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Review of Blind Deconvolution Technique for Image Restoration

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ABSTRACT: It is difficult to extract correct information from blurred image; hence there is a need of Image restoration. The blur image signifies the corrupted form of image because of defectiveness in the imaging and capturing method. The point spread function (PSF) is not known in blind deconvolution; therefore it needs to be estimated. There are various PSF estimation techniques available of blind category. All of these techniques vary according to the blur type. The objective of our research is to study various blind deconvolution techniques and categorize them on the basis of various approaches and implementation strategies. In this paper, we attempt to analyze and classify the various blind deconvolution techniques of image restoration.

Keywords: Blind Deconvolution, Non Blind Deconvolution, Blur, Peak Signal to Noise Ratio.

Abbreviations: PSF, point spread function, BID, blind image deconvolution, TV, total variation, PSTG, Particle Swarm-based t-way Test Generator.

I. INTRODUCTION

In the recent development of the image restoration of non-blind and blind deconvolution, various mathematical techniques have been designed in the field of probability and statistics. Accuracy and computational complexity is a key issue while designing image restoration. In the current variety of the applications, there is a need for the development of various PSF estimation techniques to restore images. Although, Non-blind deconvolution is easy but doesn't provide adequate quality of the restored image. Blind deconvolution technique can help to restore images with better quality as it involves various approaches to design BID (Blind Image Deconvolution) method. The estimation techniques helps to restore the original images so that desired missing information can be obtained in the field of medical imaging, astronomy, criminal, forensic and other applications [50]. In blind deconvolution, PSF is important for deciding the quality factor of restored image as it is complex to estimate a partially determined or unknown point spread function (PSF). Researchers are studying about blind deconvolution methods for a number of decades and are working for development of solutions in different directions. In iterative BID technique, the approximation and the PSF improves for after every iteration. An extreme a posterior estimation and expectation-maximization algorithms are encompassed in iterative method. The convergence is faster with the appropriate evaluation of the PSF, however, not always. There are various approaches of blind restoration like Priori Blur Identification method, ARMA Parameter Estimation method, Zero sheet separation, Non-parametric Deterministic Constrained algorithm and High Order Statistics method. But here we have categorized all the methods on the basis of implementation strategies, so that researchers can focus in particular domain of research area.

II. REVIEW OF LITERATURE

The astronomers have been using the deconvolution method since 1980 for the sharpening of images obtained by telescope; it reverses distortion produced by recording information. It was also used in the fluorescent microscopy. In medical and academic world, the importance of blind image deconvolution is improved due to its theoretical and practical inferences. After this, so many researchers have worked upon PSF estimation methods and contributed various methods; their techniques have set foundation for the new development obtained from practical analysis. There are numerous applications in various zones like satellite imaging, medical imaging, biological imaging, remote sensing, etc. in the field of Blind image deconvolution.
Literature review contains details about some of the major contributions from different researchers in the field of PSF estimation for blind deconvolution techniques.

A. Bayesian technique

Previous techniques of Bayesian [7] followed expected linear association among the unique blurred image strength, the silver density noted on film, and the film-grain noise. Restoration techniques using the D-logE curve indicates non-linear association among intensity and film density. Generalized Gaussian Markov random field model (GGMRF) [9] provided Maximum A Posterior (MAP) based solution for edge modeling. The GGMRF model was similar to the generalized Gaussian distribution. It was also robust in detection and estimation. The model exhibited advantageous properties for MAP estimation in terms of analytical and computational aspects, ultimately providing a unique solution. Space-adaptive regularization algorithm [87] helped resolving estimation of blur along with the piecewise smoothness of images. The piecewise function was defined by four multiple sub-functions, composed of polynomial functions. It possessed a high degree of smoothness at the places where the polynomial pieces connected with many practical PSF's like the out-of-focus blur and motion blur. Restoration of the image and estimation of the parameters were simultaneously done using two iterative algorithms [47]. The evidence analysis was used in the hierarchical Bayesian framework. The restoration step of these algorithms was similar to the first algorithm of normalized constrained least-squares filter and the second algorithm of linear least mean square-error filter. Hence, it offered a solution for the parameter estimation problem of the RCTLS filter and additionally another method was provided for expectation-maximization framework to develop a parameter estimation algorithm for LMMSE filter. To resolve Bayesian implication problems, an intricate probabilistic model [1] was applied using variational methodology. To enhance hyper spectral imagery, it is important to focus on the high-resolution panchromatic data. To improve the spatial resolution of an image, there may be need of any number of spectral bands estimation of primary and auxiliary sensor. A spatially changing statistical model [56] was employed to utilize local correlation among the primary and auxiliary image. Gibbs priors were the global hyper parameter, which multiplied the Hamiltonian in Bayesian image estimation where parameters of the prior, the hyper parameters, played an important role. Information collected using Gibbs prior helped to recover deblurring using maximum likelihood estimation of an image. A MAP based restoration method [54] was implemented by incorporating prior information on natural image statistics. Augmented Lagrangian was applied as image priors P(u) which was comparatively heavy-tailed than Laplace distribution. A technique for motion blur [53] was implemented using current investigation in usual image statistics based on the learning technique [48], which states that the photographs of natural scenes usually track specific image gradients distribution. The limitation of this method was generating ringing artifacts. Another technique [62] utilized variational distribution approximations for designing of total variation (TV) related image restoration. The total variation (TV) and the observation model were used for the first phase of the hierarchical Bayesian theory. The different values of posterior distributions were estimated for the prior information and by utilizing variational framework; hidden variables concerning the degradation process were also obtained.

