Efficient Blind Image De-Blurring using Dark Channel Prior

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Declaration

I, *Jawad Ahmad* declare that this thesis titled "Efficient Blind Image De-Blurring using Dark Channel Prior" Model" and the work presented in it are my own and has been generated by me as a result of my own original research.

I confirm that:

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This thesis is dedicated to *my beloved parents*

Abstract

Image de-blurring is classified into blind and non-blind image de-blurring. In non-blind image de-blurring, blurring function is known during the extraction of the true image from the degraded one. In blind image de-blurring, blurring function and true image are unknown. Therefore, blind image de-blurring is double ill posed problem as there is no unique solution to blur kernel and restored image. Dark channel constitutes of minimum intensity pixels and prior is selection of minimum intensity pixels.

Existing methods make assumptions on blur kernels, latent images or both. Numerous methods assume sparsity of image gradients, which has been widely used in low-level vision tasks including de-noising, stereo and optical flow. Secondly, De-blurring methods formulated within maximum a posterior framework favors blurry images over clear images so they use heuristic selection method which increases computational complexity. State of the art image de-blurring techniques perform better for specific images like face, text or low illumination. To overcome above problems blind image de-blurring using dark channel prior is proposed due to its computational efficiency.

The proposed technique employs discrete wavelet transform to improve the efficiency and L_o regularization to minimize the dark channel of the recovered image. The proposed method favors clean images over blurred images in the restoration process. The L_o norm is highly non-convex and the optimization involves a non-linear minimum operation. An approximate linear operator based on look-up tables is used for the min operator and to solve the linearized L_o minimization problem by half-quadratic splitting methods. The algorithm does not require heuristic edge selection steps or any complex processing techniques in kernel estimation. The proposed algorithm converges quickly in practice and can be extended to non-uniform de-blurring tasks.

Experiments are conducted on face, text and low illumination blur image data sets to evaluate the performance of proposed method. Experimental results show that dark channel prior based image de-blurring is effective for uniform and non-uniform de-blurring. The proposed algorithm performs better on de-blurring natural images, and performs favorably against specialized methods for faces, texts, and low illumination conditions.

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Introduction

1. Introduction

1.1. Overview

Image is most trusted source of information and indispensable in science and in modern day life. Images are very important sources of information in various fields of science like engineering, forensics, astronomical and medical images. The process of retrieving and analyzing information from images using digital means is known as digital image processing.

Digital image processing fundamental techniques are following [1]:

1. Image analysis
2. Image modelling
3. Image restoration
4. Image enhancement
5. Image reconstruction
6. Image compression

While obtaining images many factors causes degradation in images like movement while using hand held cameras, lens defocus, relative motion, atmospheric blurring and in some cases like in medical images where rays are used intentionally high rays are not used because it may hurt patient. Images are captured at different illumination levels and are sometime ephemeral and cannot be reproduced. These degradation causes result in noise and blur in images. Blurred images are of less importance and viewer may get frustrated that an important information in image is unclear. So retrieving and analyzing information form these images is called image restoration. And image restoration will be dealt in this thesis.

Now days there are high tech cameras which can handle imperfection which causes degradations. The main goal behind the advancement in camera technologies is to remove blur. These high tech cameras are costly. Despite these high tech cameras motion blur is addressed in limited manner [2]. So post processing of image is better because it is a low cost solution. These solutions estimate the images to acceptable level.

1.2. Image Restoration

Image restoration is required in most of image processing applications. Restoring an image from degradation which are blurring and noise to a true image is called image restoration. Working on digital image restoration starts back in 1960’s [3]. Image is usually described by two components reflectance and illuminance. In this restoration of blurred is discussed. Blurred image is represented as

$$\mathbf{B = I \otimes k + n} \qquad 1.1$$

In this equation '**B** 'represents blur image whereas '**I'** is latent image which convolve with '**K'** blur kernel and '**n'** is the noise in image.

1.2.1. Types of Blur Images

Blur image restoration problem classified in two types:

1. Classical Image Restoration
2. Blind Image Restoration

When there is prior information available about degradation or it can be said that blur function is known which is used to blur the image it is called classical image restoration. As we are not completely blind that how image is degraded and prior information helps to reconstruct the image.

Whereas in blind image no prior information is available that how image is degraded. So it usually called double ill posed problem. As one task is to recover blur image and secondly no prior information is available about degradation process.

Classical image restoration is comparatively easy as blur function is known so degradation process can be inverted using one of many algorithms. But in blind image it is convolution of true image with linear-shift invariant blur which is also known as point spread function (PSF) is unknown. And additive noise in blurred image is assumed zero. Considerable amount of research is done on this double ill posed problem but it is still a challenging problem for researchers [3-7].

1.3. Key Motivation for Blind Image De Blurring

As it is clear that blind image restoration is difficult task to do but it has wide area application which made research this field attractive. Some of motivation which made research on this topic are following:

1. There are solutions to overcome blurring while taking images but all these solutions are very costly. It's because they use high cost adaptive optic systems and requires high energy. And as compare to that post processing of degraded image is a low cost solution.
2. In medical imaging high quality images are required for better examination. For which high intensity beams are required but these beams are hazardous for patient's health. So blurring is inevitable.
3. In some applications like in video conferencing de blurring cannot be done by predetermining point spread function. There are online image de blurring techniques but they create ringing artifacts in restored image.
4. Last but not least to acquire prior information about degradation in any scenarios is very costly and mostly it is not possible to have prior information about point spread function. So post processing of image is most feasible and low cost solution to this problem.

1.4. Research Scope

The research deal with image degraded by linear shift invariant blur. Blur can be parametric or non-parametric point spread function. And it will be applicable on both types of image which are real life blurred or artificially blurred. Additive noise in the blurred image equation is assumed zero.

1.5. AIM

Research aim is to develop an efficient blind image de blurring scheme which can applicable to real life and artificially blurred image of different types. And the technique should be efficient in estimation of point spread function and computation.

1.6. Objective

Main objectives of this research are following:

1. Review already carried out research on blind image de blurring in order to develop understanding.
2. To design an algorithm that efficiently remove the blurring effects in the images.
3. Can handle both parametric and non-parametric point spread function.
4. Test proposed algorithm on different type of blurred images e.g. natural, text, face and low illumination images.

1.7. Thesis Structure

In first chapter blind image de blurring introduction, motivation and objectives of this research are discussed.

Chapter 2: Literature review of blind image de blurring is discussed.

Chapter 3: Proposed algorithm of blind image de blurring is discussed.

Chapter 4: Results of our proposed algorithm and quality measures algorithm are discussed.

Chapter 5: Conclusion and future work of blind image de blurring is discussed.

Chapter-2

Literature Review

2. Point Spread Function

Point spread function characterizes the ill-effect of blur which is caused by degradation. The PSF is the electromagnetic radiations propagated from a point source. Image quality mainly depends upon the blurring effect of point source. The PSF is used to define the impulse response of a point source [8]. This is depicted in Fig. 2.1. When images are captured by some camera, their pixel's intensity value is proportional to the intensity of the region that is being captured. But this is not true in practical situation, where intensity of the image is affected by some other factors like noise. As stated above, the PSF describes the process of blurring in an image. It is expressed by the extent of the variation of pixel intensity value at a specific position (i, j) in the original image F by the intensity value at position (s, t) in the blurred image G.

