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Assessment of Effectiveness in Image deblurring using Blind Deconvolution Methods

Sudharshan Banakar[1], Chandrashekhar K[2]

[1]Research Scholar, Department of Electronics and Communication, VTU, Belagavi, Assistant Professor, Department of ECE,RYM Engineering College, Ballari, Karnataka, 583104,India

[2]Professor and Research Supervisor, Department of Electronics and Communication, VTU Belagavi, RYM Engineering College, Ballari, Karnataka, 583104, India

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Abstract- Blind deconvolution is a critical image restoration technique aiming to recover latent sharp images from blurred optical images without prior knowledge of the point spread function (PSF). With advances in deep learning, convolution-based blind deconvolution methods have shown significant promise in addressing challenges posed by complex optical degradations in various advanced imaging applications like natural images. This study assesses the effectiveness of these methods by reviewing state-of-the-art algorithms, analyzing their mathematical foundations, and demonstrating their performance through experimental metrics like PSNR and SSIM. This study further provides details of current challenges, future research directions.

Keywords: *Blind Deconvolution, Image Deblurring, Convolutional Neural Networks, Point Spread Function*

1. INTRODUCTION

Image degradation caused by blurring is a common problem in optical imaging systems, limiting the clarity and usability of images across fields like medical imaging, remote sensing, and microscopy. Traditional non-blind deconvolution techniques require prior knowledge of the blur kernel, which is often unavailable or difficult to estimate in practice. Blind deconvolution methods aim to simultaneously estimate both the latent sharp image and the unknown blur kernel, making them highly relevant for advanced optical applications. Recently, deep learning models, especially convolutional neural networks (CNNs), have introduced powerful data-driven solutions, leveraging large datasets to model complex blurring phenomena and restore high-quality images robustly.

The goal of image deblurring is to restore sharp features from a blurred input image, thereby enhancing its optical clarity. It is crucial for various applications, including security, traffic monitoring, surveillance, medical imaging, and art restoration. If the point spread function (PSF) of the blurring process is known in advance, non-blind deconvolution can be applied, but this requirement is often difficult to satisfy for natural images. Because of this limitation, blind deconvolution has been developed to simultaneously estimate the sharp image and the unknown blur kernel. Despite its usefulness, many challenges remain because the space of unknowns is much larger than in non-blind deconvolution and effective regularization is required to produce plausible recovered images with realistic sharp edges. The same challenges also make it difficult to develop a general-purpose blind deconvolution approach that can handle a broad spectrum of images and blur kernels. Conventional approaches rely on handcrafted image priors and kernel constraints to reduce the number of plausible solutions compatible with the observations. These priors are often expressed as penalty functions or probabilistic distributions that are integrated into a maximum a posterior (MAP) framework. Although such handcrafted priors perform well on a constrained set of images, they typically fail to work for images that deviate from the assumed prior statistics.

Levin, A. et al. [1], Blind deconvolution is typically expressed with a convolution constraint, i.e., the blurry image is obtained by convolving a sharp image with a blur kernel, and oftentimes also additive noise. This operation takes place in the spatial domain and the blur kernel is commonly referred to as the PSF. Finding the blur kernel and the sharp image that explains a blurry observation is known as blind image deconvolution. Because the convolution operation is essential to formulate the problem, its properties and implementations deserve a brief introduction. Deblurring is one of the most complicated restoration processes, since most approaches require accurate PSF estimation. Numerous deconvolution algorithms have been proposed, including Wiener filter, Richardson–Lucy method, and variational Bayesian reconstruction. Recently, machine learning techniques have demonstrated promising results high-quality de-blurred images are obtained without explicit PSF estimation. These approaches usually demand more complex infrastructure and larger databases for training; nevertheless, deep learning is gradually emerging as a significant technique for blind deconvolution

Sorel et al [2], For every approach, the quality of the de-blurred image is evaluated on the basis of the peak signal-to-noise ratio (PSNR), structural similarity (SSIM) index, and visual inspection. Extensive experimental results demonstrate the effectiveness of these methods on synthetic and real-world images. When applied locally, the results can be fused to enhance the overall image quality, especially for spatially variable blur such as camera shake with rotational motion. Approximating a spatially varying PSF by interpolating adjacent kernels yields further improvement

1.1 Understanding Image Blur and its types

Image blur occurs due to various reasons and accurate distinction of each type is important for modelling and restoration. Williams et al [3], The majority of blur types can be categorized into the following four classes:

- **Motion blur:** This occurs when an object moves significantly during the time the shutter is open.

