of the most interesting results are based on data priors. This has been the starting point to the proposed blind image deblurring system. In particular, this study explores the potential of the sparse representation widely known for its efficiency in several reconstruction tasks. In fact, we propose a sparse representation based iterative deblurring method that exploits sparse constraints of edge based image patches. This process includes the K-SVD algorithm useful for the dictionary definition. Our main contributions are (1) the application of a shock filter as a pre-processing step followed by filter sub-bands applications for an effective contour detection, (2) the use of an online training data-sets with elementary patterns to describe edge-based information and (3) the recourse to an adaptative dictionary training. The experimental study illustrates promising results of the proposed deblurring method compared to the well-known state-of-the-art methods.

## 1 INTRODUCTION

### 1.1 Background

Blind image deblurring, similarly known in the literature as blind deconvolution or shape estimation from defocus or motion blur, is the estimation of the blur kernel and the latent sharp image from a blurry image. Mathematically, the problem is generally modeled as follows:

$$Y = K \otimes X + n; \qquad (1)$$

where $Y$ is the blurry degraded image, $K$ is the blur kernel, $X$ is the latent image, $n$ is noise, and $\otimes$ is the convolution operator. The given deblurring problem is a significant ill-posed problem. Its solution consists in recovering both $X$ and $K$ from $Y$. Various investigations looking for adequate solutions are presented. The recourse to image priors have been noticed in recent approaches to improve final results.

### 1.2 Related Works

One of the most interesting deblurring results are based on data priors and, in particularly, the priors that are deeply related to edge preserving properties. Tensor driven approaches are among important solutions that offer promising issues due to their efficiency in edge preservation (Guemri and Drira, 2014); nevertheless, they do not exploit the images similarities which are very useful in improving the overall performance. In fact, the redundancy of the image features is very noticeable and argued the success of the non-local means defined as the estimation of a pixel value by the weighted average of the similar structure pixels (Buades et al., 2005). Different image deblurring solutions based on this concept are later proposed. Furthermore, other existing solutions of blind deconvolution algorithms encompass explicitly edges for kernel estimation. For instance, the methods of Joshi et al. (Joshi et al., 2008) and Cho et al. (Cho et al., 2011) extract blurry edges to estimate the blur kernel useful for the overall deblurring process. These methods efficient in the case of small scale blur remain very limited in the case of large blur kernels. As a solution to this limitation, Cho and Lee (Cho and Lee, 2009) method incorporates a coarse to-fine fashion process to restore sharp edges and to estimate the blur kernel. A further extension of this method was proposed by Xu and Jia (Xu and Jia, 2010) who introduced a measure of the usefulness of the image edges via gradient image selection. Another category of methods



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exploit patch priors on edges of the latent image. For instance, Sun et al. (Sun et al., 2013) employed patch-based priors to focus on the image regions that are more informative for blur kernel estimation. Michaeli and Irani (Michaeli and Irani, 2014) adopted the internal patch recurrence property for estimation of the exploited blur kernel. Wei-Sheng et al. (Lai et al., 2015) utilized the normalized color-line prior to restore sharp edges without altering edge structures or enhancing noise.

The study of the state-of-the-art reveals that the promising solution to deal successfully with patch priors is the use of the sparse representation (Aharon et al., 2006; Elad et al., 2010). Especially, this representation exploits an over-complete dictionary from which few elements are linearly combined to describe an image patch. Among the existing sparse coding based deblurring methods, we can give as examples the methods of Lou et al. (Lou et al., 2011), Hu et al. (Hu et al., 2010), Liu et al. (Liu et al., 2013) and Yu et al. (Yu et al., 2010).

### 1.3 Contributions

Attracted by the simplicity and the efficiency of the Hu et al. method (Hu et al., 2010), we propose in this study to investigate the properties of this sparse representation based method by adding specific constraints on the edge based information inspired from the Sun et al. approach (Sun et al., 2013). In particular, the proposed edge based method exploits sparse representation using a dictionary learned directly from edges' patches of the blurred image. Indeed, the detection of these patches is with a binary mask that indicates the location of pixels with largest filter responses from a filter bank. The proposed method requires only the blurred image itself and utilizes sparsity constraints to iteratively estimate the deblur kernel and then applies a standard non-blind deconvolution algorithm to recover the deblurred image.