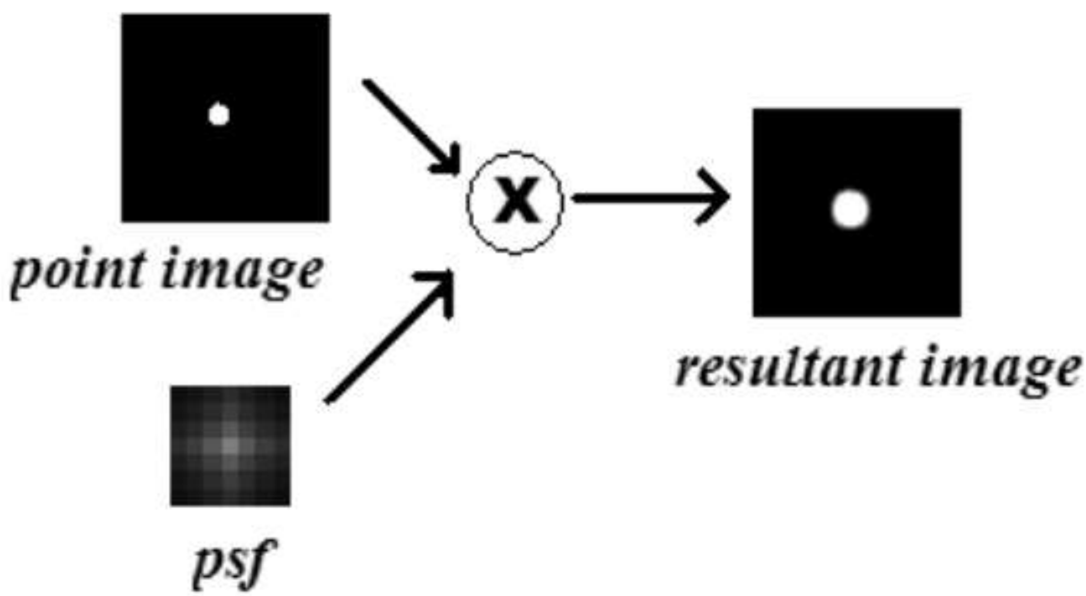


Figure: 2.1 Point spread function

2.1. Types of Blurring Function

Two types of blurring function are used depending on the impacts of blurring function on the blurred images.

- **Spatially Invariant Blur:** In this type of blurring function blurring impact is same in very pixel of blurred images. In Fig 2.2 two original and blurred images are shown. From this figure it can be seen that blurring effect is same everywhere in the blurred images. This is due to the spatially invariant blurring function which equally blurs all regions of image. Mathematically Spatially invariant blurring function (PSF) is expressed as

$$g(s,t) = \sum_{i=1}^{M} \sum_{j=1}^{N} f(i,j)h(s-i,t-j) \qquad 2.1$$

Where g (s,t) and f (i,j) are the intensity values at position (s,t) and (i,j) in blurred and original images respectively. Equation (2.1) shows that the PSF is a linear operator. This means that each pixel value in blurred image is obtained by linear combination of its neighboring pixel intensity. Additionally, convolution of original image F and PSF will result in blurred image G. However, it is not true in all cases.

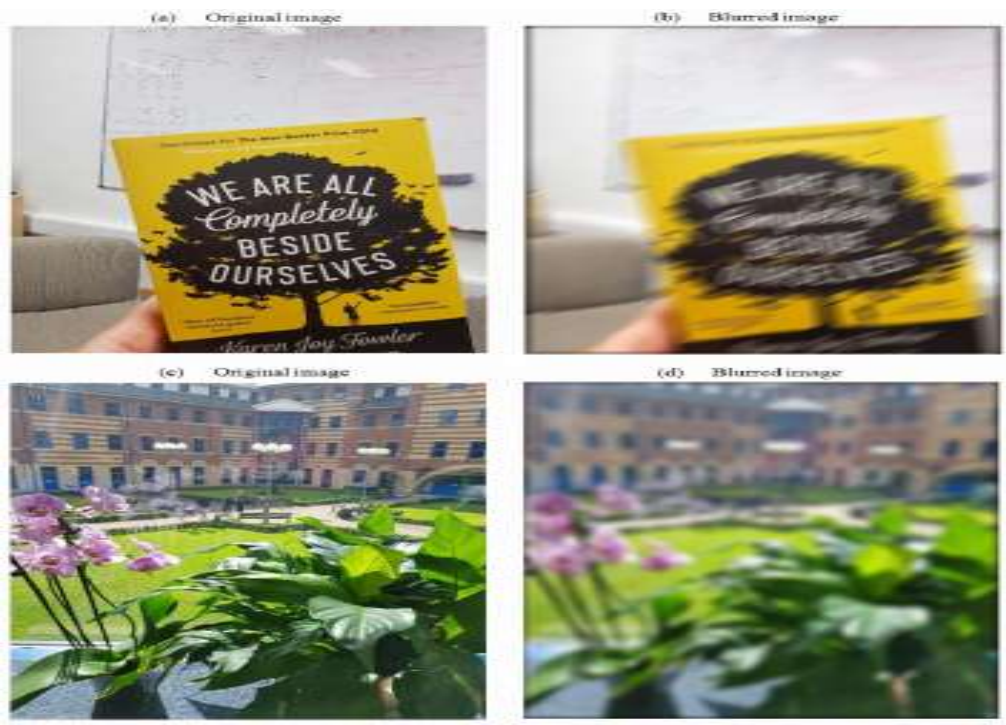


Fig 2.2 Spatially Invariant Blur

- **Spatially Variant Blur:** The effect of this type of blurring function is not same all over the image. Some regions of the image are more blur than others. In Fig. 2.3 effect of spatially variant blurring function is depicted. It can be seen from this figure that foreground regions are less blur than the background regions of the images.

Fig 2.3 Spatially Variant Blur

There are many sources that may cause blurring during image capturing. It may be due to the environmental effects, camera lens and camera motion etc. Followings are some most common blurs**.**

- **Gaussian Blur:** This type of blurring is due to the environmental effects or lens error. Gaussian blurs decays exponentially from the center of the image.

- **Motion Blur:** This type of blur is due to the motion of object or camera in x-direction during capturing of image. Equation (2.2) describes the motion PSF [9].

$$h(i,j;L,\varphi) = \begin{cases} \frac{1}{L} & if \quad \sqrt{i^2+j^2} \leqslant \frac{L}{2} \quad and \quad \frac{i}{j} = -\tan\varphi \\ 0 & elsewhere \end{cases} \qquad 2.2$$

where φ and L represent the angle and length of motion.

- **Out-of-focus Blur:** Camera focuses a particular sight during capturing of image. The regions outside the focused sight cause defocused blurring. Equation (2.3) describes the out of focus PSF.

$$h(i,j;R) = \begin{cases} \frac{1}{\pi R^2} & if \quad \sqrt{(i-k)^2+(j-l)^2} \leqslant R^2 \\ 0 & elsewhere \end{cases} \qquad 2.3$$

Figure 2.4 shows a sample image and its corresponding out of focus, gaussian and motion blurred burred images.

Fig 2.4 Blurred Image example

2.2. Filters for Image Restorations

There are many blind image de-blurring algorithms used to restore the blurred image. The blind image de blurring algorithms are mainly divided into two categories [10]:

1. One method is to separately estimate the PSF and use this PSF later with the classical algorithms for image restoration.
2. The second method produces more complex algorithms. It incorporates the procedure of estimating PSF with the restoration technique. Hence, it merges both the estimation and the point spread function true image at the same time.

There are many algorithms for BID problem but here we only discuss some of the famous algorithms for BID.

2.2.1. Inverse Filtering

Inverse filtering is one of the simplest methods in image de-blurring techniques. In inverse filtering, the inverse of the identified PSF is calculated and applied the inverse PSF to the blurred image in order to calculate the original image. In frequency domain, when there is no noise it is quite easy to calculate the inverse and apply it to the distorted image. Mathematically it can be represented as [9]:

$$\boldsymbol{\hat{I}} = \boldsymbol{G^{-1}F} \qquad 2.4$$

In the above equation, $\boldsymbol{\hat{I}}$ is the estimated exact image. As we all know, in most of the blurred image cases the PSF is not known. But in some cases the PSF can be estimated, when the linear translation is the reason for blur image or image is blurred due to the hand motion of capturing devices. In these cases, sine function can be used to represent the PSF in frequency domain. Hence, in frequency domain the inverse PSF can be multiplied with blur image in order to get the original image. Still, inverse filtering is the simplest method and cannot be used directly in most of the practical cases. Because in these cases, the estimation and calculation of the inverse PSF is very difficult due to presence of noise.