A hierarchical Bayesian model [59] was further enhanced basic technique [49] by using various priors like indefinite image blur, hyper parameters for the image, and noise priors, all assessed concurrently. To avoid uncertainties, unidentified posterior distribution estimation was calculated using a variational inference approach [25] and spatially weighted Total Variation (TV) was used as a prior. These priors provide spatial weights along with the capture of local image features. These priors along with variational approximation were used in Bayesian inference for image restoration. To stabilize the smooth areas of the image, there were two regularization terms used which were contained in the weights of the spatial adaptive matrix. New edge detector as image prior method [39] was a new learning technique which was used to resolve the ill-posedness of the blind image. A new edge detector captured the details of main edges of the image. The well-defined filters were used in a parametric way to handle unconfined blurs. Total variation (TV) was employed on the image model [63] using natural image statistics. A technique spatial adaptive (SA) prior restoration [88] was solved using a Large-scale Total Patch Variation (LS TPV) Prior model by Bayesian image restoration. Here, each pixel's prior is a mixture prior form of one weight entropy prior and one patch similarity prior called as singleton conditional probability. A Bayesian approach was resolved repeatedly with the Expectation maximization algorithm [90] to divide it into a deblurring problem and denoising.The approximation was achieved for the hyper spectral image and was a combined statistical model for HS and MS images. Hyper spectral images make use of hundreds of adjoining spectral bands, while multispectral images required only ten of discrete spectral bands. A possible drawback of this technique was the use of Gaussian prior model. The deconvolution restoration of multi-scale algorithm based on Bayesian technique [8] utilized two priors, the Total Variation prior and a variant of the non-convex quasi norm based prior. The estimation of various parameters was done using the Bayesian frame. The observed blurred image was down-sampled into various low-resolution images using multi-scale approach. The blur estimated and up-sampled image was considered at each measure of convergence for the higher resolution algorithm, which was continuously repeated until the satisfying level of resolution was attained in the image and blur estimation. A restoration technique [74] was used as a piecewise smooth image using sparse gradient image prior. The image reconstruction and registration of Bayesian Super Resolution image prior technique [60] was combined as a prior related to the $\ell 1$ norm of first-order differences that are vertical and horizontal. Along with this, the sparse image priors a Total Variation prior, and non-sparse Simultaneous Auto Regressive prior were also used. In this way, a different posterior distribution was formed from an individual prior of the simple High Resolution image. This method also used Kullback–Leibler (KL) divergences. These techniques were enforced on HR images as well as SR images to observe the differences. Maximum a Posterior probability estimation (MAP) based restoration technique of blind deconvolution [31] was executed by defining cost function using sharp image and blur kernel estimation simultaneously. On the basis of generic framework [78] MAP, was an efficient technique of image reconstruction. Application specific algorithms are used for image reconstruction mostly, because of parameter tuning and an unidentified signal distortion level they have generalization issues as well. These algorithms are applicable for improvement of the restoration accuracy and repress visible artifacts in various image/video processing applications such as interpolation, denoising, deinterlacing etc. The technique [86] was used for solving signal recovery problems in the presence of non-Gaussian noise. The framework for internal patch based image restoration approach [42] was done by assuming identical parameters for similar patches.