The rest of the paper is organized as follows. Section 2 gives an overview of the Hu et al. (Hu et al., 2010) method that represents an Adaptive Dictionary learning (ADL) based blind Deblurring method. A modified variant of this method via the introduction of edges-based constraints represents the underlying idea of our proposition detailed in Section 3. Section 4 gives numerical experiments to demonstrate the efficiency of the proposed method within a comparative study. Section 5 presents a conclusion including an overview of our contributions and a presentation of further investigations to deal with, looking especially for improving the proposed method.

## 2 BLIND SINGLE IMAGE DEBLURRING WITH SPARSE PRIORS

### 2.1 Numerical Formulation of the Sparse Coding for Image Deblurring

Sparse coding has been successfully used in image representation tasks mainly for addressing inverse problems like resolution enhancement (Walha et al., 2015b) and denoising (Walha et al., 2015a). Thus, it becomes a widely known approach in computer vision to learn dictionaries of image patches. In particular, the key idea of the sparse coding algorithm is to represent an input signal as a linear combination of a small number of elements, called atoms, selected from an over-complete dictionary. Mathematically, given an over-complete dictionary $D \in \Re^{n\times m}; n,m \in \Re$ with $m$ atoms and $n \prec m$, an image $X \in \Re^n$ could be sparsely represented by $D$ as follows (Aharon et al., 2006):

$$X = D\alpha; \tag{2}$$

where the representation cœfficient $\alpha \in \Re^m$ is sparse. This problem is formulated as the given optimization problem (P0)

$$(P0) : min_\alpha \|\alpha\|_0 \, s.t. \, \|X - D\alpha\|_2^2 \leq \rho; \tag{3}$$

where $\|\alpha\|_0 = card\,\{k \;\; \alpha_k \neq 0\}$ is the $l_0$ pseudo-norm of $\alpha$ (i.e. number of non-zero elements in $\alpha$) and $\rho$ characterizing an allowable error reconstruction. Looking for a simplification of the NP-hard problem (P0), the $l_0$ pseudo-norm is substituted by the $l_1$-norm as follows:

$$(P1) : min_\alpha \|\alpha\|_1 \, s.t. \, \|X - D\alpha\|_2^2 \leq \rho. \tag{4}$$

Moreover, the learning of a dictionary D from the training data Y according to the sparse coding principle is defined by

$$D = argmin_{D,\alpha} \|Y - D\alpha\|_2^2 + \lambda \|\alpha\|_1 ; \tag{5}$$

where $\alpha$ is the sparse representation of the training samples $Y$ over the dictionary $D$, and the constant $\lambda$ is a regularization parameter used for balancing sparsity of the solution and fidelity of the approximation to $Y$. Faced with the deblurring problem and given the linearity of the convolution operator, the blurred image could be formulated as follows:

$$Y = K \otimes X = K \otimes (D\alpha) = (K \otimes D)\alpha = D_b\alpha. \tag{6}$$

By adapting equation 5 in the context of deblurring, the reconstruction of an image patch $y_i$ could be addressed by solving the following optimization problem:

$$(P1) : \hat{\alpha}_i = argmin_{\alpha_i} \|\alpha_i\|_1 \, s.t. \, \|y_i - D_b\alpha_i\|_2^2 \leq \rho. \quad (7)$$

We must notice that the input blurry image $Y \in \Re^n$ is considered as an arranged set of image patches and the restoration is performed on each image patch $y_i$. After that, the optimal solution to $(P1)$ is thus applied to recover the deblurred image patch $x_i$ based on a deblurred version of the dictionary $D_b$ as follows:

$$x_i = D\hat{\alpha}_i. \quad (8)$$

## 2.2 Case Study of the Adaptive Dictionary Learning based Method

The Adaptive Dictionary learning (ADL) based blind Deblurring method is able to estimate blur kernels and thereby deblurred images (Hu et al., 2010). In fact, the main steps of this method could be summarized as follows: (1) an iterative process to encode each image patch with sparse coefficients and using an overcomplete dictionary in order to converge to the latent image, (2) estimation of the blur kernel, (3) Dictionary update without any additional information. The deblurred image is finally recovered once the deblur kernel is estimated.