2.2.2. Wiener Filtering

Unlike the inverse filtering, the wiener filtering is not sensitive to additive noise. This restoration algorithm is based on the least squares approach. It is used to linearly estimate the original image. This technique is based on the stochastic model. Mathematically, it can be represented as follows [11]:

$$\hat{\mathcal{F}} = \left[\left(\frac{\mathcal{H}^*}{|\mathcal{H}|^2 + \delta} \right) \right] \qquad where \quad \delta = \frac{|\mathcal{G}|^2}{|\mathcal{F}|^2} \tag{2.5}$$

Where the above filtering process is represented in frequency domain, it require the exact knowledge about original image $\boldsymbol{F}$. Whereas, $\boldsymbol{\widehat{F}}$ is the linear transform of the original image. As it uses the mean square error approach, it is resistive against the additive noise and computes the blurring function by smoothing the additive noise. The linear filters also have some disadvantages, as it produces artifacts around edges due to partial de-blurring. For wiener filtering technique it is assumed that the ratio of noise to signal power and PSF are known [7]. The figure below represents the performance of wiener filtering approach.

Figure 2.5 Performance of Wiener Filtering Approach

In Fig. 2.5, (a) and (b) represent the original clear image and distorted image respectively, while (c) is the restored image generated by wiener filtering.

2.2.3. Iterative Blind De-Convolution Approach

The iterative blind de-convolution approach used the Fast Fourier Transform, non-negativity constraints and deterministic constraints as finite support to restore the blur image. The iterative blind de-convolution is also a convolution based approach.

The distorted images, which are too large in spectral domain, can also be restored in spatial domain by using convolution in IBD method. The BID method is also useful when the prior knowledge such as image intensity positivity is not present in spectral domain [12].

The iterative blind de-convolution algorithm can be represented as [13]:

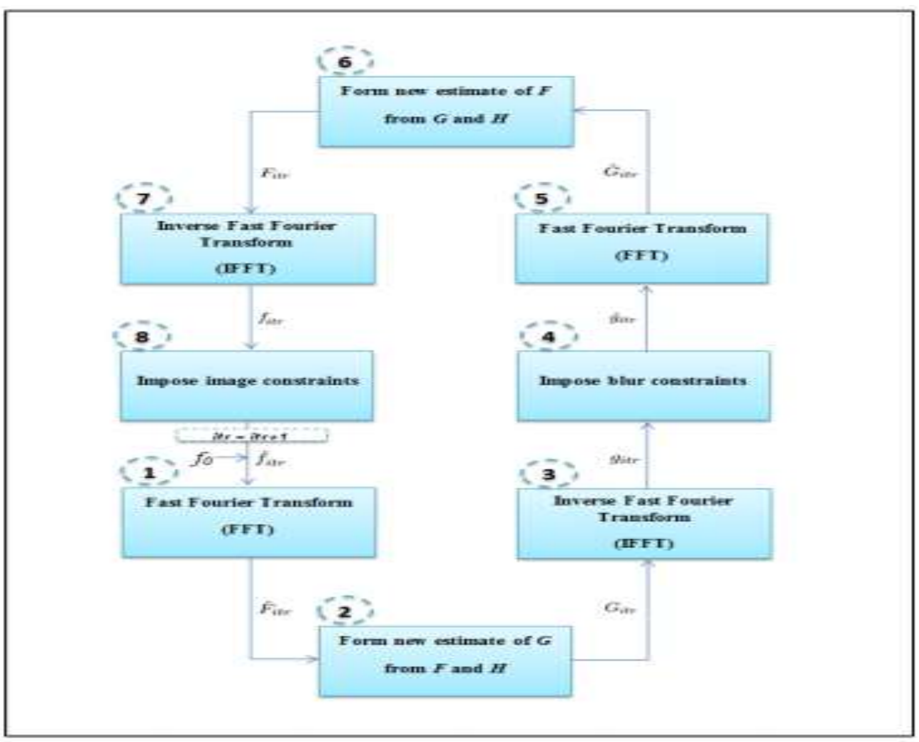


Figure 2.6 Iterative blind de-convolution algorithm

In Fig. 2.6, H, G and F indicates the FTT of the corresponding signals of degraded image g, the computed PSF h and estimated image f respectively. Following steps are performed in iterative blind de-convolution algorithm:

1. In the first step, FFT is applied to the initial estimated non-negative estimated image f.
2. Then the inverse filtering is applied on the output of the previous step to compute the estimated G.
3. The inverse FFT is applied to the $\boldsymbol{G_{itr}}$.
4. Then the non-negative constraints are imposed.
5. Then FFT is applied to the output of the previous step.
6. In this step, inverse filtering is applied to the $\boldsymbol{G_{itr}}$ and multiplied to the H, to compute the estimated F.
7. Then inverse FFT is applied on F to compute new estimated $\boldsymbol{f_{itr}}$
8. In the last step image constraints are imposed on estimated$\boldsymbol{f_{itr}}$.

The above steps indicate the single iteration of the iterative method. These steps have been repeated unless two positive functions with the required convolution have been calculated.

There are two main disadvantages for IBD method.

1. For very small values of inverted function it is very difficult to calculate inverse filter.
2. *F* and *G* have spectral zero, means one cannot get any information about spatial frequency of the blurring process.

The IBD technique is resistive to noise and has less complexity, which makes it suitable for restoration process [13]. But IBD also has some drawbacks, it suffers from convergence, complexity of initial image estimation and instability.

2.2.4. Richard-Lucy Technique

The Richardson-Lucy technique was another blind de-convolution technique, based on conditional probability [9]. In this proposed technique the blurred image, original image and PSF were all treated as probability functions. The proposed conditional probability (Bayes' theorem) for image de-blurring can be represented as follows:

$$P(F|G_{itr}) = \frac{P(G_{itr}|F)P(F)}{\sum_{i,j=1}^{M,N} P(G_{itr}|F)P(F)} \quad 2.6$$

Where G and F represented the blurred image and original image. Where *itr* represents the number of iterations taken by the algorithm. M x N is the size of image and (i,j) represents the pixel location.

The major drawback of the proposed technique is that it required initial estimation about the support size of the point spread function. To run this algorithm one should know or estimate the size of point spread function. The Fig. 2.7 represents the performance of Richardson-Lucy technique.

Figure 2.7 Performance of Richardson-Lucy Approach

2.2.5. Regularization Based Restoration Method

Most of the BID techniques used inverse approach, due to which small error in the input become high frequency error at the output step [10]. That's why in noisy environment the inverse approaches worked poorly. Hence, it was suggested to use least square error methods or regularization-based approaches. These approaches minimize the noise effect by using the prior knowledge about original data. To de-blur an image through regularization-based method, noise power and exact PSF should be known. The noise power can be computed as:

$$\boldsymbol{NP} = \|\boldsymbol{I} - \boldsymbol{T}\|_{\boldsymbol{T}}^{\boldsymbol{2}} \qquad 2.7$$

Where NP indicates the noise power, subscript T is the frobenius norm. In Fig. 2.8 image restoration through regularization-based method is shown.

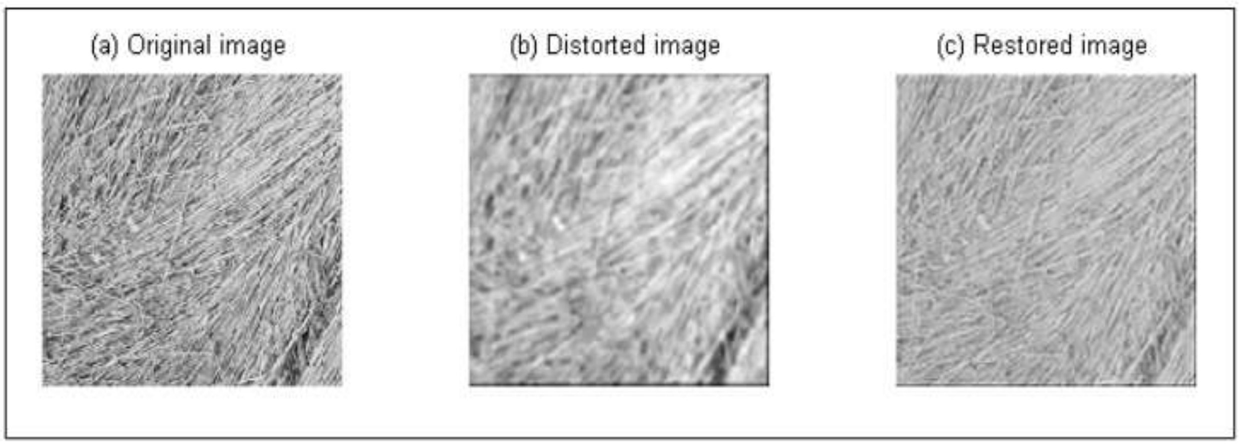


Figure 2.8 Performance of Regularization-Based Algorithm.