B. Regularization method

The concept of original regularization is used to find a suitable solution from an imperfect data for which the problem should be stated entirely using some priori information. Image restoration algorithm [3] is regularized and iterative in nature. The analysis of the properties of the soft constraint and prior knowledge constrains gave a set of feasible solutions, described geometrically by using the bounding ellipsoids. The total variation minimization based blind deconvolution algorithm [73] was used to recover the edges of an image. Total variation norm is a really useful technique for motion blur and out-of-focus blur. To improve the image and concurrently recognize the point spread function (PSF), alternating minimization technique was designed. The linear Tikhonov–Miller filter [79] was utilized as regularization factor for the estimation of non-linear iterative image restoration algorithm. The method [41] involves total variation minimization for regularizing the estimated image which was especially useful in preserving sharp edges without penalizing the smooth image. This method helped to include total variation regularization truncated and eigenvalue into blind deconvolution scheme of a nonlinear recursive inverse filter (RIF). Multichannel Blind Iterative Image Restoration [22] is a combined approach of an eigenvector-based method of restoration of Mumford–Shah and current anisotropic denoising techniques of total variation. In this algorithm linearization scheme of half-quadratic regularization was used collectively through a cell-centered finite difference discretization and delivered an integrated method for the clarification of total variation or Mumford–Shah. In this method, there was no requirement of exact estimation of mask orders and it gave better output even for noisy images. A technique of total variation [51] was used as it is an important concept for the recovery of image features. Piecewise smooth components were used to check in a general convex programming framework in total variation. By adding additional constraints, restoration process was improved using block iterative process, helped to solve optimization problem efficiently. An alternating minimization algorithm with total variation regularization [69] helped to deblur an image. A new half-quadratic model was initiated which supported both anisotropic and forms of TV discretizations. Rectified total variation method [93] used median filter whereas in [94] total variation was rectified using minimization method. Recursive method was used to capture noisy pixels. Deblurring was applied first, and then TV regularization scheme was applied, Chambolle's projection was also used. Total variation minimization problem was solved using an alternating minimization algorithm along with adaptive median filter and adaptive center-weighted median filter. Variational framework based on Hessian-based regularization methods [68] was used for image restoration problems. Extension of total-variation was used for regularization, which included matrix standards of the Hessian operator by adding second-order differential operators. The alternation of total variation function helped dealing efficiently through the staircase effect. It gave better output even for large images and retained its properties. Alternating direction restoration [65] used balanced regularization. To solve balanced regularization approach, alternating directional method and variable splitting strategy were used. It helped to maintain reliability and smoothness of the solution. Regularized image restoration method [5] used non-quadratic regularizer which suppressed noise and at the same time preserved edges of the image. For regularization, synthesis approach was followed by designing cost function which included data fidelity term and regularizing parameter. The technique used non-circulant method which helped to prevent artifacts in an image. It also used variable splitting scheme, joint with the AL framework and alternating minimization, which developed simple linear systems. The idea behind using variable splitting was to divide the problem into sub-problems to solve it individually. Fast algorithm [10] was used to solve the constrained TV restoration problem using the split Bregman scheme. It consisted of two auxiliary variables to represent Du and the TV norm, respectively, using variable splitting technique. This method had no inner iteration and in each iteration the regularization parameter adjusted in a closed form. This constrained problem could have been solved efficiently with a separable structure without any inner iteration to achieve the fast computation speed. A spatially adaptive multiscale variable exponent-based anisotropic variational PDE method [77] helped to overcome over smoothing and staircasing artifacts. Using image data with a coherence exponent map helped this model to balance between Tikhonov and total variation (TV) regularization effects automatically. This coherence exponent map built with spatially varying edge using the eigen values of the filtered structure tensor. The multiscale exponent model developed which lead to a novel restoration method that preserved edges. It also allowed to selectively denoising an image without generating artifacts for both additive and multiplicative noise models. A new variation model [33] was used by combining high-order total variation regularization and $l1$ regularization. The staircase effect is reduced and the edges can be preserved quite well in the restored image.

C. Wavelet Based Approaches

In wavelet-based estimation, orthogonal wavelet expansion is used to represent the image. It is very difficult to use convolution operators in wavelet domain. The technique developed using algorithm of image deconvolution which was based on MPLE (maximum penalized likelihood estimator) [45], but it couldn't be described in a closed form, hence, expectation maximization algorithm was used to numerically compute it. The algorithm was designed using the alternative iterative fast Fourier transform based on the E-step and M-step based on DWT. Majorization-minimization framework [44] was based on wavelet by taking three probable majorization strategies into account. Images were represented here using standard convention as vectors in some predetermined order by stacking all the pixels. Fuzzy image restoration technique [52] was designed based on the wavelet transform theory where various types of wavelet were constructed using different filters. It helps to get the approximate part of motion blurred image, and identification of the point spread function. The accuracy of the final point spread function directly affected due to different wavelet basis and different decomposition level. The thresholding technique using wavelet transform was a new approach which aided in noise reduction [97].

