AN APPROACH FOR IMAGE DEBLURRING: BASED ON SPARSE REPRESENTATION AND REGULARIZED FILTER

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Abstract - *Deblurring of the image is most the fundamental problem in image restoration. The existing methods utilize prior statistics learned from a set of additional images for deblurring. To overcome this issue, an approach for deblurring of an image based on the sparse representation and regularized filter has been proposed. The input image is split into image patches and processed one by one. For each image patch, the sparse coefficient has been estimated and the dictionaries were learned. The estimation and learning were repeated for all patches and finally merge the patches. The merged patches are subtracted from blurred input image the deblur kernel to be obtained. The deblur kernel then applied to regularized filter algorithm the original image to be recovered without blurring. The proposed deblur algorithm has been simulated using MATLAB R2013a (8.1.0.604). The metrics and visual analysis shows that the proposed approach gives better performance compared to existing methods.*

Key Words: **Image deblurring, Dictionary learning based image sparse representation, Regularized filter**

1.INTRODUCTION

Image deblurring is one of the problems in image restoration. The image blurring causes due to camera shake. The image blur can be modelled by a latent image convolving with a kernel K.

$$B = K \otimes I + n, \qquad (1)$$

Where B, n and I represent the input blurred image, latent image and noise respectively. The $\otimes$ denotes convolution operator and the deblurring problem in image are thus posed as deconvolution problem [13].

The process of removing blurring artifacts from images caused by motion blur is called deblurring. The blur is typically modeled as the convolution of a point spread function with a latent input image, where both the latent input image and the point spread function are unknown. Image deblurring has received a lot of attention in computer vision community. Deblurring is the combination of two sub-problems: Point spread function (PSF) estimation and non-blind image deconvolution. These problems are both independently in computer graphics, computer vision, and image processing [13].

Finding a sparse representation of input data in the form of a linear combination of basic elements. It is called sparse dictionary learning and this is learning method. These elements are composing a dictionary. Atoms in the dictionary are not required to be orthogonal [10]. One of the key principles of dictionary learning is that the dictionary has to be inferred from the input data. The sparse dictionary learning method has been stimulated by the signal processing to represent the input data using as few possible components.

To unblurred an image the non-blind deconvolution blur Point Spread Function (PSF) has been used [14].The previous works to restore an image based on Richardson-Lucy or Weiner filtering have more noise sensitivity[15 16]. Total Variation regularizer heavy-tailed normal image priors and Hyper-Laplacian priors were also widely studied [17].Blind deconvolution can be performing iteratively, whereby each iteration improves the estimation of the PSF [8].

In [3] found that a new iterative optimization to solve the kernel estimation of images. To deblur images with very large blur kernels is very difficult. to reduce this difficulty using the iterative methods to deblur the image. From [1] found that to solve the kernel estimation and large scale optimization is used unnatural $l0$ sparse representation [1].The properties for latent text image and the difficulty of applying the properties to text image de-blurring is discussed in [2].Two motion blurred images with different blur directions and its restoration quality is superior than when using only a single image [5].A deblurring methods can be modelled as the observed blurry image as the convolution of a latent image with a blur kernel[6].

The camera moves primarily forward or backward caused by a special type of motion blur it is very difficult to handle. To solve this type of blur is distinctive practical importance. A solution to solve using depth variation[8].The feature-sign search for solving the $l1$-least squares problem to learn coefficients of problem optimization [9][10] and a Lagrange dual method for the$l2$-constrained least squares problem to learn the bases for any sparsity penalty function.