- **Out-of-focus blur:** This refers to the capture of an image without proper focus.

- **Gaussian blur:** This describes the distortion of an image due to the camera lens.

- **Atmospheric turbulence blur**: This is caused by variations in the refractive index of light between the imaged object and the capturing setup.

The understanding of these blur types is relevant to the design of blind-deconvolution methods.

2. LITERATURE REVIEW

2.1 Classical Blind Deconvolution Methods

Traditional blind deconvolution methods treat the problem as an inverse problem using iterative optimization methods are alternate minimization, expectation maximum. Regularization is used to reduce the instability and ambiguity of solutions. Regularization techniques are Total variation (TV) regularization, sparse gradient regularization, and natural image priors. Bayesian Approaches provide a probabilistic framework for blind deconvolution. Maximum A posterior estimation and Variation Inference are the Bayesian approaches[21].

2.1.1 MAP-Based Iterative Estimation (Bayesian):

Levin et al[1] employed maximum a posterior (MAP) estimation, where the latent sharp image and blur kernel are estimated by maximizing their posterior probability. This involves alternating minimization where one is optimized and other is held constant and Vice-versa. Priors like sparsity, edge preservation are crucial for regulating the ill-posed nature of the problem. Despite producing interpretable kernels, these methods suffered from local minima and high sensitivity to noise, often requiring manual tuning of hyper parameters.

2.1.2 Richardson-Lucy Algorithm (Iterative)

It is originally developed for non blind deconvolution, Richardson-Lucy algorithm can be adopted for blind deconvolution. It is an iterative method based on Bayesian statistics targeting to find the image and PSF that maximizes the likelihood of observing the blurred image. Accelerated and damped versions exist to improve convergence and stability[22]

2.1.3. Total Variation (TV) (Regularization)

It is frequently incorporated into blind deconvolution methods specially within MAP frameworks, It promotes piecewise constant solutions, effectively preserving edges and reducing noise while suppressing ringing artifacts which are associated with deconvolution[23].

2.1.4 Expectation-Maximization (EM) and Variation Inferences: These probabilistic frameworks alternated between kernel estimation and image restoration steps. While statistically sound, they were computationally expensive and prone to artifacts in severely blurred optical images[24].

2.1.5 Dictionary Learning and Sparse Representation

To address noise sensitivity and improve robustness, convolutional dictionary learning and sparse coding emerged. Wang et al.[4] proposed a convolutional dictionary learning framework that models both latent images and blur kernels as sparse combinations of learned atoms. Applied to Optical Coherence Tomography (OCT), this approach reduced speckle noise and enhanced contrast significantly compared to baseline methods, achieving average PSNR improvements of 3–5 dB. Sparse models encouraged image smoothness and sparsity of kernel estimates, mitigating noise amplification common in classical deconvolution.[27]

2.2 Deep Learning–Based Blind Deconvolution methods

CNN-based blind deconvolution has emerged as a promising approach for image deblurring in medical imaging due to its ability to effectively handle unknown and complex blur patterns. Convolutional Neural Networks (CNNs) can learn blur characteristics directly from data, enabling them to estimate both the blur kernel and the latent sharp image without prior knowledge of the blur type. Through training on large datasets, CNNs develop robust capabilities for identifying and removing diverse blur effects, such as those caused by motion or defocus, which are common in medical imaging[25]

Generative Adversarial networks(GANs) are used to handle complex and real world blurs and Recurrent neural network(RNNs), where progressive refinement is useful, these can literally refine image clarity, particularly effective for non-uniform or spatially varying blur[26]

Ren et al [5] introduced SelfDeblur, a neural blind deconvolution algorithm leveraging deep image priors without explicit training data. It used a fully convolutional network to simultaneously estimate the blur kernel and latent image, outperforming MAP-based methods in both synthetic benchmarks and real optical images by a PSNR margin of 1.5 dB on average.

Kurimoto et al [6] developed a multi-frame blind deconvolution method for X-ray microscopy using untrained neural networks that adaptively refined PSF estimates across multiple frames, achieving resolution enhancement beyond classical approaches and effective artifact suppression.

These CNNs implicitly encode complex blur models, including spatial variations and nonlinear effects, which traditional kernels fail to capture.