D. Intelligent technique

With the evolution in the various methods of image restoration, some of the recent methods based on advanced techniques have been developed. To eliminate noise without damaging image data, a fuzzy technique was utilized in Histogram-Based Fuzzy Filter method [35]. The parameter of output intensity map with initial parameters was designed by Fuzzy-based Histogram Technique. Fuzzy-neuro filters were employed to remove noise, which increased the performance. A discriminative transfer learning method [83] is incorporated formal proximal optimization and the flexibility of generative models. And thus it merges the strengths of both discriminative and generative models. It maintains the flexibility of generative models, but at the same time incorporated formal proximal optimization. A learning-based method [55] was used to detect the type of blur for patch of each input image, and then to estimate the blur parameter using advantages of the regression ability of GRNN and classification ability DNN. The problem of blur analysis can be solved using Pre-trained DNN and GRNN for the first time. A supervised DNN was trained to recognize the blur type which helped to classify it easily. Then projecting the input samples into a discriminative feature space. Particle Swarm-based t-way Test Generator (PSTG) [6] was used testing strategies as t-way based on Artificial Intelligence. As far as the size of the array is concerned PSTG always outperformed its AI counterparts and other existing testing strategies. By the lightweight computation of the particle swarm search process, PSTG can support high interaction strengths of up to t = 6. Based on soft-decision blur identification and hierarchical neural networks approach [36] authors integrated the information of eminent blur models. To provide an adaptive, perception-based restoration, the hierarchical cluster model was employed as a nested neural network where a new cost function was desgined to represent optimization scheme. The computational cost of restoration was reduced by sparse synaptic connections. And blur identification is done using conjugate gradient optimization. Neural network based restoration scheme [61] was designed in terms of varying regularization parameter for adaptively training the weights. The flexibility of this algorithm easily allows the changes of parameters such as blur statistics and regularization value. A regional processing approach is also used here, based on local statistics. A very deep fully convolutional encoding-decoding framework [81] is the advanced technique for image restoration. End-to-end mappings were done using the network of multiple layers of convolution and de-convolution operators. By removing the noise and adding the abstraction of image information, the convolution layers played a role as the feature extractor. Then, the image details were used to recover using de-convolution layers. Image restoration method [66] was used to leverage denoising auto-encoder networks as priors. The output of an optimal denoising auto-encoder was a local mean of the true data density, and the auto-encoder error was a mean shift vector. The magnitude of this mean shift vector was used as the negative log likelihood of our natural image prior in image restoration. The likelihood was maximized using gradient descent by backpropagating the auto-encoder error. The neural network based on principle component analysis (PCA) method was developed using Generalized Hebbian Algorithm (GHA) for the reconstruction of an image [96].

E. Cepstrum based approach

The radial blind deconvolution restoration method based on the medical ultrasound images [75] was designed using seven different cepstrum-based methods. The spectral root cepstrum method and generalized cepstrum method were the first two methods which were not very popular. The remaining five methods supported complex cepstrum having dissimilar methods of computation in the spatial and frequency domain. Ultrasound scanners implementation was done by higher-order statistics for selecting a specific cepstrum-based radial deconvolution method. With the complex cepstrum via phase unwrapping or polynomial rooting via vivo radio frequency data from a clinical scanner provided the finest image along with generalized cepstrum method. Cepstral analysis technique [28] helped to estimate through normal camera experiencing a 2D curved motion. For prolonging the traditional cepstral study, author derived PSF supposition effects in the cepstrum domain.