In spite of the efficiency and the simplicity of the Adaptive Dictionary learning based blind Deblurring method, the deblurred output image still contain ringing artifacts around edges. Looking for improving its efficiency, a possible solution to overcome this limitation is mainly the exploitation of an edge patch based dictionary. This represents the core idea of our proposition further detailed in the next section.

# 3 PROPOSED BLIND IMAGE DEBLURRING METHOD

## 3.1 Motivation

Recently, edge based information has been exploited as a useful solution for the high-quality kernel estimation. This is due to their specificity compared to other image regions like flat or textured areas. Indeed, the blur tends around the edge image to attenuate its peaks and to smooth it in directions depending on the blur itself. Consequently, restoring the edge image could provide reliable edge information for kernel estimation. However, according to (Xu and Jia, 2010), not all the salient edges are useful in the process of kernel estimation since strong edges could degrade it under certain circumstances. That's why we propose to exploit sparse representation for an edge based dictionary learned online or in other words directly from the patch edges of the blurred image. Next sections detail the different steps of the proposed blind deblurring method.

## 3.2 Description of the Proposed Method

Algorithm 1 summarizes the main steps of the proposed algorithm. In fact, the specificity of our proposition remains in the definition of the dictionary. The latter has a specific structure characterized by edge patches with a fixed size $12 * 12$; the same value has been already defined in the ADL based method and the overall process is described in the work of Pan et al. (Pan et al., 2014). These patches are extracted from the deconvoluted image. The edge patches are extracted with the help of a binary mask that indicates the location of the pixels with largest filter responses from a filter bank. This filter consists of the derivatives of elongated Gaussians in eight orientations. It keeps the top of 2% of pixels locations.

For instance, Figure 1 shows that the edge detected by this mask are spanning all orientations and the number of detected edges increase from iteration to other. Consequently, the blurred and the latent image contain enough information to estimate the profile of blur kernel. As illustration, Figure 2 gives an idea about the main difference between the dictionary taken into account in ADL based method and the proposed method.

It is obvious from the given description in the Algorithm 1 that the proposed algorithm iteratively optimizes at once the kernel K, the edge dictionary $D_{edge}$ and the sparse coefficient $\alpha_i$ to converge to the deblurring blur kernel $K$ using the Tikhonov regularization method. At each iteration, the recovered latent image $X$ is the weighted sum of the overlapping image patches. Indeed, each image block $x_i$ of the recovered image is the result of the multiplication of the updated edge dictionary $D_{edge}$ and the sparse coefficient (Equation8).

# 4 EXPERIMENTAL STUDY

In this section, we present results of the proposed edge based blind image deblurring method and we compare it to some state-of-the-art approaches (Xu and Jia, 2010; Hu et al., 2010; Sun et al., 2013; Shan et al., 2008) which utilize prior information on image edges. Indeed, we examine the performance of

Algorithm 1: The proposed deblurring algorithm.

**Input**: Blurry image $Y$,Kernel size, Patch size, Number of iteration
**Output**: Latent image $X$ and Blur kernel $K$
**Initialization** : $K$= Gaussian kernel, Dictionary $D_{edge}$=DCT cœfficient
**for** *each iteration* **do**
*1.* Deconvolute the input image with the estimated kernel $K$.
*2.* Apply shock filter on the deconvoluted image.
*3.* Build edge mask from the enhanced image using directional filters.
*4.* Extract edge patches from the deconvoluted image.
*5.* Update the dictionary $D_{edge}$ via KSVD algorithm using edge patches.
*6.* Generate the blurred version $D_b$ of the dictionary $D_{edge}$.
**for** *each image patch* $y_i$ *of* $Y$ **do**
*7.* Find the sparse representation $\hat{\alpha}_i$ of $y_i$ according to $D_b$ by solving the (P1) problem (Eq.7)
*8.* Compute the corresponding version $x_i$ of the image patch $y_i$ using the dictionary $D_{edge}$ via Eq.8
**end for**
*9.* Merge overlapping patches to construct the deblurred image.
*10.* Estimate the deblur kernel $K$ using Tikhonov regularization method.
**end for**
*11.* Deconvolute the input image with the estimated kernel.