2.2.1 Spatially Adaptive and Hybrid Approaches

Recent work focuses on non-uniform or spatially varying blur common in optical systems.

Dong et al [7] proposed spatially adaptive blind deconvolution that dynamically estimates local kernels across regions. Their approach applied region-based CNN kernels combined with global correction to maintain consistency, yielding superior restoration quality under challenging distortions such as defocus and motion blur.

Hybrid methods combine physics-based PSF modelling with learned priors to balance interpretability and data adaptation.

Table 2: Comparison of earlier Blind deconvolution methods

Method	Technique	Image Types	Key Results	Strengths	Limitations	Citation
MAP-based Iterative method	iterative optimization	General optical images.	Kernel estimation, Moderate deblurring.	Theoretically principled.	slow convergence, Sensitive to noise,	Levin et al. (2009)
Convolutional Dictionary Learning Sparse coding learned dictionaries	OCT(Optical Coherence Tomography)	Microscopy	Noise reduction, 3–5 dB PSNR improvement	Robust to noise,	Interpretable Requires dictionary training	Wang et al. (2022)
SelfDeblur (Neural Blind Deconvolution)	Deep image prior CNN	Unsupervised Retinal microscopy +1.5 dB PSNR	Better visuals	no training data needed, End-to-end learning,	Computationally intensive	Ren et al. (2020)
Multi-frame UNN Blind	Untrained neural	Multi-frame X-ray	Significant	Adaptive multi-	Needs multiple	Kurimoto et al.

Deconvolution	networks	microscopy	resolution gain	frame processing	observations	(2024)

3. RESEARCH ISSUES AND CHALLENGES

The high computational requirements also impede real-time performance, which is critical for applications such as autonomous driving and video surveillance. Deep models such as ESRGAN and produce high-quality results but are computationally expensive, rendering them unsuitable for real-time processing where latency low is crucial. A significant challenge in the field of deep learning for image enhancement is the capacity of models to generalize across diverse datasets and address various types of degradation. Various techniques have been proposed to enhance the interpretability of deep learning models, such as Layer-wise Relevance Propagation (LRP) and saliency maps. However, these methods are often computationally intensive and may not provide a comprehensive understanding of the model's behaviour. Developing inherently interpretable architectures for image enhancement. The efficacy of deep learning models for image quality enhancement is significantly dependent on the availability of extensive, high-quality labelled datasets. For numerous applications, real-time performance is crucial for practical deployment. This is particularly significant in scenarios such as autonomous driving, robotics, and surveillance, where image quality enhancement must be executed instantaneously to ensure timely decision-making. A significant challenge in deep learning-based image enhancement is the balance between perceptual quality and pixel-wise accuracy. Conventional loss functions such as MSE or PSNR are frequently employed in model training.

3. Proposed methodology

To assess the effectiveness of blind deconvolution methods for deblurring optical images

