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Image Deblurring Techniques – A Detail Review

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ABSTRACT

Images are nowadays an integral part of our lives, whether in scientific applications or social networking and where there is an image, the concept of blurring might occur. Blurring is a major cause of image degradation and decreases the quality of an image. Blur occur due to the atmospheric commotion as well as the improper setting of a camera. Along with blur effects, noise also corrupts the captured image. Deblurring is the process of removing blurs and restoring the high-quality latent image. Blur can be various types like Motion blur, Gaussian blur, Average blur, Defocus blur etc. There are many methods present in literature, and we examine different methods and technologies with their advantages and disadvantages.

Keywords: Blur Types, Survey, Deblurring, Blur Detection, Blur Classification

I. INTRODUCTION

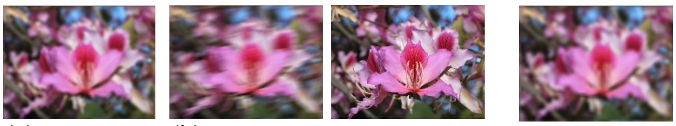
Images are blurred due to many reasons such as imperfections in capturing pictures, atmospheric problems and low-intensity level during camera exposure. The blurring of an image is a major cause of image degradation. Due to blurring, we cannot get exact details of the original image. Deblurring is a process to remove the blur and restore the image with high quality. Noise also corrupts the image so we need to perform de-noising on image [1], [2]. Image de-noising is also a part of image Deblurring. Applications of Deblurring include Iris recognition [3], Image segmentation [4], [5], Information retrieval [6], Astronomy [7], Microscopy [8], Space observation [9], Video object extraction [10], etc. There are many types of blurs like an Average blur, Motion blur, Defocus blur, Gaussian blur, etc.

Average blur: Average blur can be scattered in a vertical and horizontal direction [11]. The Average filter used to remove this type of blur and it is useful when noise present and affect the whole image.

Motion Blur: Motion blurs [12], [13], [14], [15] can be caused by relative motion between camera and scene during the exposure time.

Defocus Blur: Defocus blur [14], [16], [17], [18] is caused by an optical imaging system. Defocus blur is employed to blur a background and "pop out" the main object using large aperture lenses.

Gaussian Blur: Gaussian blur is simulated by Gaussian function. Effect of this blur is produced through a Gaussian filter that follows a bell-shaped curve. The blurring is dense in the center and fluff at the edge side [11], [19], [20].



(a) (b)) (d)

Figure 1. (a) Average Blur (b) Motion Blur (c) Defocus Blur (d) Gaussian Blur

Surroundings and outside conditions can affect the image quality during the process of the image acquiring. The blurring effect is caused by many reasons; one of the most important reasons include out of focus or camera shaken image. Image blurring is based on the degradation model. Blurring process can be formulated as the convolution of a clear or original image with point-spread-function (blur kernel) plus noise, given by

$$G(x,y) = f(x,y) \otimes h(x,y) + \eta(x,y)$$

Where $\otimes$ denotes a convolution operation. $G(x,y)$ is degraded image or blur and noisy image. $f(x,y)$ is a clear and original image. $h(x,y)$ is point-spread-function or blur kernel, and $\eta(x,y)$ is noise.

Photographical defocusing is another common type of blurring, known as defocus blur, mainly due to the finite size of the camera aperture [16]. In addition, camera shake is a common degradation in images. A small movement of the camera and object can degrade the image when the image is poorly lighted and requires a long exposure time.

Image Deblurring mainly includes two techniques: Blind Image Deconvolution and Non-Blind Image Deconvolution. In [21], many other techniques like subspace analysis [22], deblurring with noisy image pairs [23], deblurring with Richardson-Lucy algorithm [11], deblurring using Wiener Filtering [11], [12] are used. In Blind deconvolution, the PSF and clear image are being estimated but it is an ill-posed problem. In Non-Blind deconvolution, the clear image is estimated using known PSF. It includes Weiner filtering, deconvolution using RL method and deconvolution using a Regularized filter.

The organization of this document is as follows. In Section 2 (Review of State of Art Method), many deblurring methods and blurred region detection techniques have been discussed followed by conclusions and discussion in Section 3(Conclusion).