Figure 1: The increase of the number of edge detection by the binary mask .(a)the blurred image,(b) the edge detection in the first iteration, (c) the edge detection in the second iteration.

the proposed method via both qualitative and quantitative comparisons. Experimental studies are performed on various blurred images synthesized with different motion blurs as: fluff of the koala, and four test images from levin's database (Levin et al., 2011) of size 256*256.

A first experiment concerns the recovery of a blurred image (Figure 3 (a)) using the proposed method and different other methods such as (Hu et al., 2010; Shan et al., 2008; Xu and Jia, 2010). Figure 3 presents visual results of the restored images. After visual inspection, we can observe that only our result and the result of Hu et al. are the most similar to the ground-truth image, especially in the face region. For a deeper evaluation, Table 1 compares quantitatively the RMSE, PSNR, and SSIM results of the restored images. According to this table, we can see that the image reconstructed by the proposed sparse prior based deblurring method achieves the best measurement values than the other methods involved in this study.

A second experiment is performed to restore blurred images from Levin et al.'s database (Levin et al., 2011). Figure 4 provides examples of these


Figure 2: Illustration of the difference between the dictionary of the ADL based method and the the dictionary of our proposed method.

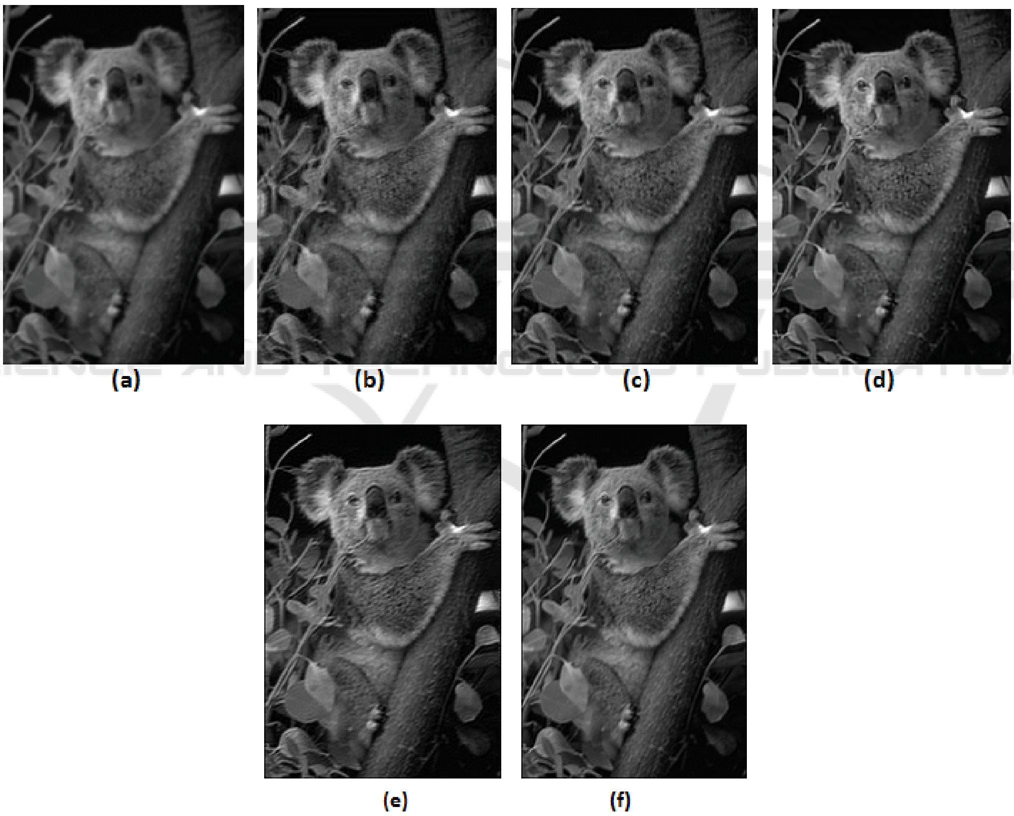


Figure 3: Visual comparative study between different methods for the reconstruction of an input blurred image.(a) The input image.(b) The result of Shan et al. (Shan et al., 2008) . (c) The result of Hu et al.(Hu et al., 2010).(d) The result of Xu et al.(Xu and Jia, 2010). (e )Our result.(f) The ground-truth image.