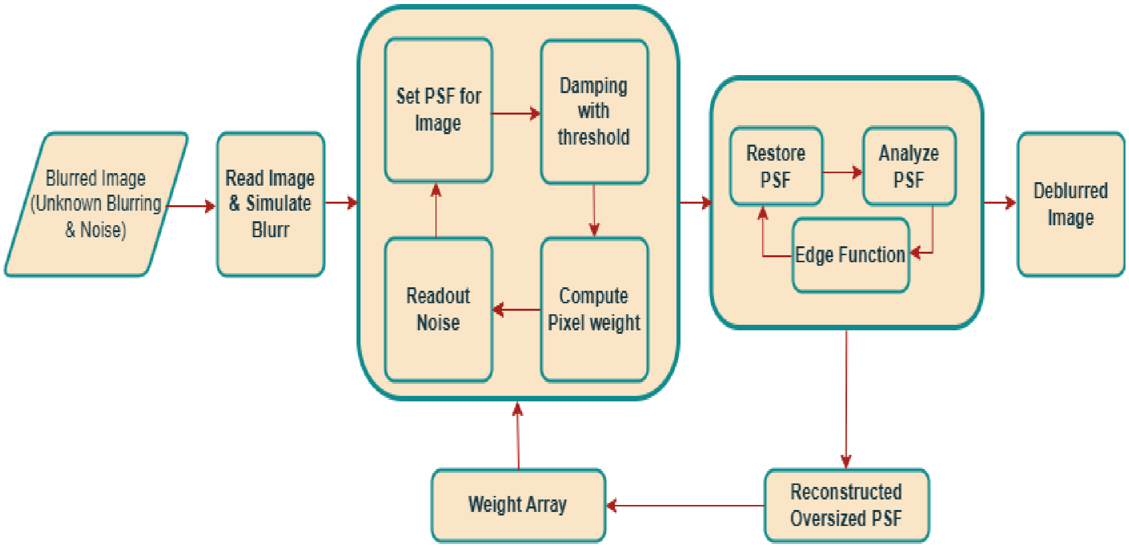

Fig 1: Image deblurring using Blind deconvolution method

The proposed methodology involves Selecting and implementing state-of-the-art blind deconvolution algorithms based on traditional and deep learning convolutional models. Using datasets of optical images blurred with unknown and varying PSFs. Evaluating restoration quality with metrics such as

PSNR (Peak Signal-to-Noise Ratio), SSIM (Structural Similarity Index) and visual inspection assessing against classical iterative blind deconvolution methods to highlight improvements.

4. MATHEMATICAL MODELLING FOR BLIND DECONVOLUTION

4.1 Forward image-formation model

Let y represent the observed blurred image, x the latent sharp image and h the unknown blur kernel. The image degradation is modeled as:

$$y=x*h+n \tag{1}$$

where

$*$ denotes convolution n is additive noise.

Blind deconvolution seeks to jointly estimate x and h by solving:

$\min (x, h \|y-x*h\|^2 + \lambda R(x, h))$ where R(x,h)

R(x,h) is a regularization term incorporating prior knowledge and λ a weighting factor.

Deep learning methods replace explicit modelling of R through learned convolutional filters and neural network architectures that implicitly encode image priors.

4.2 Optimization

(a) MAP (Penalized ML)

Assume $n \sim N(0, \sigma^2 I)$ With image prior $\phi(x)$ and kernel prior $\psi(k)$

$$\text{Min } 1/2\, \sigma^2 I \;\; \|A(k)\, x-y\|^2 + \lambda x\, \phi(x) + \lambda k\, \psi(k) \;\; \text{s.t. } k \geq 0,\; 1^{\top} k=1. \tag{2}$$

Typical choices

Sparsity of gradients / heavy-tailed

$$\phi(x) = \sum p\, \rho((\nabla x) p) \quad \text{with } \rho(t) = |t|^p \qquad \rho(t) = |t|^p \quad (0 < p \leq 1) \tag{3}$$

Total variation (TV)

$$\phi(x) = \|\nabla x\|_1 \tag{4}$$

Kernel priors

$$\psi(k) = \|k\|^2_2 \;\; \text{(smoothness)} \;\; \text{or} \;\; \psi(k)=\|k\|_1 \tag{5}$$

(sparse motion), plus support/center constraints.

Alternating minimization (AM)

x-update (nonblind deconvolution)

$$\text{Min } 1/2\, \sigma^2 I \;\; \|A(k)\, x-y\|^2 + \lambda x\, \phi(x) \tag{6}$$

Solvers are conjugate gradient, half-quadratic splitting (HQS), ADMM; frequency-domain with circular boundaries.

k-update (kernel estimation)

$$\min_{k\geq 0,\ 1^{\top}k=1} \|A(k)x-y\|^2 + \lambda k\, \phi(x) \quad (7)$$

Often solved in gradient domain using $\nabla y \approx \nabla x * k$. (8)

b) Variational Bayes / EM

Latent sharp-gradient variables $g=\nabla x$ with Gaussian scale mixtures (GSM):

$$p(g) = \prod_p \sum_m \pi_m \ N(g_p;0,\tau^2_m). \quad (9)$$

E-step: posterior over scales/latents; M-step: update x,k by expected quadratic objectives.

(c) Marginal likelihood (Type-II ML)

Integrate out x, $p(y \mid k) = \int p(y \mid x, k)p(x)\, dx$ (10)

With Gaussian priors this yields closed-form log-evidence; optimize over k.