2. IMAGE DEBLURRING WITH DICTIONARY LEARNING

To estimate the deblur kernel, an iterative method to alternately estimate the unknown variables, one at a time, which divides the optimization problem into several simple ones in each iteration. Were performed more importantly, the dictionary D is learned from the input image during this optimization process. The algorithm iteratively optimizes one of K, D, α by fixing the other two, and finally obtains the deblurring kernel. With the estimated kernel, any standard deconvolution algorithm to recover the latent image can be applied. The initial dictionary and the initial kernel value is convoluted and this result will be called as dictionary and this dictionary is subtracted by blur image.
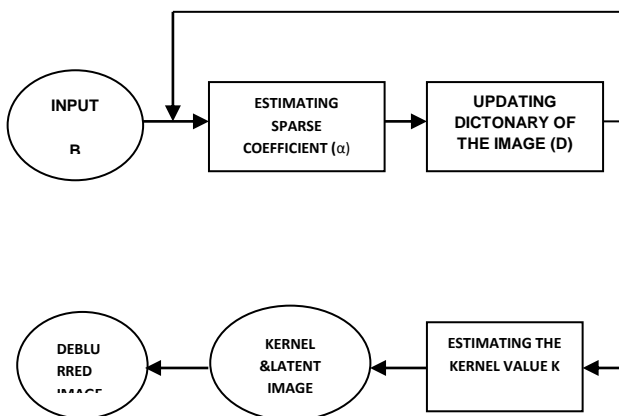

Fig.1 Block diagaram for deblurring algorithm

2.1 Estimate Sparse Coefficient

To follow the below algorithm to estimating the sparse coefficients of the given input blurred image.

ALGORITHM I

- Step 1: Get the blurred input image B
- Step 2: Spilt the B into four patches as p1,p2,p3,p4.

- Step 3: Consider first image patch p1 and find the sparse coefficient to fix K using Gaussian kernel and D as identity matrix.

$$\alpha^{(n+1)} = argmin||\alpha||_1 \qquad (2)$$

$$s.t. \ b = (K(n) \otimes D(n))\alpha \qquad (3)$$

- Step 4: For each iteration the α value should be updated into D
- Step 5: Take N iterations to estimating the $\alpha^{(n+1)}$.
- Step 6: Repeat the above 5 steps to all image patches and estimate the $\alpha^{(n+1)}$.

2.2 Updating Dictionary

In the knowledge of previous algorithm using the sprase coefficient to updating the dictionary of the image.

ALGORITHM II

- Step 1: To update the dictionary, deconvolve blurred image with kernel up to Last iteration using any deconvolution algorithm and get I_p.
- Step 2: I_p image is split into four patches.
- Step 3: Update the dictionary using $\alpha^{(n+1)}$ and D.

$$D^{(n+1)} = min||Ip - D(n)\alpha^{(n+1)}||^2_2. \qquad (4)$$

- Step 4: Repeat the steps 1 to 3 to all image patches and estimating the $D^{(n+1)}$.

2.3 Recovering Deblur Image

Consider previous algorithm to estimate the deblur kernel of the image and finally to recovered the deblur image.

ALGORITHM III

- Step 1: Find the latent image patch using

$$Ip^{(n+1)} = D^{(n+1)}\alpha^{(n+1)} \qquad (5)$$

- Step 2: Merge the all image patches of Ip.
- Step 3: The reconstructed image is subtracted from the blurred input image to obtain the deblur kernel.
- Step 4: Perform the deconvolution with the input blurred image and Deblur kernel using wiener deconvolution method.
- Step 5: Apply the regularization filter to the wiener deconvolution image to recover the original image.

After that the RMSE, PSNR, SSIM and visual perception were analyzed for various images

3. RESULTS AND DISCUSSION

To implement the deblur algorithm is simulated using MATLAB R2013a (8.1.0.604). The root mean square error, power to signal noise ratio, structural similarity index metric and visual perception were analyzed for various images. From the analysis, it is observed that the deblurring were efficiently performed.

Also carry out experiments with images blurred by randomly generated kernel. The existing deblurring algorithms are usually developed to deal with motion blur problems in which the kernels are oriented and simple. However, the camera shakes are complex and cannot be modeled well with simple blur kernels. This algorithm is able to recover the latent image with more details and better contrast.

