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Adaptive Optimized Discriminative Learning based Image Deblurring using Deep CNN

P. Hema Sree[1], D. Nagajyothi[2], K. Revathi[3], B. Janardhana Rao[4]
[1]Department of ECE
CVR College of Engineering, Ibrahimpatnam, Hyderabad, India
phemasree1@gmail.com
[2]Department of ECE
Vardhaman College of Engineering, Hyderabad, India
nagajyothi1998@gmail.com
[3]Department of CSE (AIML)
Sphoorthy Engineering College, Hyderabad, India
revathi.kandula@gmail.com
[4]Department of ECE
CVR College of Engineering, Ibrahimpatnam, Hyderabad, India
janardhan.bitra@gmail.com

Abstract— Image degradation plays a major problem in many image processing applications. Due to blurring, the quality of an image is degraded and there will be a reduction in bandwidth. Blur in an image is due to variations in atmospheric turbulence, focal length, camera settings, etc. Various types of blurs include Gaussian blur, Motion blur, Out-of-focus blur. The effect of noise along with blur further corrupts the captured image. Many techniques have evolved to deblur the degraded image. The leading approach to solve various degraded images are either based on discriminative learning models or on optimization models. Each method has its own advantages and disadvantages. Learning by discriminative methods is faster but restricted to a specific task whereas optimization models handle flexibly but consume more time. Integrating optimization models suitably by learning with discriminative manner results in effective image restoration. In this paper, a set of effective and fast Convolutional Neural Networks (CNNs) are employed to deblur the Gaussian, motion and out-of-focus blurred images that integrate with optimization models to further avoid noise effects. The proposed methods work more efficiently for applications with low-level vision.

Keywords- CNN, Deblurring, Discriminative Learning, Deep Learning, Optimization models.

I. INTRODUCTION

In many of the low-level vision applications, restoring an image has become a very longstanding problem [1,2]. Image restoration (IR) means retrieving a clean image from the degraded image. The degradation may be due to several factors, such as variation in atmospheric observations, camera motion, noise, etc. The general form of Image restoration is represented as,

$$y = Hf + n \qquad ----1$$

where, n is additive white noise, y is degraded image, f is clean image and H is degradation matrix [3]. Different IR approaches are developed based on different degradation matrices such as i) identity matrix operator for image denoising, ii) blurring operation for image deblurring and iii) composite operator for image super-resolution which performs down sampling and blurring operation.

Image restoration required prior regularization which is constrained to certain solution space [4, 5]. In many cases, Bayesian perspective $\hat{f}$ is calculated by resolving with Maximum A Posteriori (MAP)problem.

$$\hat{f} = arg \underbrace{max}_{f} \ log\ p(y|f) + log\mathrm{p(f)} \qquad ----2$$

where log p(f) is prior of ‘f ‘which does not depend on y and log p(y/f) is log-likelihood of perception of y. It can also be represented as,

$$\hat{f} = arg \underbrace{max}_{f} \frac{1}{2}\|y - Hf\|^2 + \lambda\Phi(f) \qquad ----3$$

where the fidelity factor is $\frac{1}{2}\|y - Hf\|^2$ and regularization factor is Φ(f). λ is the trade-off parameter that minimizes the energy function. These regularization and fidelity factors try to reinforce the required property for the given solution.

Basically, discriminative learning and optimization models are extracted and solved from equation 3. Prior, parameters are estimated for discriminative learning and optimization models are developed with some optimization algorithms in an iterative manner [6,7]. Generally, the objective function is given as

$$\underbrace{min}_{\Theta}(\hat{f}, f)$$

such that,

$$\hat{f} = arg\underbrace{max}_{f}\frac{1}{2}\|y - Hf\|^2 + \lambda\Phi(\mathrm{f};\Theta) \qquad \text{----4}$$

Many cases MAP estimation is used to guide the inference using discriminative learning approaches. If $\hat{f}$ is replaced with $f(y, H, \Theta)$, equation 4 works as general learning method. Methods such as NCSR [8] are optimization-based models which are used in super resolution, denoising and deblurring applications. Whereas MLP [9], SRCNN [10] and DCNN [11] are some of the discriminative learning approaches used for the above applications with the help of different training methods. Discriminative approaches have very fast testing speed but with the loss of flexibility, but optimization model-based approaches are generally time consuming with sophisticated estimation of priors to achieve excellent performance [10-14]. Consequently, considering the integration of these two approaches in an efficient manner to deblur the given degraded images is still a challenging task.