2.3. Blind Image De Blurring Techniques

Blind image de-blurring is a process in which information both original image and blur kernel/PSF in unknown or partially known. So it is double ill posed problem. Many techniques have been proposed to solve this highly ill posed problem.

Blind image is convolution of latent image with blur kernel. The task is to find a filter to de-convolve blur image. In image de-blurring when we have prior information it is called classical image restoration. To handle image de-blurring while having prior information of blur filters which are commonly used are inverse, iterative filter and least square filter. As in practical the device through which image is captured is not known so the there is no prior information that how image is degraded. It is difficult task to categorize previous image de-blurring techniques. So we categorize them as parametric or non–parametric. When we can assume that how image is blurred/degraded priory e.g. blur to motion or defocus it is parametric.

As task is to find latent image and blur kernel there are two method used previously to solve this.

1. First find blur kernel/PSF and then it can be used with any classical image de-blurring technique. Zero separation method is an example of this type.
2. To find latent image and blur kernel simultaneously. Total variation method is an example of this type.

There are many methods proposed to solve this double ill-posed problem. Some most known are following.

1. Zero Separation Method
2. Richardson Lucy
3. Total Variation
4. Maximum Likelihood
5. Minimum Entropy De-convolution

These all above mentioned method can handle to blind image de-blurring to some extent but there are few drawbacks with these methods like robustness, computational efficiency. Ringing artifacts and specially quality of the image which is restored. In real-life image is to be restored quickly so it is very important that how fast is the process of restoration of image.

This method based on the first way to solve image de-blurring technique where we first find blur kernel/PSF. This technique specifically works better for motion and defocus blurs. In this method task is to find zeros from the blurred image in frequency domain. As it is works better for motion blur because in motion blur point spread function can be found out by length. So the zeros in frequency domain are also same length away from the center of blurred image. So from zeros of blurred image in frequency domain length of point spread function can be find. Same is the case for the image which blur due to out of focus. In this we have radius. Zeros are length R away from the center of image. One of the main advantage of zero separation technique is that it is noiseless.

In [14] PSF is approximated and then blur function is separated using Richardson-Lucy filter. This technique effectively only for plan/non-rotational blur. Then Fergus work was extended in [15] no-rotational factors were added This has an additional feature when algorithm de-blurred first image then in case of second image it also uses PSF information from first image along with approximated PSF from second blurred image.

In [16] work for uniform and non-uniform blur. This method estimates point spread function using unified probabilistic graphic model. This method works effectively on image which has inherit noise and this method also handles ringing artifact better

Total variation method helps for edge detection and then there is alternating minimization algorithm which works in iteration. It serves two things recover the image and indication of point spread function.

Another method is independent component analysis [17]. In this method it is assumed that image and blur kernel are independent. Besides image de-blurring, this method is also used in different other image processing problem like de-noising, segmentation and recognition.

In [18] normalized sparsity regularization scheme is used. It produces comparatively better results in terms of de-blurred image quality. It uses L1 normalization scheme which is very fast to approximate latent image and blur kernel.

As MAP is considered complicated but in [19, 20] maximum a posterior technique is optimized and computational complexity is reduced.

Chapter-3

Methodology

3. Methodology

The main purpose of our algorithm is that it should be applicable on both natural and specific images such as text, face and low illumination images and gives comparatively better results. Beside this our algorithm should also be extended to uniform and non-uniform blurred images. Most importantly it should converge fast. In blurred images high intensity pixels are averaged with dark pixels and it results in unfurl lights in blurred image. As the image is blurred value of low intensity pixel increases. Low intensity pixels (dark channel) in blurred image are thinly scattered. And in an outdoor images low intensity pixel are near to zero. Algorithm is based on this interesting observation that dark channels of blurred images are less dark.

3.1. Proposition

Algorithm is based on proposition that in blurred image dark pixels are averaged with its neighboring pixels which are of high intensity pixels and in result of this convolution intensity of dark pixel increases. And from this proposition two properties are derived of image that is blurred.

3.1.1 Property 1

D (B) is dark channel pixel of blurred image and subsequently D (I) is dark channel of a clear image.

$$D(B)(\mathrm{x}) \geq D(I)(\mathrm{x}). \qquad 3.1$$

This equation explains that due averaging of low intensity pixels with high intensity pixels increase the area of dark pixels as compared to that of a clear image.

3.1.1 Property 2

$$\|D(B)(\mathrm{x})\|_0 > \|D(I)(\mathrm{x})\|_0, \qquad 3.2$$

In above equation Lo norm $\|\cdot\|_0$ counts the elements that are non-zero in dark pixel of clear image and blurred image. And certainly according to observation non-zero elements in dark pixels of blurred image will be greater than that of clear image.

3.2 Model and Optimization

Lo norm is used to compute how scattered is dark channel of image. Lo norm is added in equation of blurred image.

$$\min_{I,k} \|I \otimes k - B\|_2^2 + \gamma\|k\|_2^2 + \mu\|\nabla I\|_0 + \lambda\|D(I)\|_0, \qquad 3.3$$

The first term of the equation is output of restored image, in second term blur kernel is regularized; third term is about image gradient in which little information is discarded and only large gradient is retained. γ, μ, and λ are parameters used for weight.

As from the equation two things have to be estimated blur kernel and latent image.

3.2.1 Estimate latent Image ‘I’

The equation used to compute latent image will be following

$$\min_{I} \|I \otimes k - B\|_2^2 + \mu\|\nabla I\|_0 + \lambda\|D(I)\|_0, \qquad 3.4$$

Solving this equation computationally complex because Lo and non-linear term of calculating dark pixel. To handle Lo half quadratic splitting Lo optimizing approach is used and computing dark pixel auxiliary variables are introduced. So new equation will be following

$$\min_{I,u,g} \|I \otimes k - B\|_2^2 + \alpha\|\nabla I - g\|_2^2 + \beta\|D(I) - u\|_2^2 + \mu\|g\|_0 + \lambda\|u\|_0, \qquad 3.5$$

α and β in this equation are penalty parameters. And to solve the equation form latent image they should approach to infinity. Or else equation can be solved by adjusting auxiliary variables. And while adjusting auxiliary variable it does not include computing non-linear function D(.). And to solve this non-linear function used as minimum operator equation will be

$$\min_{I} \|I \otimes k - B\|_2^2 + \alpha\|\nabla I - g\|_2^2 + \beta\|D(I) - u\|_2^2. \qquad 3.6$$

The non-linear function of computing dark pixel is equivalent to a linear function ‘**M**’ which is used to vectorized image. But **‘M’** should fulfill below condition.

$$\mathbf{M}(x,z) = \begin{cases} 1, & z = y, \\ 0, & \text{otherwise.} \end{cases} \qquad 3.7$$

Pixel value are gained by multiplying **‘M’** with **‘I’**. By using previously computed interposed latent image matrix **‘M’** can be constructed according to given conditions in Eq. (3.7). To completely restore image $\mathbf{MI} = \mathbf{D(I)}$ must satisfy. Iteration of **‘M’** results in a solution closer ‘**D’.** For this **‘M’** equation to solve **‘I’** will be

$$\min_{\mathbf{I}} \|\mathbf{T}_k\mathbf{I} - \mathbf{B}\|_2^2 + \alpha\|\nabla\mathbf{I} - \mathbf{g}\|_2^2 + \beta\|\mathbf{MI} - \mathbf{u}\|_2^2, \tag{3.8}$$

$\mathbf{T_k}$ is Toeplitz convolution matrix. And this equation is solved using Fast Fourier transform. **'u'** and **'g'** solved separately as below

$$\begin{aligned} &\min_{u} \beta\|D(I) - u\|_2^2 + \lambda\|u\|_0, \\ &\min_{g} \alpha\|\nabla I - g\|_2^2 + \mu\|g\|_0. \end{aligned} \tag{3.9}$$

3.2.1 Estimate Blur Kernel 'k'

Equation for blur kernel is

$$\min_{k} \|I \otimes k - B\|_2^2 + \gamma\|k\|_2^2. \tag{3.10}$$

This equation is solved using Fast Fourier transform and after solving this equation negative value are considered zero to normalize **'k'.** This is done to gain desire result of algorithm.