II. REVIEW OF STATE OF ART METHOD

Noise present in the image is a random variation of brightness which is caused due to taking an image in low-intensity level or due to many atmospheric problems [24]. An image contains different types of noise like Gaussian noise, white noise and salt and pepper noise, uniform noise etc. Even a small amount of noise can degrade the quality of image and image de-blurring techniques are sensitive to image noise. Literature [1], [2], [25] have applied a de-noising package as a pre-processing step.

A. Blur Region Detection and Classification

Nowadays many types of research are done on how to identify blur region and blur type. Subsequently, in the literature [14], [15], [26], blur identification and classification performed based on features. Kim et al. [26] introduced a 3-way blur identification method using features like Magnitude of gradient, Directional coherence, which classified the image into defocus blur, motion blur, and non-blur regions. The linear SVM classifier is employed to estimate each pixel's label into one of the blur regions. Super-pixel segmentation technique refines the rough blur region identification.

Singular value feature and alpha channel feature is used for blur region detection and blur classification [15]. Singular value feature differentiates the blurred region from a non-blurred region and estimates the blur degree by taking a ratio between the first few significant singular values (Eigen values) and all singular values that are computed over a local image patch surrounding each image pixel. Few most significant Eigen-images of a blurred image patch usually have higher weights or singular values than an image patch with no blur. The alpha value feature is used for classifying the blur based on the gradient distribution pattern, either it may be motion blur or defocus blur. The motion blurred image regions will have much larger values of variation of distance array compared with defocus blurred image regions.

Askari et al. [27] proposed a novel blur metric, which can significantly distinguish blur and non-blur regions and generate a blur map to encode the amount of blurriness for individual pixels. Estimated blur map is segmented into blur and non-blur regions by applying a pixon based technique. Pixon is a region that is made up of a set of connected pixels with associated properties such as intensity, texture, color. The original image is constructed by the union of the pixons. The Fuzzy C-Means algorithm is used for efficient segmentation. The estimation of blurriness at each pixel is performed by considering three different size blocks around each pixel. The purpose of taking these three blocks is to increase accuracy in estimating the blurriness value. The average value of these three blocks is defined as the blurriness value of the corresponding pixel.

Blur region detection and blur classification of partial blur image are challenging but some features are used which is based on spectral, gradient, and color information [14]. Blur features modeled by gradient histogram span [28], [29], maximum saturation, power spectrum slope is used to identified blur image regions from the partially blurred image. The whole image is segmented into patches and all operations are performed on these patches.

Gradient Magnitudes of natural images usually follow a heavy-tailed distribution. A blurred region rarely contains sharp edges which result in small gradient magnitude. The distributions of the log gradient magnitude for blurred regions should have shorter tails.

The maximum value of saturation in blurred regions is consequently expected to be smaller than the un-blurred regions and un-blurred regions have more vivid colors than blur regions. Power spectrum slope of a blurred region tends to be steeper than that of an un-blurred region. If the power spectrum of the whole image is less than the patch, then this patch is considered as a blurred patch.

Local autocorrelation congruency is used for blur classification whether it is motion blur or defocus blur. This function is measured how well a signal matches a time-shifted version of itself.

Shi et al. [28] present a method for constructing a blur feature representation directly from an input image. Image Gradient distribution, Spectra in Frequency Domain and Local Filters are used to differentiate blurred region from un-blurred. The image is divided into patches and the peakedness of a gradient distribution is measured by Kurtosis from these patches. Peakedness of blur region is less than the un-blurred region. Average Power spectrum for the blurred patch is smaller than the sharp patch. Groups of linearly independent filters are used to best separate blurred and un-blurred patch sets. Local filters are like as a Gabor filter and spatial filters that used for blurred detection task. They capture local band-pass or high-pass information that supplements frequency and gradient domain features.

Dong Yang and Shiyin Qin represented the restoration algorithm for a partial blurred image which is based on blur detection and blur classification [29]. Blur detection can be implemented using image segmentation. Each region is compared with its neighbor regions. For each region of a partially blurred image, we count the number of the blurred points and the number of the points in the region. If this ratio is greater than a threshold then this region is treated as a blurred region.