Miscellaneous

The technique of blind image deconvolution of image restoration [14] was suitable for the image that contained a limited support object in opposition to consistently black, grey, or white contextual, which arises in particular application of image processing. The cost function of blurred image was minimized using recursive function. The parametric double regularization (PDR) scheme [38] helped in calculating the significance of parametric blur information. The parametric double regularization method followed parametric structure up to a certain level. By adding the fuzzy blur structure to the existing PDR scheme, a soft parametric modelling system was projected. A method of restoration [15] helped to improve the quality of diffused images to be restored through creating a self-focusing standard into the optical track and applied correlation as they transmitted. A novel, unsupervised information-theoretic adaptive filter (UNITA) [71] helped to restore pixels by finding similarities in pixels of similar neighbourhood. UINTA doesn’t need priori knowledge, but should have information about entropy of natural images. The primary criterion depends on the measure of goodness of information-theoretic along with image statistics of the non-parametric model. Reestablishment technique [19] was an iterated quadratic programming optimization problem for bi-level objects like vehicle license plates, bar code, signatures etc. This method consists of thresholding as post processing method after basic restoration. In single channel blind deconvolution, multiple observations of blurred images were needed, so many version of same blurred image were taken by shifting techniques. With principal component analysis [11] in multichannel case, each image was reshaped into column vectors. Rest of the steps were similar in both single channel and multichannel like- to take average of images generated, finding centering, computing empirical covariance matrix and lastly computing the eigenvector. A hyper spectral image deconvolution problem [67] was solved together using spatial, spectral and non-negativity information. The regularized least-squared criteria was reduced and utilized to design image deconvolution technique. This method included FFTs based implementation for a closed-form solution where there was no knowledge of unconstrained problem. It described the amalgamation of positivity restrain into the estimate, effortlessly. The best linear unbiased estimator (BLUE) [72] was used for filtering additive white Gaussian noises in an image. BLUE filter was derived from the estimation theory based on statistics. Signal and noise variances in images can be measured using this method by simulation of Gaussian simulation in geostatistics. These parameters could be further used for image restoration technique of the adaptive Wiener filter. Invariable splitting technique [18] of image restoration filled the corrupted or lost area of the image by suitable information using an image inpainting method. In this work, degradation was done for different images; one using blurring and by adding noise to the original image and the other one to lose a percentage of the original image pixels. Then the degraded image was restored by the proposed method. A linear restoration method based upon the total variation regularizer was used. The Lagrangian augmented method was also used. Inpainting based algorithm [4] was based on edge information. For the restoration of the missing areas, a skeleton image structure was created using edge information. The various attributes of edges were considered to design proposed algorithm. An approximation of how well one edge continues into another one, the colors of the objects they separate, and the spatial order of the edges the various properties which aided to restructure an image. The numerical interpretation of the sequential order of edges and pixel filling technique were the main constraints of this method. Partition-Based Weighted Sum Filters method [37] was used for restoration by partitioning the observation space on the concept for constructing a general class of filters. Every observation vector was plotted to one of M partitions containing observation space and each partition had an associated filtering function. Vector quantization employed on partitioning the observation space helped to maintain linearity within each partition of the filtering function. Based on FIR filter, a restoration technique [24] was designed using blind FIR blur identification and order determination patterns. The unapproachable input image was permitted to be deterministic or disorganised and of unidentified color of distribution, away from a minimal determination of the excitation condition. The occurrence and distinctiveness results were recognised, which assured that single input/multiple-output FIR blurred images could be reinstated blindly, however, faultlessly in the lack of noise, via linear FIR filters. Alternating minimization of the Kullback–Leibler (KL) divergence based ML blind image restoration [2] estimation was a multivariate normal. This method utilizes KL divergence minimization for the distribution of the observed data. The algorithm converges only after few iteration and give closed form expressions for the parameters to be updated. Optimal sparse representation method [40] used quasi extreme likelihood using the blind deconvolution of images. An approximation level of absolute value was employed for demonstrating the record probability density function which remained appropriate on the behalf of sparse sources. A technique of sparsification was offered, which decided blind deconvolution of sources through arbitrary distribution, and it helped to catch ideal sparsifying alterations through training. The asymptotic restoration error was very less after using sparsely represented sources, which ultimately improved the blind deconvolution. Using imaging sensor, restoration technique [82] was designed as an image sequence acquired in general anisoplanatic scenarios. During capturing of an image sequence, atmospheric turbulence occurred due to the air between the scene and sensor. To reduce the spatial variation of PSFs over the whole image, space