The initial kernel K0 is set to be the Gaussian kernel with σ =1, and Γ is set as 1 and identity matrix I. The colour images are used for experiments and crop a small portion (e.g. 512×512 pixels) of the tested image to estimate kernel using the algorithm as given in Chapter 2.The regularized filter algorithm has been used to reconstruct image I. The final deblurred image can be recovered once the deblur kernel is estimated.
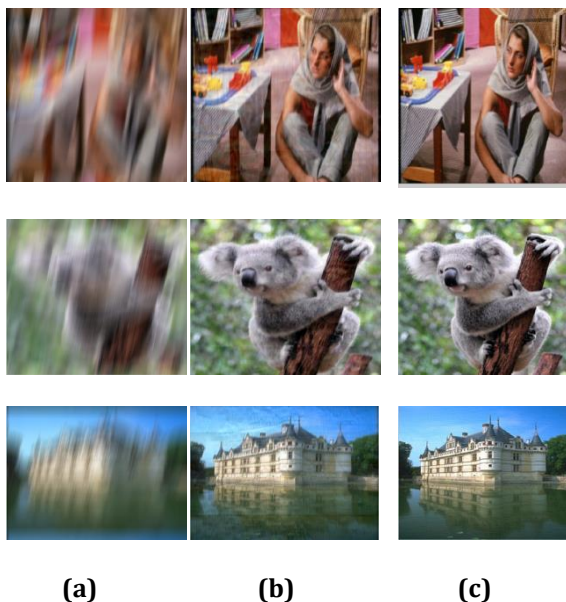

| (a) | (b) | (c) |

Fig.**2.**Experimentel results of deblurring algorithm.(a) blurred image (original size is 256 × 256);(b) deblurred image 1;(c)final deblurred image

3.1 Performance Measurement

The root mean square error(RMSE), power to signal noise ratio(PSNR), structural similarity index

metric(SSIM) and visual perception were analysed for various images. From the analysis, it is observed that the deblurring were efficiently performed for the use sparse representation of the image. If the accuracy of the estimated kernel is improved at each iteration, the proposed algorithm will be find a reasonably good solution. Further reducing the RMSE comparable to other methods.

Table -1: RMSE VALUES UNDER DIFFERENT ALGORITHMS

Image	Fergus [11]	Shan [12	Zhe Hu [13]	Deblur Image(1)	Deblur Image(2)
Barbara	5.53	7.02	4.61	**3.51**	**1.27**
Koala	5.41	6.57	5.10	**3.21**	**1.06**
Castle 1	7.87	7.46	6.73	**3.12**	**1.05**

Table -2: PSNR VALUES UNDER DIFFERENT ALGORITHMS

Image	Fergus [11]	Shan [12]	Zhe Hu [13]	Deblur Image(1)	Deblur Image(2)
Barbara	33.27	31.20	34.85	**37.21**	**46.03**
Koala	33.46	31.77	33.97	**37.87**	**47.54**
Castle 1	30.21	30.67	31.57	**38.23**	**47.57**

RMSE and PSNR comparison for different deblurring methods shown in the table. The experiments are conducted using four test images, namely Barbara, koala, castle1.

Table -3: SSIM VALUE OF IMAGES

Image	Deblur Image(1)	Deblur Image(2)
Barbara	0.7354	0.5427
Koala	0.7592	0.5486
Castle 1	0.8124	0.6495

From the analysis, it is observed that the deblurring were efficiently performed. Because of the ssim value should be less than 1.

4. CONCLUSION

In this paper, we propose an effective deblurring algorithm with dictionary learning using one single image were simulated. By decomposing the blind deconvolution problem into three portions deblurring and learning sparse dictionary from the image, our method is able to estimate blur kernels and thereby deblurred images. Experimental results show that this algorithm achieves favourable performance. In future the deblurring algorithm is to be implement on FPGA with suitable architectures

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