4.3 Deep learning variants

- **Direct kernel predictor:** $k = f_\theta(y)$ then non-blind deconvolution for x
- **End-to-end restoration:** $x = g_\theta(y)$ where the network implicitly learns priors; the forward model still informs losses:

$$L = \|x-\hat{x}\|^1 + \beta \|y-\hat{x}*\hat{k}\|^2_2 + \text{perceptual/TV}. \quad (11)$$

5. RESULTS AND DISCUSSIONS

The proposed DnCNN model was tested on Gopro datasets of blurred and sharp images, The model was trained to distinguish non blurred images from blurred images. Each step of the image processing, model prediction and output generation is explained below, followed by quantitative results comparing the model's performance with existing deblurring deconvolution methods.

Step 1: Data acquisition

High-quality datasets of blurred and sharp images, such as GoPro, GOPRO-Large, or real-world datasets, are used for supervised training. Pre-processing includes resizing, normalization, and data augmentation. Encoder-Decoder is utilized to capture global context (encoder) and refine local features (decoder). The Encoder composed of convolutional layers to extract features while down sampling and the decoder is symmetric to the encoder with up sampling layers to reconstruct the image. Residual Blocks are used to preserve detailed features and stabilize training. Link encoder and decoder layers to retain spatial details and ensure gradient flow. The Loss Functions indicate, **Pixel-Level Loss** - differences between reconstructed and ground-truth images (e.g., MSE or L1 Loss). **Perceptual Loss** - Leverages pre-trained deep networks (e.g., VGG-19) to ensure high-level similarity.

Step 2: Image Pre-processing

Pre-processing of the input images was performed to standardize the data and enhance the quality for model input. The following steps were applied to each image:

1. Initial stage: A **PSF** is set for the image. **Pixel weights** are computed to adaptively handle variations in noise and blur. Threshold-based damping is applied to ensure stability during the restoration process and to minimize noise amplification. The reconstructed PSF is analyzed to identify the **Edge Function**.

2. Resizing:. Batch Size Typically 16-32, based on computational constraints.

3. PSF estimation: Edges and boundaries are used to **restore the PSF** more accurately. The refined PSF is used to deblur the image, resulting in a **de-blurred output**.

4. Optimizer: Adam optimizer with learning rate scheduling is done.

Step 3: DnCNN model training,

The DCNN was trained using the pre-processed grey scale images. Including the number of filters, kernel size, and learning rate. The training process iterated over a total of 100 epochs, with an initial batch size of 32. During each iteration, the model adjusted its parameters based on the accuracy of the blur classification task.

Output during Training: Training loss decreased, and accuracy increased as the model learned to classify blurred images effectively.

Step 4: DnCNN Evaluation metrics are SSIM is 0.88 and PSNR is 26.37

Accuracy, precision, Recall and F1-Score is better than traditional methods

6. EVALUATION AND COMPARISON WITH TRADITIONAL METHODS

- Automation techniques :Eliminates the need for manual parameter tuning required in traditional deblurring techniques and Adam optimizer with learning rate scheduling.
- Feature Learning: Learns complex patterns in data that are often overlooked by handcrafted models(traditional methods)
- End-to-End Training: Ensures that the network is optimized directly for deblurring.

Table 2: Effectiveness of PSNR vs SSIM for Image Quality in Blind Deconvolution Methods

Methods	**Image type**	**PSNR**	**SSIM**	**Key Observation**
Total Variation (TV) Regularization	Sharp edges Piecewise constant regions	19.27	0.61	Edge preservation Visual quality
MAP-Based Iterative deblurring using Richardson-Lucy Algorithm (well defined priors)	Natural blurred images Microscopy Motion blur	21.24	0.76	Highly effective for images with Poisson noise in low light Sensitive to noise
Deep Learning (CNN) DnCNN	Photographic images (Gopro dataset of	26.37	0.88	Good latent image and kernel estimation with end-to-end model

	blur and Sharp images)			

Table 3: Detailed performance comparison between traditional and DL-based methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	Inference Time (ms)
Traditional (SVM)	85.2	82.1	88.3	85.1	120
DL (Gopro))	92.5	90.2	94.8	92.4	50