This paper is based on the design of an effective deblurring method by integrating discriminative based denoisers with optimization model-based approaches. Convolutional Neural Networks (CNN) are used for learning the deblurring with Rectifier Linear Units (ReLU) [10], Adam [15], batch normalization [16] and dilated convolution [17] design networks with an efficient model. This model is further concatenated with the Iterative graph-based image restoration method.

The remaining paper is described as follows: the literature survey and the related works of the deblurring methods are presented in section 2. The proposed deblurring method is discussed in section 3. Section 4 describes the implementation of the proposed work, the experimental results of the proposed deblurring method are presented in section 5, the conclusion is presented in section 6.

II. RELATED WORK

Detection of blur is a challenging problem. In [19], the features of blur are modeled with patches using slope of power spectrum, maximum saturation, histogram gradient span. Shi et al. [20] used frequency domain spectrum, local filter and gradient distribution. Dong Yang and Shiyin Qin [19], represented the restoration algorithm using edge features of Fourier transform and Radon transform. In [21], Zhang et al uses edge information and KNN interpolation to estimate blur map. The blur map is segmented based on the amount of blur in local regions and kernels are obtained using contours. These local kernels and BM3D (non-blind method) are used for deconvolution. In [22-23], blur in an image is detected using Haar wavelet transform. The kernel is estimated by exploiting consistent edges and eliminating outliers, in transitional latent image. MAP outline is used to estimate the initial kernel. Further, to restore the image, the estimated kernel uses the Iteratively Re-weighted Least Squares (IRLS) method to reduce optimization problems with appropriate objective functions using Maximum Likelihood approach.

In [24], the kernel element is predicted by Gaussian Conditional Random Fields, which obtains the relation among adjacent elements of the kernel. The MAP algorithm uses Maximum likelihood estimation method. Blind deconvolution methods are used to deblur the images in [25-28]. [29] uses non blind methods of deconvolution which includes Lucy-Richardson method [30], Wiener filtering [31], Regularization approach [32], etc.

To reduce the ringing artifacts, least square optimization methods are used along with controlled gain deconvolution method [33]. To attain PSF of the blur image as uniform, Kumar et al. [34] employed neural networks under learning-based techniques for deblurring process. Linear-Time-invariant-Regularized-Backward-Heat-Diffusion (LTI-RBHD) developed by Wang et al. [35] estimates blur kernel with different widths which results in better performance compared to wiener filtering method. An iterative method was developed by Leon Lucy and William Richardson to reconstruct the latent image from blurred image with known power spectral density. A Nash equilibrium method is used to obtain decoupled iterative BM3D deblurring method known as IDDBM3D in [36]. Gong et al. [37], Sun et al. [38] and Zhang et al. [39] developed deep learning methods based on CNN and RNNs.

The proposed deblurring technique has the following major contributions,

1. A hybrid framework for image deblurring is implemented by combining Iterative-Graph based image restoration.
2. Optimization technique and discriminative learning Deep CNN are implemented.
3. Improved performance metrics are obtained compared to state-of-the-art techniques.