tested images which are blurred with various kernels (Figure 4(a), Figure4(d), Figure 4(g)and Figure 4(m)). In this experiment, we compare the performance of the proposed method with Hu et al.'s method. According to Figure 4, we observe that our method conserves the structure of the objects and the texture region does not contain ringing artifacts but the blur still exist in the deblurred results. Consequently, the visual comparison is difficult to determine the best result. That is why the quantitative anal-

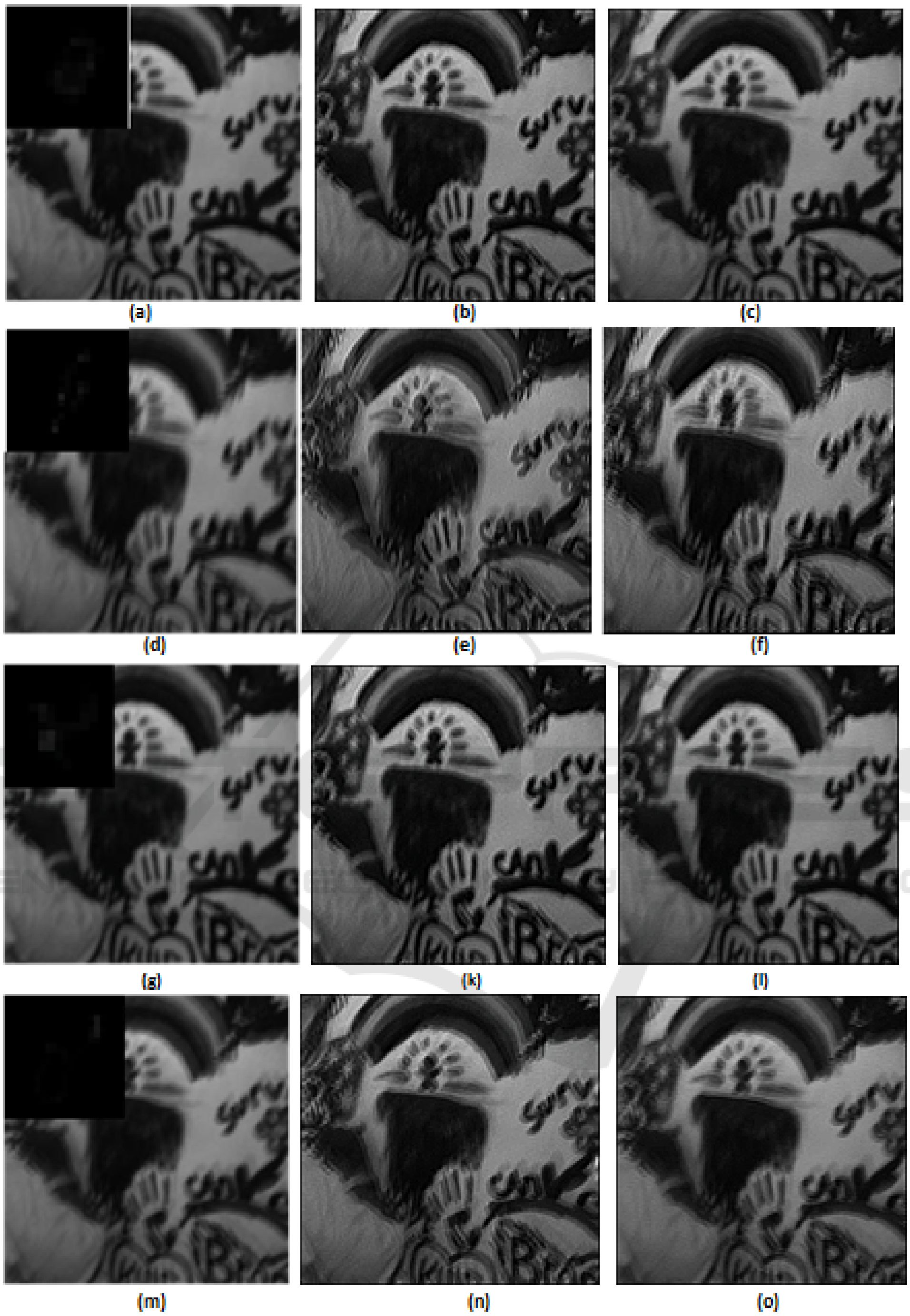


Figure 4: Qualitative comparison between images degraded with various motion blur and reconstructed using Hu et al.'s method((b),(e),(k),(n)) and our method ( (c), (f), (l),(o)).

ysis using the image metrics is important in this stage. Table 2 presents the results which are evaluated by calculating the PSNR and the SSIM values. Experimental results reported in this table clearly demonstrate the effectiveness of the proposed method.