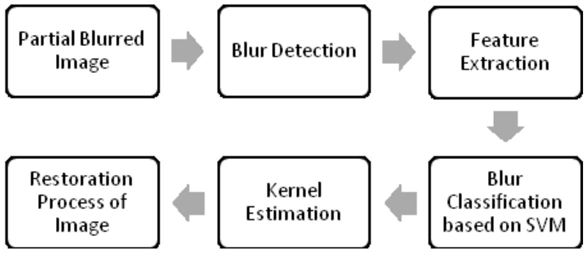


Figure 2. Restoration of Partial Blurred Image [29]

Gradient feature, Radon transform feature and an edge feature of the Fourier transform are used to classify the blur. Image gradient feature and radon transformation differentiates blur into non-defocus and defocus blur. After taking logarithmic Fourier transformation of a non-defocus blur, we classify the blur into motion blur and blend blur. The central area of the Fourier Transformation image of the defocus blur image is in the form of disk while motion blur have a strip of lines and blend blur have a combination of both. The non- blind de-blurring algorithm is used for restoration of blurred regions in the partially blurred image.

B. Kernel Estimation for Image Deblurring

In literature [1], [17] , [18], [30] various methods are available for kernel estimation. We can derive the kernel from the blur map and blur map can be created based on neighbor's behavior. Zhang et al. [17] proposed a method to remove the spatially defocus blur based on the estimated blur map and blur map is estimated by utilizing the KNN interpolation and edge information. By segmenting the blur map according to the blur amount of local regions and image contours, we get the local kernels. For Deconvolution, they used the local kernel and BM3D based non-blind deconvolution method.

Tang et al. [18], creates a blur map based on two assumptions: 1). If two neighbor image regions share the same color and belong to the same object then they should share similar blurriness, and 2). If two neighbor image regions share same gradient distribution then it also shares similar blurriness. This blur map is being used for blur detection refinement. The kernel can be estimated by parameters like blur angle, blur length, etc.

Hough transform method [2], [31] is used to detect the blur angle and blur length. Using this parameter and augmented Lagrangian method, the kernel is estimated.

Hough transform was one of the methods for motion blur angle estimation in which dark lines are observed in the Fourier spectrum of the blurred image after taking logarithmic transformation. Blur angle is between the corresponding x-axis and these dark lines. Once the locations of dark lines are found the blur angle can be calculated. Some central lobes are found by rotating the blurred image by blur angle and this blurred image has maximum values of pixels are found in all the column of an image and stored in a one-dimensional matrix. Blur length is calculated by; the mean lobe width is divided by the width of the image.

Cepstrum [29], [31] and radon transform [29], [32] are available for estimating these parameters but they are not accurate and contain many drawbacks especially when the number of columns and rows are not equal which leads distortion.

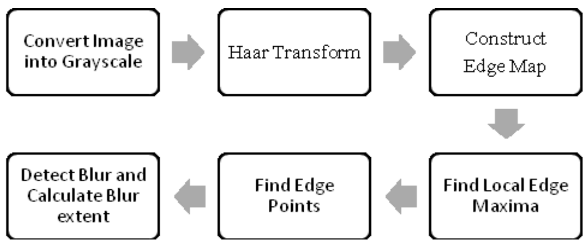


Figure 3. Blur Detection using Haar Transform [33]

Literature [33], [34] used the Haar wavelet transform for blur detection in the image. In [33], firstly it converts the image into gray scale and applies HWT for the edge analysis. Based on the analysis the edge map is constructed and then finds the local edge maxima for each local area. The process of finding local edge maxima is repeated by three times. If the ratio of image edges and edge points is less than a threshold, then it is a blurred region. An edge point is calculated by the local edge maxima and it is stored in edge vector. HWT is used due to its faster performance and better effectiveness. In literature [34], For de-blurring, alternating direction method of multiplier (ADMM) technique is used.

Pan et al. [35] proposed an algorithm by exploiting reliable edges and removing outliers in the intermediate latent image for robust kernel estimation. Initial kernel estimation can take place using the MAP framework and this framework also deals with the outlier. The Intermediate latent image can be obtained by the initialized kernel and the hyper-laplacian prior. The intermediate salient edges are selected from blurred image and outlier is detected from these selected. After detecting these outliers, the outliers are removed and the estimated kernel is updated. IRLS (Iteratively Re-weighted Least Squares) method used this estimated kernel to restore the image. IRLS is used to solve certain optimization problems with objective functions. It is performed using Maximum Likelihood approach.