III. PROPOSED METHOD

The performance of the image restoration is based on the regularization term in equation 3. Some of the existing deblurring methods are based on optimization model-based approaches viz. Gaussian Mixture Models (GMM) [40], Total Variation (TV) [41], Non-Local Means (NLM) [42-43] and K-

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SVD [44]. Each method has its drawbacks such as, high computation load is suffered with K-SVD method, water-color based artifacts are created using TV method, Irregular structures are over smoothed using BM3D and non-local means approaches. Irrespective of the performance and speed, color image prior plays an important role in real time application. Many images acquired from modern digital cameras are in RGB format and correlation between color channels should be jointly handled to achieve good success rate. Present methods focus mainly on gray image modelling approach and only very few methods concentrated on color modelling approach such as CBM3D [45]. But this method uses hand-pipeline design technique.

The block diagram of the proposed deblurring method is shown in figure 1. It is the combination of discriminative based and optimization-based methods.

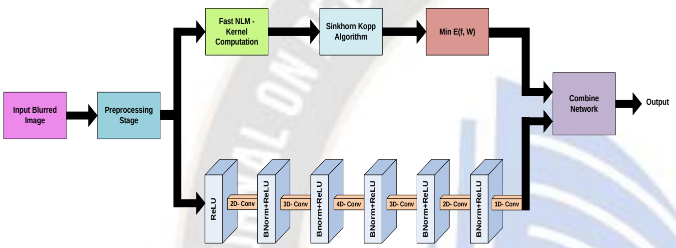

Figure 1. Block diagram of Proposed Image Deblurring method

The degraded image is given simultaneously to discriminative model (Deep CNN) and to optimization model (Iterative graph-based image restoration method). The deblurred images from both models are concatenated to obtain finest image.

IV. IMPLEMENTATION DETAILS

The image that has deblurred is given to preprocessing stage which is resized to 128 X 128 and using appropriate filter some noise is removed. This modified image is given simultaneously to both discriminative method and optimization method. In discriminative process to deblur an image is implemented using Deep CNNs. The architecture design techniques for residual learning and batch normalization are implemented with Deep CNNs. CNNs are more efficient because of the following reasons i) Ability to compute parallelly, ii) Has deep architecture with high modeling ability, iii) Its performance is further improved by combining with BM3D and iv) Excessive training and design procedures. The Deep CNN has seven layers with three blocks named as 1) First layer with Dilated Convolution and ReLU blocks, 2) Middle layer with five Dilated Convolution, Batch Normalization and ReLU blocks and 3) The Last layer with Dilated Convolution block.

The first to last layers are set to 1,2,3,4,3,2,1 expanded convolution with 3x3 as dilation factor.

Feature map of 64 is set to each middle layer. Basically, using the dilated filter, the context information enables to reconstruct the degraded image in the case of deblurring. To acquire context data, CNN enlarges the receptive field with the process of forward convolution procedures either by increasing the depth or filter size. But using these methods, computational burden increases [46] because of the design of CNN network has spread large complexity. So, CNN network is designed with 3 x 3 filter having large depth size making convolution process dilated to achieve appropriate network depth and receptive filed. This method is having advantage over the traditional convolution process. The dilation factor (s) of a dilated filter is interpreted as 2s+1 x 2s+1 sparse filter with non-zero 9 fixed entry positions [47]. The corresponding layer in the receptive field is 3,5,7,9,7,5 and 3. Therefore proposed network has 33 x 33 receptive field [48].

The performance of deblurring [49] is improved with batch normalization and residual learning which fastens removal of various levels of noise along with zero padding method. It regenerates a neat latent image. The deblurred image is applied to optimization method simultaneously. In this process, an iterative-Graph-based image restoration algorithm is implemented that consists of outer iterations and inner iterations. In this optimization process the data adaptive matrix 'M' is estimated from unknown image and later it is improved with iterations. The weight matrix "W" is found for each iteration which defines objective function as,

$$E(f) = (y - Af)^T \left(I + \beta(I - W)\right)(y - Af) + \eta z^T \ (I - W) f \qquad \text{----5}$$

where parameter related to blur is β > -1 and noise is η > 0. The filtered and blurred part of input y is determined in the first term. Based on the amount of blur and noise, the frequency selectivity is specified by β. The data-adaptive difference is the second term determined by normalized-Laplacian matrix. Further filtering the equation 5, the objective function is represented as,

$$E(f) = ||\{I + \beta(I - W)\}^{1/2}(y - Af)|| + \eta|| (I - W)^{1/2} f|| \qquad \text{----6}$$