In a third experiment, we evaluate the performance of the proposed sparse prior based blind deblurring method against a non-blind deblurring method that requires the kernel motion blur as an input parameter. For instance, the non-blind deconvolution of the Lucy image is involved in this study. Results of this experiment are presented in Figure 5

Table 1: Quantitative comparison based on PSNR, SSIM and RMSE results of images recovered by different deblurring methods.

| Image quality metrics | Result of (Hu et al., 2010) | Result of (Shan et al., 2008) | Result of (Xu and Jia, 2010) | Result of the proposed method |
|---|---|---|---|---|
| PSNR | 23.943 | 24.235 | 26.747 | 27.965 |
| SSIM | 0.602 | 0.652 | 0.756 | 0.806 |
| RMSE | 16.1937 | 15.659 | 11.727 | 10.192 |

Table 2: Comparative study between the proposed method and Hu et al.'s method for the deblurring for different motion blur kernels.

| Input images | Image quality metrics | Results of (Hu et al., 2010) | Our results |
|---|---|---|---|
| Image(a) | PSNR | 21.694 | 24.595 |
| | SSIM | 0.669 | 0.844 |
| Image(d) | PSNR | 21.321 | 22.581 |
| | SSIM | 0.617 | 0.731 |
| Image(g) | PSNR | 21.635 | 23.276 |
| | SSIM | 0.690 | 0.768 |
| Image (m) | PSNR | 22.007 | 22.169 |
| | SSIM | 0.641 | 0.680 |

Table 3: Quantitative evaluation between blind and non-blind deblurring methods.

| | Result of the non-blind deblurring Lucy's method | Result of the proposed blind deblurring method |
|---|---|---|
| PSNR | 19.541 | 23.276 |
| SSIM | 0.556 | 0.768 |

and Table 3. Quantitative and qualitative evaluations prove the efficiency of the proposed method that outperforms the non-blind deblurring method involved in this study.

## 5 CONCLUSIONS

In this paper, a novel edge based blind image deblurring method is proposed. This method exploits iteratively sparse priors using an online learned dictionary that adaptatively includes only edge patches extracted from the intermediate latent images. Indeed, the detection of these patches is successfully performed using shock and directional filters. This adaptative edge based-dictionary is useful for a more accurate estimation of blur kernels and hence improving deblurring images. The impact of the given contribution is studied visually and quantitatively on different test images and interesting results have been achieved. Further investigations, currently in progress, test the performance of the proposition with the help of two dictionaries; one devoted to patch based edges where as the other to the patch-based texture synthesis. Further tests would study the impact of various directional filters.

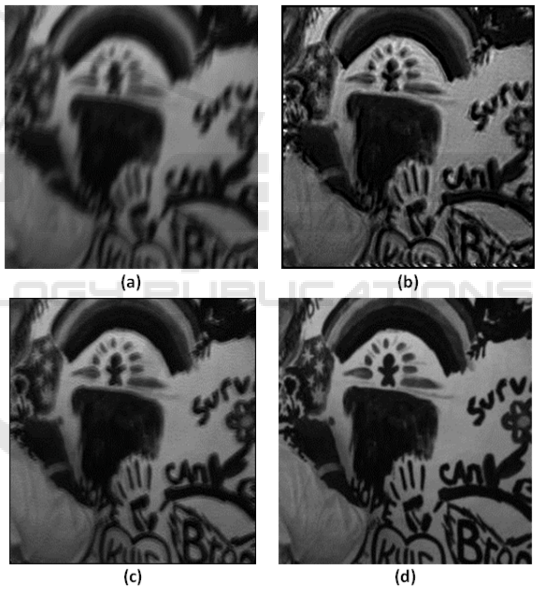


Figure 5: Qualitative evaluation between blind and non-blind image deblurring methods.(a) The blurred image,(b) the result of Lucy method,(c) Our result,(d)The groundtruth image.

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