An approach of kernel fusion stated that each kernel contributes to the final kernel and combining multiple kernels from different methods can lead to better kernel [36]. In baseline method, combination strategy takes the average of all individual estimated kernels but a disadvantage is that they compromise the good kernel. Another method is Gaussian Conditional Random Fields (GCRF) which predicts the kernel value at each kernel element individually and captures the relationship between the values of adjacent kernel elements. Performance of GCRF is better than baseline method.

Since a small amount of noise can degrade the quality of blur kernel estimation [1], for removing the noise, series of directional low pass filtering are applied on a blurred input image. The directional filter applies on a different orientation of the image. After filtering, blur kernel from each filtered image is estimated using inverse Radon transform. It also introduces a noise tolerant non-blind deconvolution technique that generates a high-quality final image. When we apply the directional filter, it damages the kernel.

C. Blind Image Deconvolution

Image de-blurring includes Blind Image deconvolution which jointly estimates the clear image and blur kernel [37]. It is ill-posed problem due to the loss of information on both images and blurring process [38]. Blind Deconvolution as the name indicates, works blindly where there is no information about point spread function. Point spread function is a point input, represented as a single pixel in the “ideal” image, which will be reproduced as something other than a single pixel in the “real” image [11], [39]. There are two approaches to blind deconvolution; projection based and maximum likelihood restoration based.

In former approach ([11], [40], [41]) it restores the true image and PSF by making the initial estimation. The technique is cylindrical in nature. This cyclic process is repeated until a predefined convergence criterion is met. The advantage of this method is, it is insensitive to noise. This approach involves the simultaneous evaluation of the recovered image and PSF that leads to a more sophisticated computational algorithm.

In latter approach, the maximum likelihood [42] estimates the parameter like PSF and covariance matrices. The PSF estimation is not unique in factors like symmetry, size etc. The definition of PSF separately from the restored image means the use of this information later by applying one of the known classical methods of restoration. Estimation of the image restoring and PSF are a separate procedure. The algorithm applied to implement such methods is computationally simple. It has low computational complexity and also helps to obtain blur, noise and power spectra of the true image. Maximum likelihood estimation can be seen as a special case of maximum a posteriori estimation (MAP). Literature [12], [16], [43], [44] uses blind deconvolution for de-blurring the image.

Shan et al. [12] proposed the method to de-blur the image using a unified probabilistic model of both blur kernel estimation and blurred image restoration. These terms include a model of spatial randomness of noise in the blurred image as well as new local smoothness prior that reduces ringing artifacts. Using this method input kernel is assumed to be quite inaccurate so the optimization is performed by MAP approach.

Literature review of many de-blurring techniques is given in [16], [45], [46], [47]. Removing motion blur from images is a typical blind problem. Blind image restoration is iteratively performed as linear and nonlinear processing. The nonlinear processing technique is used that is based on the compact representation of the image edge by means of Local Radon Transform (LRT) [32]. Radon transform is used to estimate the blur kernel and the overall restoration produces a sharp and focused image. The blind image deconvolution considers estimating the blur kernel in the gray domain. As a result, Xu et al. [43] present an estimation of blur kernel which is performed through RGB channel and it also stated that the blur effects for each color channel are usually different. The cost function is required for kernel estimation in this literature.

Blind image de-blurring only makes weak assumptions about the blurring filter. To overcome the ill-posed problem, the method includes a technique which initially focuses on the main edges of the image. The initialization of kernel estimation is performed using this edge information [48].

For estimating the kernel, different methods are used like kernel estimation using MAP approach, Kernel estimation through TV (Total Variation) regularization approach. Blur kernel estimation and image restoration can be done using MAP framework [35], [49] and this task can be solved by the minimization problem. For kernel estimation, it is assumed that the set of disjoint segmentation mask is given and fixed. In [50], kernel estimation is performed using a TV regularization method. TV regularization is widely used since it has good edge-preserving property. This approach makes the restoration algorithm achieved much better-recovered quality. TV Regularization and MAP approaches are closely related to the method of Maximum Likelihood (ML) estimation. The blind deconvolution methods have the inability to obtain preliminary information about the scene.