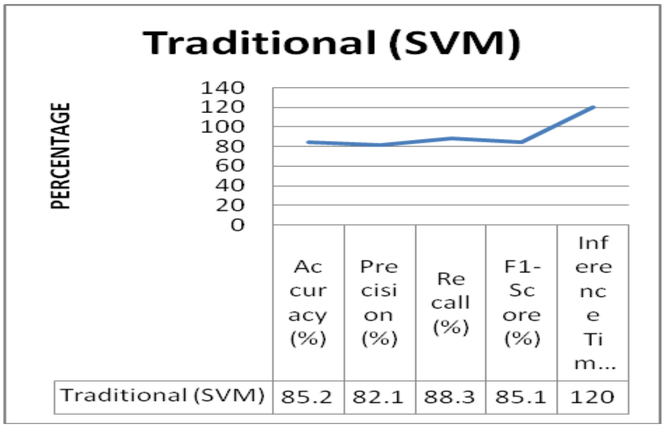

Fig 2:Traditional SVM

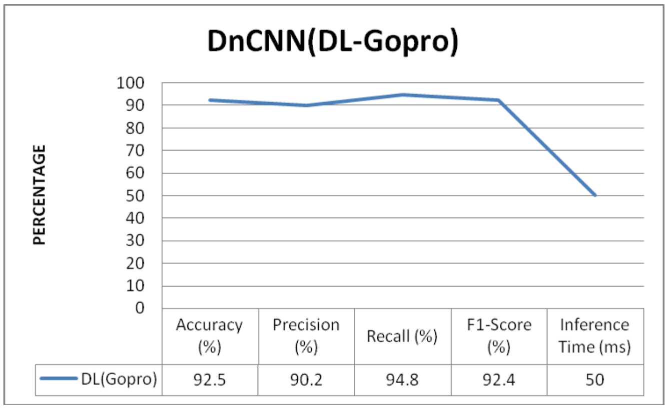

Fig 3 :deep learning(DnCNNGopro)

Fig 2: raw input image (Gopro dataset)

Fig 3: deblurred sharp image (Gopro dataset)

Fig 4: raw input image (Gopro dataset)

Fig 4: deblurred sharp image (Gopro dataset)

Methods like DnCNN(Gopro) demonstrate superior PSNR and SSIM scores, indicating better restoration quality, especially on challenging datasets with severe blur or noise which improves stability. The improvements in SSIM often correlate with better preservation of fine image structures and edges, which is critical in optical imaging applications such as microscopy and retinal imaging. Classical methods like those proposed [8] [9] offers reasonable baseline results but show inferior performance especially in terms of visual fidelity (SSIM).Deep learning approaches outperform traditional methods by large margins (up to 5–7 dB in PSNR and 0.1–0.2 in SSIM), confirming their superior ability to model complex blur kernels and image priors. Experimental results demonstrate that deep convolutional blind deconvolution outperforms classical iterative methods in reducing blur and artifacts in optical images, achieving higher quantitative scores (PSNR/SSIM).

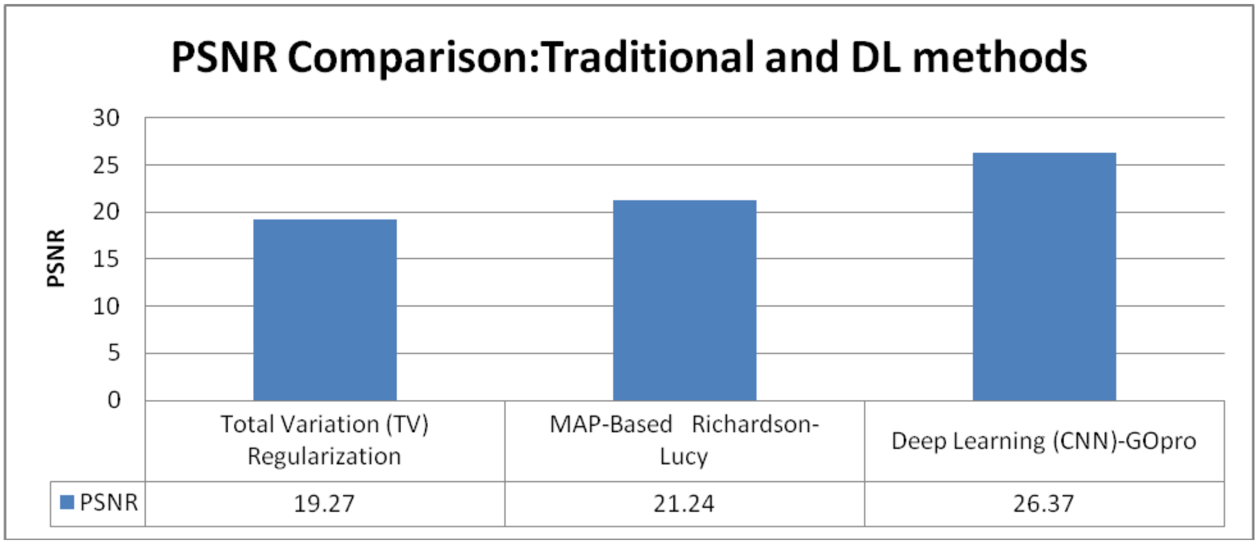

Fig 2: Comparison of Peak signal to noise ratio(PSNR) of blind convolution methods