3.2 Discrete Wavelet Transform

The DWT is used to decompose an image into its low frequency and high frequency sub bands [3]. In image processing coefficients of low frequency sub-band are used as image features as these coefficients are less affected by the blurring effects and illumination variations. The advantage of using DWT in image de blurring is that it filters out the noise (high frequency information) of the image.

Computational complexity of the de-blurring process is also reduced due to the image compression [20]. Fig. 3.1(a) and 3.1(b) show a sample image and its 2-D wavelet decomposition respectively. Upper left sub-band of Fig. 3.1(b) contains the low frequency information of image while other three contain the information of horizontal, vertical and diagonal edges.

(a) Sample image (b) Wavelet Decomposition

Figure 3.1 Wavelet decomposition of a sample image

3.3 Adjunct of Non-Uniform De-Blurring

This algorithm can also handle non-uniform blurring. Non-uniform blur can be stated as

$$\mathbf{B} = \sum_t k_t \mathbf{H}_t \mathbf{I} + \mathbf{n}, \quad 3.11$$

'I' and **'n'** are same as of uniform blur model; **'t'** is number of sample pose; '**Ht'** homograph matrix and **'Kt'** is used as weight parameter. Simply this equation cab also be written as

$$\mathbf{B} = \mathbf{K}\mathbf{I} + \mathbf{n} = \mathbf{A}\mathbf{k} + \mathbf{n}, \quad 3.12$$

For uni-uniform de-blurring above equation can be solved by optimizing

$$\min_{\mathbf{I}} \|\mathbf{K}\mathbf{I} - \mathbf{B}\|_2^2 + \lambda \|\mathbf{D}(\mathbf{I})\|_0 + \mu \|\nabla \mathbf{I}\|_0$$

$$\text{and} \qquad \min_{\mathbf{k}} \|\mathbf{A}\mathbf{k} - \mathbf{B}\|_2^2 + \gamma \|\mathbf{k}\|_2^2. \quad 3.13$$

Fast forward approximation will be used to obtain **'I'** and **'k'.**

Chapter-4

Results & Analysis

Experiments are performed on natural, text, face and low illumination image deblurring datasets to verify the effectiveness of proposed algorithm. Natural image dataset by Kohler et al. [16] is used that contains four images. Image dataset [26] contains 15 clear text images. Blurred images captured under low-illumination conditions often have saturated pixels that interfere with the kernel estimation process. Therefore, these images are particularly challenging for most deblurring methods. DE blurring of face images is also challenging due to the face image texture. De-blurred image quality depends upon weight parameters γ, μ, and λ. Multiple values of these parameters are tested but favorable results are obtained for $\lambda = \mu = 0.004$ and $\gamma = 2$.

4.1 Performance Evaluation Parameters

Over the past years, many blind de-blurring algorithms have been proposed so far, these algorithms have some positive and negative consequences over the other deblurring algorithms. Now, the important issue is how to assess the performance of different techniques, the de-blurred image quality assessment is a necessary but difficult issue. Different image quality assessment techniques have been proposed to measure the performance of different de-blurring techniques.

The quality assessment techniques for de-blurring can mainly be divided into two categories:

- Subjective Analysis (Qualitative Analysis)
- Objective Analysis (Quantitative Analysis)

4.1.1 Subjective Analysis

For different applications, the human perception about the de-blurred resultant image is mainly important. Hence, as a result, the performance of the de-blurred image is usually assessed by the subjected (qualitative) criteria. Over the past 30 years, qualitative analysis has been used to assess the performance of print as well as digital images.

In qualitative analysis, a group of participant analyzes the de-blurred resultant image with reference image sequence, on the bases of visual parameters. However, the performance of subjected analysis largely depends upon the experience and knowledge of the participants. The process of subjective analysis is often expensive and time-consuming, while it is also not possible to guarantee the same parameters and conditions for the assessment test.

4.1.2 Objective Analysis

Quantitative or objected analysis is based on mathematical modeling, the pre-defined quality measures are used to evaluate the performance of the de-blurred image. The quantitative analysis are further divided into two categories:

- Reference-based
- Without Reference-based

4.1.2.1 Reference-based Techniques

Some of the reference-based quality assessment techniques are as follows:

- Root Mean Square Error (RMSE)
- Mean Bias (MB)
- Correlation Coefficient (CC)
- Signal to Noise Ratio (SNR)
- Relative Dimensionless Global Error (ERGAS)
- Peak Signal to Noise Ratio (PSNR)
- Percentage Fit Error (PFE)
- Universal Quality Index (UQI)
- Spectral Angular Mapper (SAM)
- Mutual Information (MI)
- Structural Similarity Index Measure (SSIM)

4.1.2.2 Without Reference-based Techniques

Some of without reference-based quality assessment techniques are as follows:

- Standard deviation
- Spatial Frequency (SF)
- Fusion Similarity Metric (FSM)
- Entropy (He)
- Fusion Quality Index (FQI)
- Cross Entropy (CE)
- Fusion Mutual Information (FMI)
- Degree of Distortion (D)

There are numerous reference and without reference-based techniques to analyze the performance of de-blurring algorithm but here we only discuss the techniques, that have been used in this thesis to quantify the performance of the proposed algorithm.

4.1.1 Peak Signal to Noise Ratio (PSNR)

PSNR calculates the peak signal-to-noise ratio, in decibels, between reference image (I_{ref}) and de-blurred image I_{deb}. Higher value of the PSNR shows better quality of the de-blurred image. PSNR is calculated using following formula

$$\boldsymbol{PSNR_{db} = 10log_{10}\left(\frac{\max(I_{rec})^2}{MSE}\right)}$$

Where MSE is the mean square error that represents the cumulative error between the de-blurred image and reference image that is calculated using following equation.

$$MSE = \frac{\sum \|I_{ref}(x,y) - I_{recon}(x,y)\|^2}{\sum I_{ref}(x,y)}$$

4.1.2 Artifact Power (AP)

The idea of AP has taken from "Square Difference Error". AP of the reconstructed image I_{deb} will be calculated on the basis of a reference image (I_{ref}) as given in eq (). Lower value of AP shows better quality of the reconstructed image

$$AP = \frac{\sum \|I_{ref}(x,y) - I_{recon}(x,y)\|^2}{\sum |I_{ref}(x,y)|^2}$$

4.1.3 Structural Similarity Index Measure (SSIM)

Structural Similarity Index Measure is the reference-based technique, used to measure the deterioration of structural information in the de-blurred image. It compares the three parameters: contrast, luminance and structure between reference and de-blurred image to compute the SSIM score. The maximum score for SSIM is 1, that indicates that the input and resultant are perfectly matched. While, the lowest value is 0, means the two image have no similarity. Mathematically, SSIM can be represented as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

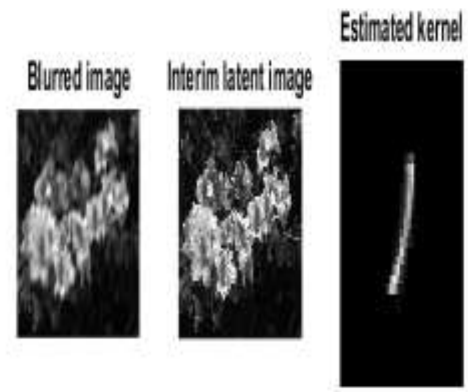
Where x and y are the two images, whose SSIM has been computed, μ_x and m_y are the luminance component for image x and y respectively. And σ_x, σ_y represent the standard deviation for image x and y respectively. C_1 and C_2 are the constants used to avoid instability \cite{wang2004image}.