Deblurring using Motion Density Function (MDF): In Literature [11], [51] was proposed only for a single blurred image to remove camera shake. MDF represents the motion of camera and MDF is used for recording that time fraction which was spent in each discretised part of the space of all the possible camera poses. This method is useful for directly estimating spatially varying PSF and cannot work for multiple images. At any location in the image, MDF can be used to generate the kernel. This approach is used to model the spatial variation of blur kernels to run a blind deconvolution method at each pixel.

D. Non-Blind Deconvolution

Non-Blind deconvolution estimates only the clear image using known kernel. The prior knowledge about the parameters of blur kernel is required (point spread function length and angle). Non-blind deconvolution is used in the literature [1], [30]. Non-Blind deconvolution is performed by an already estimated kernel. Kernel estimation can be performed using radon transform [1] and it also states that small amount of noise can affect the kernel estimation task. Yang et al. [30], performed non-blind deconvolution using the kernel which is estimated and calculated by dark channel and minimization can be performed using a MAP approach and the regularized term is used for minimization computational term. The Dark channel is the smallest value in a local neighborhood and it also proves that the dark channel of a blurred image is less sparse than the original image.

Non-Blind Deconvolution Technique includes Wiener filtering [17], [52] Lucy-Richardson method [31], [53], Regularization approach [54], [55] etc.

Deconvolution using Wiener Filter: Some knowledge about point spread function is required in this approach. An estimate of a target random process can be made by Wiener filter using Linear Time Invariant (LTI) of an observed noisy image. Wiener deconvolution can be used effectively when adaptive noise and the frequency characteristics of the image are known. Wiener filtering is optimal in terms of the mean square error. It minimizes the overall mean square error in the process of inverse filtering and noise smoothing and it is a linear estimation of the original image. In the absence of noise, the wiener filter reduces to the ideal inverse filter [31]. Wiener filtering is used to store latent image in [17], [46], [56].

Wiener filtering also performs de-blurring using estimated kernel. Zhang et al. [17] presented a method in which kernel can be estimated by segmenting the blur map which is constructing using KNN interpolating method and edge information. After estimating kernel deconvolution can be performed using Wiener filtering. Wiener filter minimizes the MSE between the desired process and estimated processes [57]. Three conditions must be executed for guaranteeing the MSE: 1). The undistorted image and noise do not correlate with each other. 2). The undistorted image or noise must have zero average value. 3). The estimation linearly depends on the distorted image. Wiener filter has relatively higher noise immunity.

Deconvolution using Lucy-Richardson Method: William Richardson and Leon Lucy [58], [59] invented the LR which is an iterative procedure for recovering a latent image that has been blurred by a known PSF. In this case, PSF is identified but no information is available for the noise. One main problem with basic LR method is how many times process should repeat. If the numbers of iterations are very large then it will slow down the computational process and also introduce ringing artifacts. The equation of Richardson-Lucy algorithm is [45], [60]

$$f^{n+1} = f^n \, H^* \left(\frac{g}{Hf^n} \right)$$

Where f^{n+1} the new estimate from the previous one is f^n, (g) is the blurred image, (n) is the number of the step in the iteration, (H) is the blur filter (PSF) and (H*) is the Adjoin of (H).

The LR algorithm reduces the effect of noise amplification. It is time consuming because more iteration is required. In literature [60], [61], [62], RL algorithm is being used to restore the final and latent image. Shaked et al. [60] represent an extended version of RL algorithm for estimation of medical images for their blurred measurements corrupted by Poisson noise and it's particularly simple algorithmic structure which implies straightforward implementation. Blind deconvolution is performed using RL algorithm in the literature [63]. Each iteration of RL method is used to guess the PSF and using this PSF image is restored. RL was developed from Bayes's theorem. A blurred image can be reconstructed using a combination of RL algorithm and Pyramid structure [62]. By using pyramid structure, the images with different frequency bands are generated. The combination of these two reduces the computational complexity and avoids the ringing effect.

The reason for the popularity of the RL algorithm is its implementation of maximum likelihood and its apparent ability to produce a reconstructed image of good quality in the presence of high noise levels [64]. RL provides the good estimation of the blurring function and gives the better PSNR within limited iterations.