The term $E(f) = ||\{I + \beta(I - W)\}^{1/2} = 0\Lambda^{1/2}0^T$ is used for filtering which is semi definite and symmetric matrix. This term acts as a sharpening filter. To avoid deblurring problems in real world images, different derivates are taken by the fidelity term. Unpleasant artifacts due to ringing and noise effects are avoided by the process of regularization to store finest information in the restored image. The cost function is minimized in each step to set its gradient to zero.

$$\nabla E(f) = -2A^T\left(I + \beta(I - W)\right)(y - Af) \ + 2\eta(I - W)f = 0$$

which are positive definite and symmetric linear equations.

$$\left(A^T(I+\beta(I-W))A+\eta(I-W)\right) = A^T(I+\beta(I-))y \qquad ----7$$

Conjugate Gradient is implemented to interpret A and A^T. In many cases, at least three outer iterations are performed to meet expected output (deblurred).

$$E(f) = (y-f)^T(I+\beta(I-W))(y-f) \qquad ----8$$

The objective function is optimized further by using steepest decent technique.

$$f' = f' - 1 + \mu(I+\beta(I-W))(y-f'-1) \qquad ----9$$

In the first iteration, by setting initial values to zero and selecting step size as one(μ=1), the function is of the form,

$$f'_l = (I+\beta(I-W))y \qquad ----10$$

The data adaptive sharpening procedure is determined by equation 10. High pass filtered part if input is combined adaptively when β>0.

Some part of the high pass filtered version of the input image is added adaptively with β>0. W consists of some amount of information of the original image and also about the nature of blurring process. Therefore, data-adaptive sharpening technique is provided by equation 10. From each outer iteration, (f'^{M-1}), Kernel-similarity matrix 'M' is calculated from final valuation of the previous step. Fixed parameter values of the regularization terms (η and β) are considered for all test images based on variance in noise and blurring consequence. Generally, η and β is chosen between [0,0.4] and [0,1]. These values can be changed based on severity in noise level and nature of blurring. The algorithm is initialized with suitable estimate in each step with prior analysis so that this algorithm converges fast. Depending on the nature of degradation, the outer and inner iteration numbers are assigned in advance. Based on Predicted Mean Square Error (PMSE) estimate, the iterations are stopped. The PMSE is denoted as,

$$PS\widehat{ME}(q,k) = \frac{||\widehat{A}f - Af'^{(q)}_k||^2}{n^2} \qquad ----11$$

Where the deblurred image is represented as Af'. Once the following conditions are satisfied, the Conjugate Gradient Iterations are stopped.

$$PSM\widehat{E(q,k+1)} > PS\widehat{ME}(q,k) \qquad ----12$$

The obtained deblurred image from this optimized stage is combined with Deep CNN output and the resultant restored image has attained very good Peak signal to Noise Ratio (PSNR)

V. EXPERIMENTAL RESULTS

The efficiency of this algorithm is tested by experimenting with some set of blurred images. Gaussian, out-of-focus and non-linear camera motion blurred images are considered. MATLAB functions are used to implement this deblurring process. Set of color images are convolved with Gaussian blur(25x25) with standard deviation (σ) of 1.6 to obtain Gaussian blur images. Out-of-focus blurred images are obtained by using a disk function (radius r =5) and motion blurred images are produced based on the method in [50]. Even Gaussian white noise is further added to these blurred images with different variances (1 and 0.2).

The experiment is implemented by taking patch size as 5x5, search neighborhood size as 11x11, inner and outer iterations as 20 and 3 respectively. The metric that is used to decide how closely the resultant image resembles the original image is Peak Signal to Noise Ratio (PSNR). Figure 2 shows different images such as butterfly, Lenna, number plate, etc blurred with out-of-focus blur with radius 7. The deblurred output obtained using the proposed method is shown in figure 3. PSNR for different set of deblurred images are summarized in table 1, table 2 and table 3.