was focused in this approach. The blur was roughly considered as spatially invariant and global deconvolution was estimated to improve the estimation accuracy of the latent image content. Diffraction-limited blur was effectively removed by incorporating natural image statistics. Incorporation fusion process and temporal kernel regression reduced PSF variation and avoided noise effect respectively. A swarm intelligence parameter optimization of the support vector machine [13] was designed for blind image restoration. To get a factual mapping of images from the detected noisy blurred image a Support vector regression (SVR) was employed. The limitations of SVR were enhanced with particle swarm optimization technique. The blur-SURE (Stein's unbiased risk estimate) technique [21] was used for estimating an unknown point spread function (PSF) using Wiener processes. A scaling factor that controls the blur size was one of the PSF parameter in SURE-based technique. An automatic film archive restoration technique [43] was described for film dirt removal using the optimization of multi-dimensional greyscale soft morphological filters. The optimization was implemented using genetic algorithm based on mean absolute error. Soft dilation, soft erosion, soft closing, soft open-closing are various operations were used in soft morphological operations. Hybrid sensor network in image deblurring technique [47] was based on gradient cepstrum analysis (GCA). The algorithm used an alternating direction method (ADM) and provides fast convergence. The restoration technique [20] were generated multiple error-parameter curves at different parameters using wiener filter. These curves helped to estimate PSF to improve the quality of the restored image. Blind deconvolution algorithms [58] were designed using the Principal Component Analysis (PCA) and VQ-Nearest Neighborhood approaches. The sets of codebooks designed for the blind restoration problem were using bandpass frequency information of the degraded images. Richardson–Lucy algorithm was used in image restoration where the optimised PSF was generated by the use of Genetic Algorithm (GA)[64]. Non-local patches with similar structures were grouped together to form group-based sparse representation (GSR)[32]. Split Bergman technique helped to increase efficiency of GSR based image restoration. A flexible learning framework [85] was based on the idea of non-linear reaction diffusion models. Non-linear diffusion models were improved with time-dependent parameters and by including the filters. Gaussian image denoising, single image super resolution and JPEG deblocking are various applications of the TNRD (Trainable Nonlinear Reaction Diffusion) method. Recently popularized bilateral filter [27] was used for image denoising, upscaling, interpolation, fusion, by evolving kernel regression [29]. Eigen structure-based direct multichannel blind image restoration technique [30] was used as a new subspace-based approach of matrix operations which requires less computational complexity. Matrix operations were used to resolve these optimization problems by choosing the appropriate constraints. The parameter estimation technique [12] was based on Discrete Periodic Radon Transform (DPRT), which combined circular convolution property and the discrete Fourier slice theorem. The new approach was designed using two modified Radon transforms of parameters estimation [34] for out-of-focus blurs and linear uniform motion blurs. This method had less computational time as it was not iterative and suitable for natural images as it used approximation. Multi-channel based image deconvolution problem [26] was the extension the Bussgang blind equalization algorithm. The technique not only addressed the restoration of ill spatial correlated images but also addressed intensely correlated ordinary images. In case of spatially uncorrelated image, an algorithm was established in terms of minimum mean square error criteria and non-linear design for spatially correlated image. A modified version of iterative blind deconvolution algorithm [70] was applicable to different types of astronomical data. The use of convolution and support constraints band limit, multiple images and Fourier modulous constraints were also applied to recover the image and PSF. Fast algorithm [10] was used to solve the constrained TV restoration problem in the split Bargeman scheme using variable splitting technique. The method had no inner iteration and after each iteration, the regularization parameter adjusted to a closed form. The method achieved fast computation speed. A New Alternating Minimization Algorithm [91] supported both the types of TV discretizations i.e. anisotropic and isotropic which initiated from a new half-quadratic model. The TV/ L2 model was computationally more difficult due to the non-linearity and non-differentiability of the TV functions. In spite of several efforts, isotropic TV/ L2 model was much slower comparative to Tikhonov-like regularization models. This problem was resolved by using discrete convolutions and achieved high computational efficiency of an algorithm. Using feasible direction technique [23], one could resolve problem of image restoration as an optimization problem. It computed a feasible search direction to solve a trust region sub-problem with the truncated Conjugate Gradient method of Steihaug. Variation in the trust region radius was employed to prove global convergence. Derived adaptive regularization parameters and norm selection used maximum a posterior method [84] to improve the quality image restored image. A heavy-tailed sparse gradient distribution of natural images was modelled using Hyper-Laplacian with the norm. Gradient distribution model and estimated residual was used with Hyper-Laplacian and Gaussian, respectively. The iterative alternating optimization utilized a Maximum Posterior Probability. The exclusive solution of the problem of blind deconvolution [46] needed a priori information, for example, non-negative of the image, the support of the image, the parametric form of the PSF, etc. Prior information was used as the remedy of ill- posed problems. Precision of prior information depended on structural information of an image.