Deconvolution using Regularized Filter: This technique is useful when limited knowledge about noise is present. The blurred and noisy image is restored by a constrained least square restoration algorithm that uses regularized filter [47]. The regularization filter is often chosen to be a discrete Laplacian. This filter can be understood as an approximation of a Wiener filter. Although the wiener filtering is the optimal tradeoff of inverse filtering and noise smoothing, in this case when the blurring filter is singular, the wiener filtering actually amplifies the noise. The implementation of the regularized inverse filter involves the power spectrum estimation spectrum of the original image in the spatial domain.

Wang et al. [55] developed a Linear Time Invariant Regularized Backward Heat Diffusion (LTI RBHD) method that estimates the blur kernel with low and high width, better results are achieved with right kernel width and it is better than wiener filtering. The prediction of the original image is obtained from the watermark image by using the regularized filter [54]. By subtracting the predicted image from the watermarked image we can recover embedded watermark image blindly and this is the combination of blind and a regularized filter. Wiener filtering has a better result than a regularized filter.

Deblurring using Blurred/noisy pair images [23] can also be done. Both the blurred and noisy images are used to estimate the exact blur kernel, which otherwise is very difficult to get the blur kernel from a single image. The initial kernel can be assumed by simple constrained Least Square Optimization technique. Using both images, deconvolution is performed and this significantly reduces the ringing artifacts. The remaining ringing artifacts are further suppressed by gain controlled deconvolution process. Non-blind deconvolution can be divided into two parts: non-blind kernel estimation and non-blind image deconvolution.

In kernel estimation, the very accurate initial kernel can be recovered from the blurry image by exploiting large-scale, sharp image structures in the noisy image. The main advantage of this approach is that it takes both the blurred and noisy image, as a result, it produces high-quality latent image [40]. The disadvantage of this approach is that the point spread function is invariant.

Deblurring using subspace analysis [40], [65] can be done by constructing a feature space which includes blurred images which are degraded by same point spread function. A statistical model that represent prior knowledge of predefined point spread function sets in feature space is learned which estimates the blur kernel of a query image and compare with each model in feature space and selects the closest one for PSF inference [22]. The given query image is de-blurred using the blur kernel corresponding to that particular model. The inferred PSFs were used to sharpen both target and query images. This approach has not yet been proven for images blurred with multi unknown factors like camera shake.

Liao et al. [66] present a novel algorithm for hyperspectral image de-blurring with Principal Component of Analysis (PCA) and total variation. The first step is to de-correlate the hyperspectral image and separate the information content from the noise using PCA. The first k PCA channel contains most information about the HS image and remaining B-k channels contains the information about noise. If de-blurring is performed on these high-dimensional B-k PCs and noise, then it will amplify the noise of the data cube and cause high cost of computation during data processing, which is not desirable. Therefore fast TV denoising and de-blurring methods are applied for first k PCs and a soft-thresholding denoising scheme is applied to remove the noise from remaining B-k PCs.

Kumar et al. [67] presented a learning-based image de-blurring technique using an artificial neural network. Using this approach blur PSF is assumed as uniform. The image is divided into patches and deconvolution algorithm is applied on different patches. The network is then trained using back propagation algorithm. When we give the blurred patch to the neural network as an input, the center pixel of this patch is considered as the output of original patch.

Various blind and non-blind deconvolution based methods are compared in Table 1 and Table 2, respectively.

Table 1. Survey On Blind Deconvolution Based Image Deblurring Methods

Ref.	Blur Type	Kernel Estimation	Type of Kernel	Features used	Dataset	Classifier
[2]	Motion Blur	Estimate blur angle and length by Hough transform, TV regularization	Regularized filter		In-house	
[14]	Motion Blur, Defocus Blur		Gaussian filter	LPSS, GHS, MS, LAC	Flickr.com and PBase.com,	Naive Bayes
[15]	Motion Blur, Defocus Blur		Low pass filtering	SVF, ACF	In-house	
[18]	Defocus Blur, Motion Blur	Blur map can be created by blur metric which is based on assumption		Log spectrum	Public blurred image dataset	
[24]	Motion Blur	Using TV regularization approach	Low pass filtering		In-house	
[43]	Motion Blur	By predicting image salient edges and using Gaussian prior and cost function is required	Gaussian filtering, shock filter		In-house	
[32]	Motion Blur	Using Radon transform	Wiener filter		In-house	
[49]	Motion blur	Jointly solve blur segmentation and PSF estimation, MAP framework, two-phase kernel estimation,			In-house	Naive Bayes
[35]	Motion Blur	Removing the outliers, using MAP approach	Shock filter		Benchmark dataset	
[51]	Motion Blur	Motion Density Function used to generate PSF at any location			In-house	
[33]	Motion Blur, Gaussian blur	Using Haar Wavelet Transform blur detection performed			Caltech-256 Object Category, INRIA Holidays and LabelMe, ARCHIVES	SVM
[34]	Motion Blur	Estimate the PSF and LI using ADMM	Edge Filter		In-House	
[26]	Motion blur, Defocus blur			MG,DC	Google Image, Flicker, and DPChallenge	SVM
[27]	Motion blur, Defocus blur	Estimating Blurriness using Pixon based technique, different size of blocks is used for accuracy in estimation of blurriness	Low pass filtering		In-house	Naive Bayes
[28]	Motion Blur, defocus Blur		Gaussian filter	IGD, SFD, LF	In-house	Naive Bayes