4.1 Simulation Results

The proposed technique is tested on blurred natural, text, low illumination and face images. Image quality of de-blurred images is evaluated for different values of λ and γ. Reconstructed natural images along with their estimated kernels and interim latent images are shown in Fig. 4.1. Quantitative analyses are performed on these reconstructed images and their values are depicted in Table (4.1).

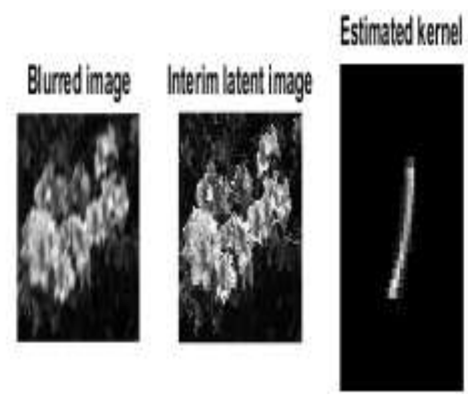
(a)

(b)



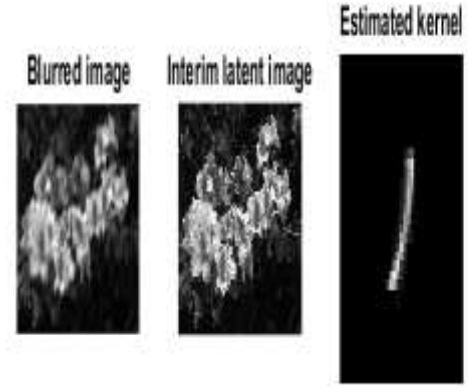
(c)

(d)



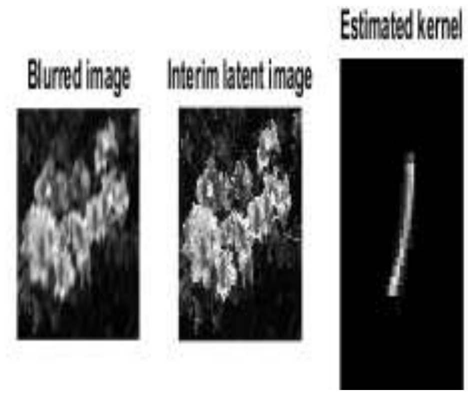
(e)

(f)



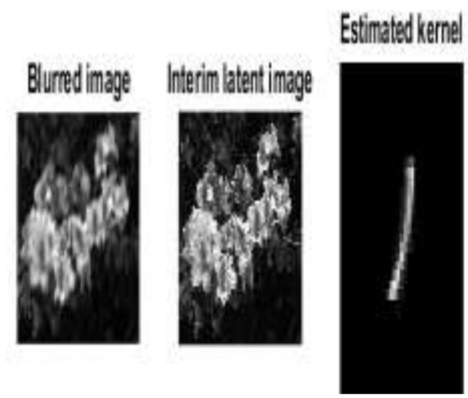
(g)

(h)



(i)

(j)



(k)

Fig. 4.1: (a) Blurred Image, (b) De-blurred Image for λ=0.002, (c) Interim Latent Image and Estimated kernel for λ=0.002, (d) De-blurred Image for λ=0.003, (e) Interim Latent Image and Estimated kernel for λ=0.003, (f) De-blurred Image for λ=0.004, (g) Interim Latent Image and Estimated kernel for λ=0.004, (h) De-blurred Image for λ=0.005, (i) Interim Latent Image and Estimated kernel for λ=0.005, (j) De-blurred Image for λ=0.006, (k) Interim Latent Image and Estimated kernel for λ=0.006

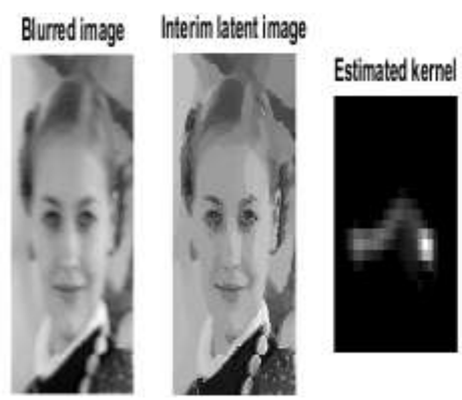
Table 4.1: Quantitative Measures for Natural Image

Sr #	Weighting Parameter (λ)	SSIM	PSNR (dB)	Artifact Power (AP)
1	0.002	0.9858	40.9252	0.0047
2	0.003	0.9700	38.3093	0.0069
3	0.004	0.9575	37.1980	0.0083
4	0.005	0.9476	36.5680	0.0093
5	0.006	0.9476	36.5680	0.0093

It is clear from this table that image quality degrades as the value of weighting parameter (λ) is increased. Qualitative results on face images are shown in Fig. 4.2 for different values of weighting parameter (λ) while keeping the weighting parameter (γ) constant to a value of 1.

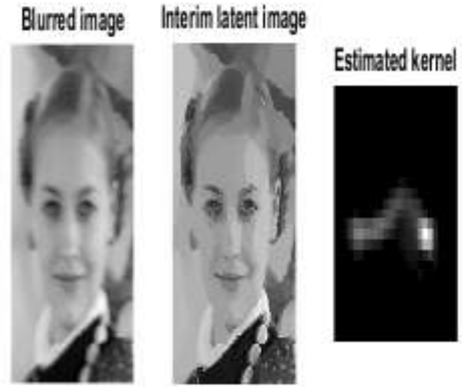
(a)

(b)



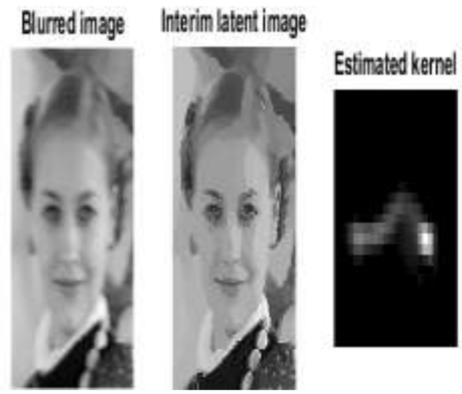
(c)

(d)



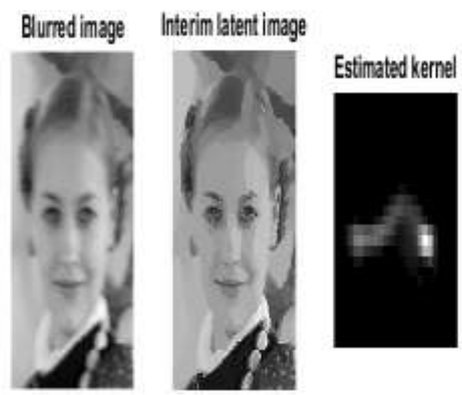
(e)

(f)



(g)

(h)



(i)

Fig. 4.2: (a) Blurred Image, (b) De-blurred Image for λ=0.002, (c) Interim Latent Image and Estimated kernel for λ=0.002, (d) De-blurred Image for λ=0.004, (e) Interim Latent Image and Estimated kernel for λ=0.004, (f) De-blurred Image for λ=0.005, (g) Interim Latent Image and Estimated kernel for λ=0.005, (h) De-blurred Image for λ=0.006, (i) Interim Latent Image and Estimated kernel for λ=0.006

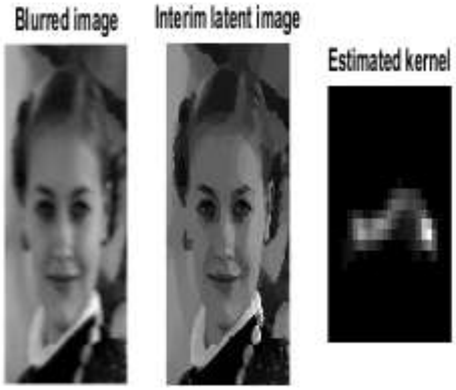
Table 4.2 summarizes the quantitative measures for de-blurred face images using weighting parameter **(**γ=1) and varying the value of (λ)**.** Image quality improves as the value of λ is increased.