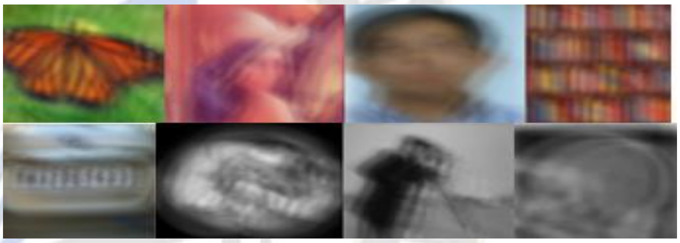

Figure 2. Out-of-focus blur for different images

Figure 3. Deblurred Output from proposed method for different images

TABLE 1: PSNR PERFORMANCE WITH KERNEL SIZE OF 25 X 25 FOR GAUSSIAN BLUR

Blur/Images	Gaussian (σ^2 = 0.6)			Gaussian (σ^2 =2)		
	BM3D	**WNN**	**Proposed**	**BM3D**	**WNN**	**Proposed**
Butterfly	30.26	31.22	32.44	30.21	30.87	**31.46**
Lenna	30.99	30.42	31.76	28.92	28.68	**30.39**
Human Face	29.90	28.80	34.16	27.24	28.78	**31.21**

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Number plate	31.37	31.10	32.47	29.71	29.53	**30.12**
CT-abdomen	28.89	29.72	31.70	27.82	28.93	**29.13**
Cameraman	30.45.	31.23	32.11	29.45	29.61	**30.18**
Brain Scan	29.42	29.62	30.40	28.12	28.31	**29.4**

TABLE 2: PSNR WITH DISK FUNCTION OF RADIUS 7 FOR OUT-OF-FOCUS BLUR GENERATED IMAGES

Blur/Images	**Out-of-focus (σ^2 = 0.2)**			**Out-of-focus (σ^2 =1)**		
	BM3D	**WNN**	**Proposed**	**BM3D**	**WNN**	**Proposed**
Butterfly	29.13	29.73	30.20	29.03	29.61	29.41
Lenna	28.42	28.76	30.44	28.02	28.1	28.32
Human Face	31.09	29.87	33.21	27.3	27.5	32.67
Number plate	30.42	28.01	29.09	27.01	27.28	27.52
CT-abdomen	28.5	30.11	29.69	28.42	28.65	29.05
Cameraman	30.01	28.5	30.18	27.2	27.49	28.15
Brain Scan	29.36	28.5	29.46	27.12	27.40	27.42

TABLE 3: PSNR AND SSIM PERFORMANCE OF AN ITERATIVE GRAPH-BASED METHOD AND HYPER-LAPLACIAN METHOD FOR CAMERA MOTION BLUR.

Blur/Images	**Motion (σ^2 = 0.2)**		**Motion (σ^2 =1)**	
	Hyper-Laplacian Method	**Proposed**	**Hyper-Laplacian Method**	**Proposed**
Butterfly	29.13	30.20	29.03	29.41
Lenna	28.42	30.44	28.02	28.32
Human Face	31.09	33.21	27.3	32.67
Number plate	30.42	29.09	27.01	27.52
CT-abdomen	28.5	29.69	28.42	29.05
Cameraman	30.01	30.18	27.2	28.15
Brain Scan	29.36	29.46	27.12	27.42

VI. CONCLUSION

A hybrid framework for image deblurring is implemented by combining Iterative-Graph based image restoration optimization technique and discriminative learning Deep CNN. It is observed that experimental results demonstrated by integrating these two techniques are more effective, fast and flexible than other image restoration methods. By using multiple priors, deblurring performance has been improved. This technique can be further extended to deblur the images that are degraded with complicated non-uniform blurring conditions.

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