LPSS = Local Power Spectrum Slope, GHS = Gradient Histogram Span, MS= Maximum Saturation, LAC = Local Autocorrelation Congruency, SVF = Singular Value Feature, AVF = Alpha Value Feature, IGD = Image Gradient Distribution, SFD = Spectra in Frequency Domain, LF = Local Filters, SVM = Support Vector Machine, LI = Latent Image, MG = Magnitude of Gradient, DC = Directional Coherence

Table 2. Survey On Non-Blind Deconvolution Based Image Deblurring Methods

Ref.	Blur Type	Kernel Estimation	Type of Kernel	Features used	Dataset	Classifier
[1]	Camera Shake	from each filer image and using radon transform	Low pass filter		In-house	
[12]	Motion Blur	Kernel estimate blindly and use non-blind technique for de-blurring	Wiener filter		In-house	
[17]	Defocus Blur	Kernels derived from segmenting the blur map	BM3D Filtering, Wiener filtering		In-house	
[22]	Defocus Blur, Motion Blur	Using a feature vector the closest one selected			In-house	NN
[23]	Camera Shake	A least squares optimization and Landweber algorithm are used for iteratively update	Bilateral filtering		In-house	
[44]	Motion Blur, Gaussian Blur, Average Blur, Defocus Blur	Using MAP estimation approach	Wiener filter, Laplacian filter	Moment Invariant, HOG, Zernike Moment	In-house	
[30]	Motion Blur	Using Dark channel and minimization perform by MAP approach	Bilateral filtering		Bench-mark dataset	
[31]	Motion Blur	Estimate blur length and angle and then kernel estimated from these parameters	Gaussian filter		In-house	
[56]	Motion Blur	Kernel estimated by parameters like blur angle and blur length	Wiener filtering		In-house	
[66]	HS image	Using PCA and TV regularization			In-house	
[36]		Kernel estimate by kernel fusion in which different kernel estimate by different method	Low pass filtering		Flickr, facebook, Google plus websites for dataset	
[29]	Motion blur, defocus Blur, Blend blur	Radon transform and Cepstrum is used for kernel estimation	Wiener filter	GF, RTF,EF	In-house	SVM

GF= Gradient Feature, RTF = Radon Transform Feature, EF = Edge Feature, SVM = Support Vector Machine, NN=Nearest Neighbour.

III. CONCLUSIONS

This paper presents the review of state of art methods of image deblurring. Blind deconvolution jointly estimates the point spread function and clear image and we have no prior knowledge about PSF, types of blur, the presence of noise and the resultant image is better than any other technique but it is time consuming. We discuss non-blind deconvolution which includes three methods: Wiener filtering, Richardson-Lucy algorithm, Regularized filter. In the presence of Gaussian noise, Wiener filter gives the best result and it is optimal in terms of mean square error. Richardson-Lucy gives better results with higher PSNR but it gives ringing artifacts with an increase in a number of iterations. The regularized filter is one of the best techniques to deblurring when there is no noise in the image but when noise is present with blur, the Richardson-Lucy technique gives better performance. Many approaches use blur detection and blur classification as the blind estimation of PSF is difficult. Therefore, by classifying the blur we get the structure model of PSF and using this structure model of blur kernel we can easily estimate the true PSF. In general, blind deconvolution techniques show better results in comparison with non-blind deconvolution techniques.

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