Table 4.2: Quantitative Measures for Face Image using Weighting Parameter (γ=1**)**

Sr #	Weighting Parameter (λ)	SSIM	PSNR (dB)	Artifact Power (AP)
1	0.002	0.9985	52.1159	0.0015
2	0.004	0.9991	54.8933	9.2867e-04
3	0.005	0.9980	50.6106	0.0016
4	0.006	0.9968	48.2802	0.0021

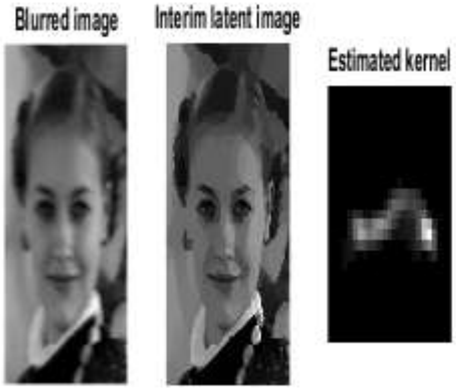
Fig. 4.3 shows the reconstructed images, their corresponding latent images and estimated kernels for different values of weighting parameter λ while keeping γ=2.

(a)



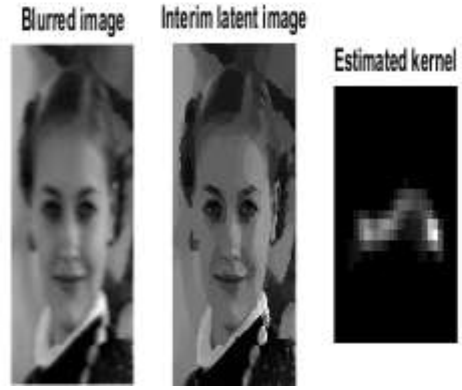
(b)

(c)



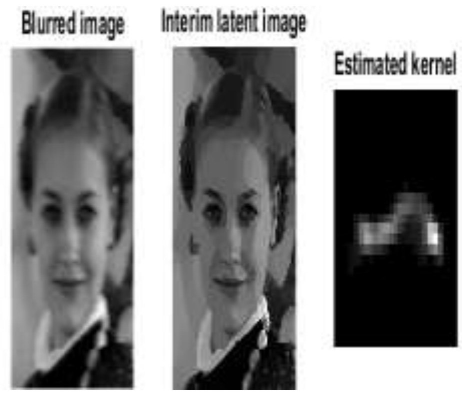
(d)

(e)



(f)

(g)



(h)

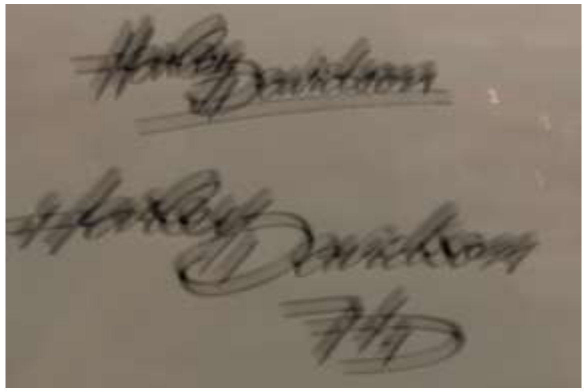
Fig. 4.3: *(a) Blurred Image, (b) De-blurred Image for* λ=0.002, (c) Interim Latent Image and Estimated kernel *for* λ=0.002, (d) *De-blurred Image for* λ=0.004, (e) Interim Latent Image and Estimated kernel *for* λ=0.004, (f) *De-blurred Image for* λ=0.005, (g) Interim Latent Image and Estimated kernel *for* λ=0.005, (h) *De-blurred Image for* λ=0.006, (i) Interim Latent Image and Estimated kernel *for* λ=0.006

Table 4.3 depicts the values of performance parameters for de-blurred face image using weighting parameter **(**γ=2) and varying the value of (λ)**.** It is evident from Table 4.2 and Table 4.3 that image quality improves by increasing the value of λ and decreasing the value of (γ).

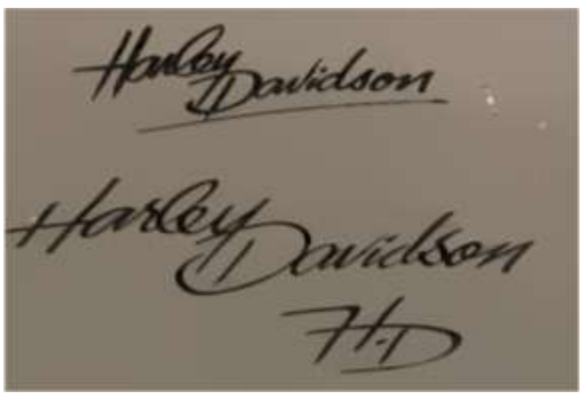
Table 4.3: Quantitative Measures for Face Image using Weighting Parameter (γ=2**)**

Sr #	Weighting Parameter (λ)	SSIM	PSNR (dB)	Artifact Power (AP)
1	0.002	0.9595	37.6444	0.0102
2	0.004	0.9656	38.1505	0.0091
3	0.005	0.9666	38.2540	0.0089
4	0.006	0.9671	38.3167	0.0087

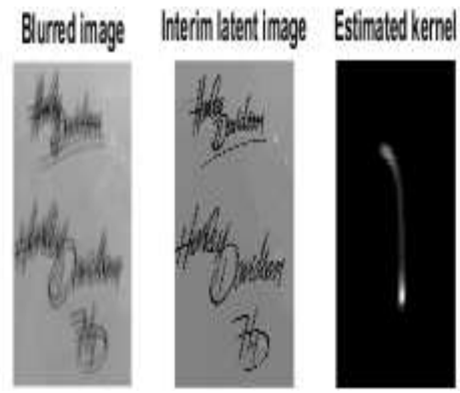
The proposed technique is applied on text images and quality of reconstructed images is determined for different weighting parameters. Interim latent images, estimated kernels and reconstructed images are shown in Fig. 4.4.



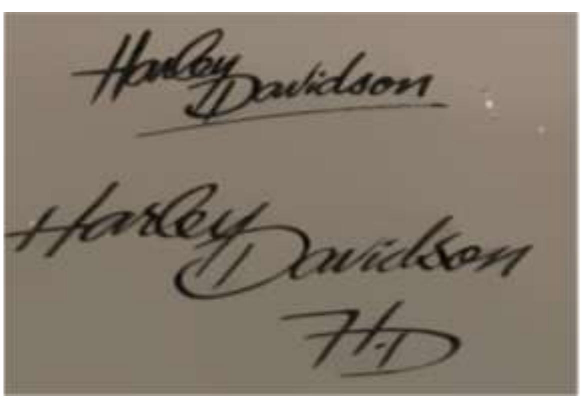
(a)



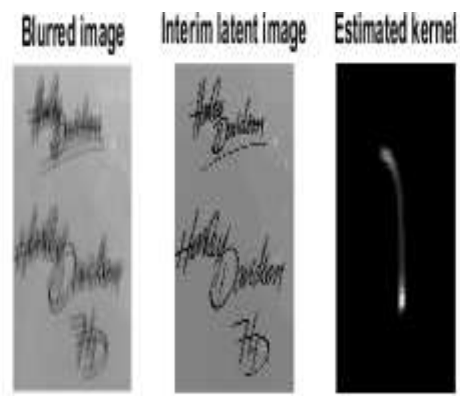
(a)



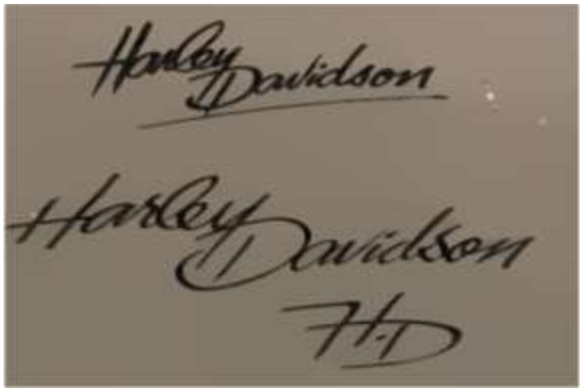
(b)