III. RESULTS AND DISCUSSION

It is concluded from Table 1 that Comprehensive review of technique, blur type, it's accuracy and limitations is essential for the overview of the literature. It gives us overview in comparative manner for different techniques along with its accuracy and limitations. From the literature survey, it is clear that most of the work has been done in the Bayesian and Regularization category. These techniques mostly useful for Gaussian, defocus and motion blur type. The cepstrum based technique; radon transform and Hough transform are mostly suitable for restoration of motion blur technique. It is difficult to apply wavelet based approach due to difficulty to apply convolution operator. Recently some advance techniques like deep learning, neural network based restoration scheme aid to find better result of blind deconvolution methods. Some other techniques like inpainting and morphology can be incorporated to implement image restoration. This study of various blind deconvolution techniques and it's categorization on the basis of various approaches would help implementation strategies in image restoration.

Table 1: Comprehensive Review of technique, blur type, it's accuracy and limitations.

No	Author	Techniques	Blur type	Accuracy	Limitaions
1	Taeg Sang Cho, *et al.,* 2012	Sparse gradient image prior using a MAP.	_	PSNR=28.05, SSIM=0.75	image quality is not improved much.
2	A.C. Likas, *et al.* 2004	Bayesian methodology	_	For Lena Image ISNR = 3:94 dB,	computational complexity is low

3	Mario A.T. Figueiredo *et al.,* 2003	Wavelet-Based Image Restoration, based on the E-step and M-step based on DWT.	_	convergence is occured in fewer iterations for larger noise variance	performance of the random-shifts based method degrades, as no. of iterations decreases .
4	Yilun Wang, *et al.,* 2008	Total variation (TV) regularization	Gaussian blur	β = 27, SNR: 13.11dB, t = 14.10s of Lena image	An algorithm work efficiently only under suitable boundary conditions
5	Li Chen, *et al.* 2005	Soft double regularization	_	It estimates the blur using fuzzy blur structure It improves convergence greatly.	It is difficult technique to implement.
6	Antonios Matakos, *et al.* 2013	Regularization method `	Uniform And motion blur	Run time was reduced Algorithm take 2.8 sec.	To handle additional complexity, needs additional splitting variable.
7	Mário A. T. Figueiredo, *et al.* 2007	Wavelet-Based Image Restoration.	Uniform blur	For Cameraman image BSNR is 40 Db.	_
8	Xiao, *et al.* 2018	Discriminative transfer learning method	_	For proposed method PSNR=29.48dB SSIM= 0.793 and Hybrid method PSNR=29.74dB SSIM= 0.809	Not suitable for image deblurring and super resolution
9	R. Yan, *et al.* 2014	Deep learning	Gaussian blur Defocus blur Motion blur	PSNR SSIM GMSD 28.96 0.8786 0.1262 26.67 0.8192 0.1702 27.94 0.8146 0.1417	_
10	T.D. Pham, 2015	The best linear unbiased estimator	_	Noise level μ=0, σ^2=0.1 PSNR=30.78 for Lena image	Not suitable for the restoration of noisy color images.
11	Shoulie Xie *et al.,* 2014	Balanced regularization technique.	---	Computational time is very fast , it takes 8.77 sec .with ISNR=15.26 for Barbara image.	----
12	Daniel P.K. Lun Lu *et al.,* 2004	Discrete periodic Radon transform.	_	Restored image accuracy is 29.3 Db for 30 Db noise level. And estimated PSF accuracy is 13.40db	PSF accuracy is less
14	Dash *et al.,* 2000	PSO based SVR	Motio blur, Out of focus Guassian	PSNR=30.23 For L=8, THETA=30,SNR=40 PSNR=33.08 PSNR =29.21	There is a scope for improvement in image quality
15	Sevket Derin Babacan *et al.,* 2007	Bayesian	Guassian blur	guassian noise with variane=220, SNR=7 Db ,MSE=196.30	-----
16	Edmund Y. Lam *et al.,* 2007	Iterated Quadratic Programming	Guassian blur Motion blur	No of iteration =10	_