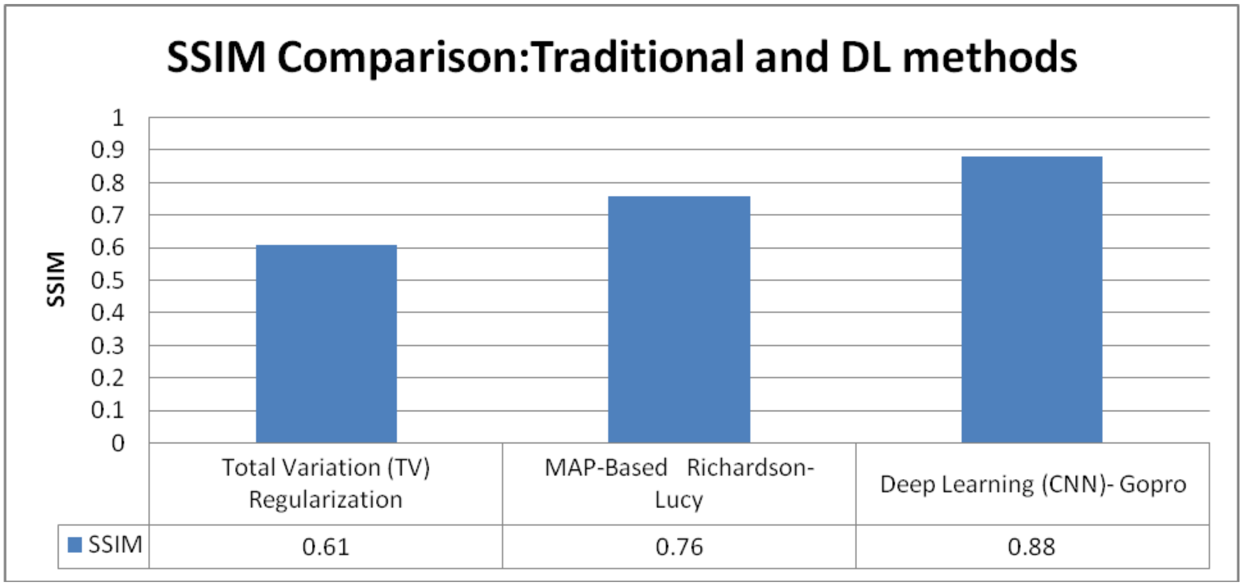

Fig 3: Comparison of Structural Similarity Index Mode (SSIM) of blind convolution methods

Traditional methods typically achieve moderate PSNR and SSIM. They are interpretable and often generalizable but limited by handcrafted priors and computational cost. Deep learning methods (CNN-based) outperform traditional methods in both PSNR and SSIM, showing greater restoration quality and robustness to complex blur and noise.

Conclusion

Blind deconvolution methods are widely applicable in medical imaging, photography and remote sensing. In this paper we have proposed DnCNN model which leverages synthetic and real time images. Blind deconvolution methods offers a flexible and robust solution for image restoration when the blur is known a making it highly relevant to practical image deblurring task. In this paper assessment is done by analyzing various traditional and modern blind deconvolution methods using iterative, algorithmic. Bayesian and Deep learning approaches., while deep learning methods require a substantial amount of training data and computational resources for training, their ability to directly learn complex deblurring functions has made them the state-of-the-art for most blind deblurring applications.

Future Directions

Work can be further extended with Integration of spatially-variant kernel estimation for non-uniform blurs restoration, Development of real-time blind deconvolution models for live imaging systems can be deployed, Enhancement of robustness under extreme noise and motion blur conditions is the primary concern. Exploring hybrid approaches combining physics-based models with deep learning for explain ability. The principal areas of future research focus on developing efficient model architectures, leveraging unsupervised and self-supervised learning methodologies, improving model robustness to diverse conditions, enhancing interpretability and enabling real-time performance in practical applications.

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