17	Dalong Li *et al.,* 2014	PCA	Atmospheric Turbulence	It take 2.2 sec. deblur	----
18	S.D. Babacan *et al.,* 2012	Variational distribution approximation	Gaussian blur Uniform blur	ISNR = 3:06 dB ISNR=6.0 dB	_
19	Ryo Nakagaki *et al.,* 2017	Principal Component Analysis (PCA) and VQ-Nearest Neighborhood	Gaussian blur	ISNR is 3.04 for 20 dB	----
20	S. Derin Babacan *et al.,* 2009	Total Variation		PSNR is 77 computational time is 1.19 sec.	----
22	Y. Marnissi *et al.,* 2017	Variational Bayesian framework	non-Gaussian noise	SSIM=07075 TIME=338 sec. SNR= 20 dB	Technique is specifically for noisy image,does not support blurred Image.
23	M. Niknejad *et al.,* 2018	Conditional random fields (CRF) and Markov random fields (MRF)	----	For GSM PSNR 33.05 For SGM PSNR=33.11	-----
24	E. Sahragard *et al.,* 2018	Total variation regularizer and Lagrangian augmented method	Guassian, uniform Motion blur	Iteration=16 Cpu time= 13.1 ISNR=7.59 MSE=29.5	--
25	R. Yan *et al.,* 2016	Deep Learning	Gussian, motion Defous blur	PSNR SSIM GMSD 28.96 0.8786 0.1262 26.67 0.8192 0.1702 27.94 0.8146 0.1417	----
26	Dong Yang *et al.,* 2016	Blur detection and classification	Motion blur, defous blur	----	Scope for addition of more feature in classification technique
27	Filip Sroubek *et al.,* 2003	Eigenvector-based method	Defocus blur	For MCAM method PMSE(u)=12.97 PMSE(h)=27.3	Low SNR's around 30dB.
30	X. Mao *et al.,* 2016	Deep neural networks	----	Average PSNR= 27.35 and SSIM= 0.7276 .	---
31	Siavash Arjomand Bigdeli *et al.,* 2018	Autoencoder networks	---	PSNR=31.67 for Lena Image.	To restore each image, it requires the solution of an optimization problem.
32	Feng Xue *et al.,* 2015	Steions unbiased risk estimate	Gaussian blur	PSNR=26.8dB	----
34	Mingzhu Shi *et al.,* 2015	Gradient cepstrum analysis	-----	13X 13 PSF size Kernel estimation time=1.45 Image deconvolution time=2.57 and total =4.02	----
35	Stamatios Lefkimmiatis *et al.,* 2012	Hessian-Based Norm Regularization	Gaussianblur uniform blur	CIL 1016 Image degraded by uniform blur of 20Db ISNR=2.92 .CIL 7762 I Image degraded by Guassian blur of 30 Db , ISNR=3.47.	

36	J. Zhang *et al.,* 2014	Sparse representation	Uniform Kernel: 9×9, σ = √ 2 Gaussian Kernel: fspecial (Gaussian, 25, 1.6), σ= √ 2	For Lena Image PSNR=30.10 FSIM=0.9281 PSNR=31.47 FSIM=0.9463	----
38	K.H. Yap *et al.,* 2003	Soft-decision blur adaptation	Uniform blur Guassian blur	The identified blur using an algorithm yields NMSE of 0.048	-----
40	Giannis Chantas *et al.,* 2010	Variational approximation	Guassian blur with variane=9 BSNR=20 Uniform blur 9X9 and BSNR=20 dB	For Lena Image ISNR=3.09 Db For Man image ISNR=3.13 dB	-----
41	Hiroyuki Takeda *et al.,* 2007	Regression	-----	RMSE=6.68	-----
44	Yuewei Liu *et al.,* 2017	Robust iterative method	Gaussian blur	PSNR of Lena image is found Minimum= 32.38 and Maximum 34.27	----
45	Dong-Huan Jiang *et al.,* 2015	Alternating directional minimization and the split Bregman iteration	---	For Lena image of σ=10 SNR=18.4483 PSNR=33.0145	produces staircase effects
46	Abdul Rehman *et al.,* 2012	Sparse representation	----	For Lena image PSNR=33.9 And SSIM=0.912	-----
47	Yang Chen *et al.,* 2011	Total Patch Variation Prior	Uniform blur	SNR using LS-TPV prior is 16.02 for Lena image.	----
49	V. B. Surya Prasath *et al.,* 2015	Regularization	-------	For Boat image PSNR = 29.07 dB, MSSIM = 0.8204	---
50	Jianguang Zhu *et al.,* 2018	High-Order Total Variation and l_1 Regularization Model	Guassian Average Disk	SNR AND SSIM for Lena image 24.56 0.7503 23.58 0.6868 21.27 0.6443	-----

IV. CONCLUSION

It is observed that blind deconvolution technique is one of the most important approach for image restoration. As per the literature, the best computational method of estimation of PSF does not necessarily mean better result, rather the appropriate PSF estimation techniques of restoration for the particular blur type needs to be studied and implemented. The major objective of this review was to assist future researchers in basic understanding of various methodologies and concepts.

V. FUTURE SCOPE

This shall help them adopt new techniques for real time application for purpose of PSF estimation technique. An important aspect for improving the restoration performance is the selection of appropriate criteria so that a reliable decision can be made for choosing best computational method depending upon the type of blur.

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