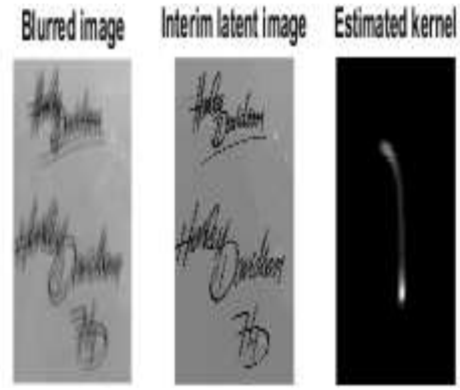


(c)

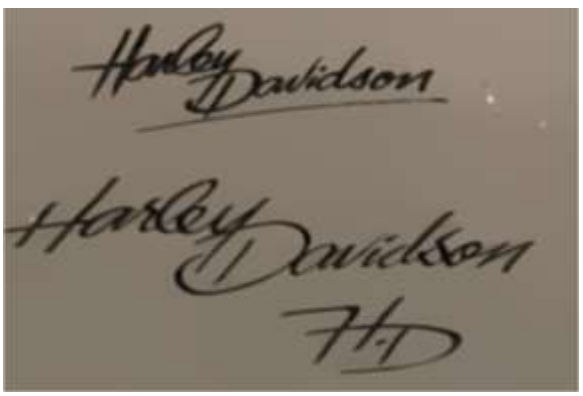


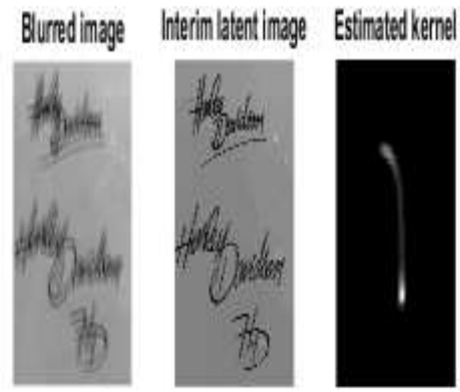
(d)



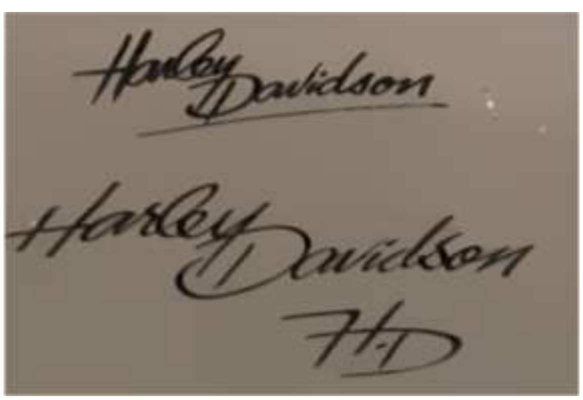


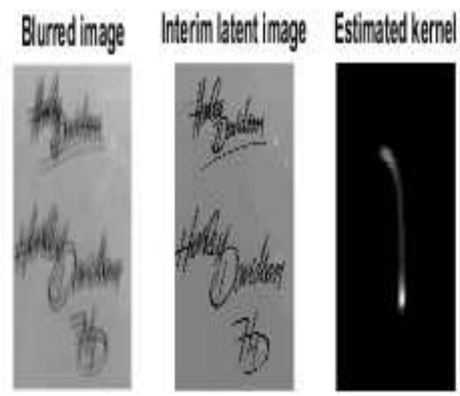
(e) **(f)**





(g) **(h)**





(i) **(j)**

Fig. 4.4: *(a) Blurred Image, (b) De-blurred Image for* λ=0.002, (c) Interim Latent Image and Estimated kernel *for* λ=0.002, (d) *De-blurred Image for* λ=0.003, (e) Interim Latent Image and Estimated kernel *for* λ=0.003, (f) *De-blurred Image for* λ=0.004, (g) Interim Latent Image and Estimated kernel *for* λ=0.004, (h) *De-blurred Image for* λ=0.005, (i) Interim Latent Image and Estimated kernel *for* λ=0.005, (h) *De-blurred Image for* λ=0.006, (i) Interim Latent Image and Estimated kernel *for* λ=0.006

Table 4.5 depicts the quantitative results on the text images. It is evident from this table that quality of de-blurred text images improves by increasing weighting parameter (λ).

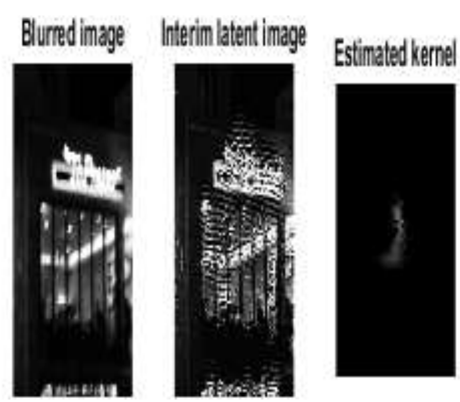
Table 4.4: Quantitative Measures for Text Image

Sr #	Weighting Parameter (λ)	SSIM	PSNR (dB)	Artifact Power (AP)
1	0.002	0.9990	51.0223	0.0014
2	0.003	0.9979	47.4502	0.0019
3	0.004	0.9971	45.9029	0.0022
4	0.005	0.9965	45.0928	0.0024
5	0.006	0.9961	44.6314	0.0025

Experiments are also conducted on low illumination images to check the effectiveness of proposed technique in deblurring images captured under un-controlled environment. Figure 4.5 shows the de-blurred images, latent images and estimated kernels for different values of weighting parameters.

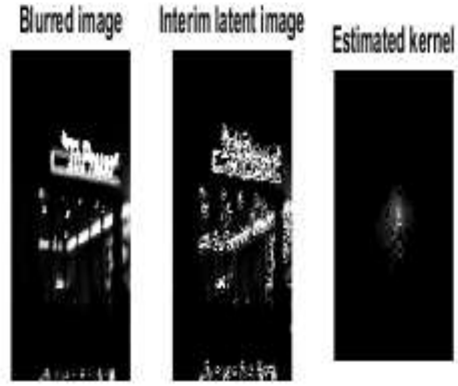
(a)

(b)



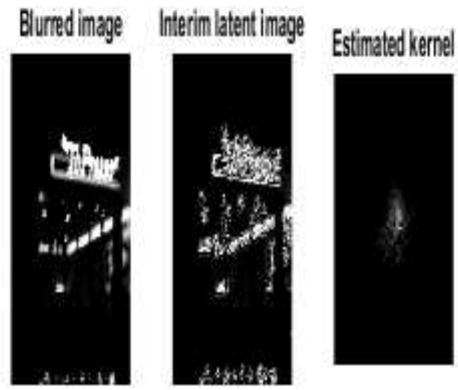
(c)

(d)



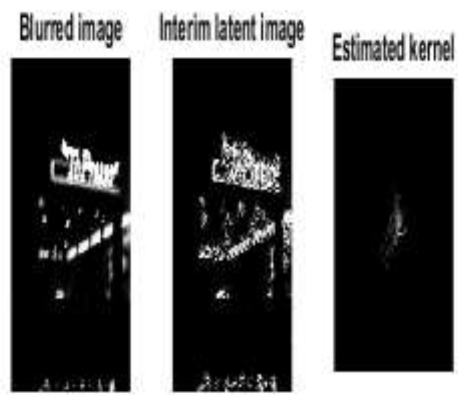
(e)

(f)



(g)

(h)



(i)

Fig. 4.5: *(a) Blurred Image, (b) De-blurred Image for* γ =1.2, (c) Interim Latent Image and Estimated kernel *for* γ =1.2, (d) *De-blurred Image for* γ =3.2, (e) Interim Latent Image and Estimated kernel *for* γ =3.2, (f) *De-blurred Image for* γ =4.2, (g) Interim Latent Image and Estimated kernel *for* γ =4.2, (h) *De-blurred Image for* γ =5.2, (i) Interim Latent Image and Estimated kernel *for* γ =5.2

Table 4.5 summarizes the quantitative measures on reconstructed images captured under low illumination conditions for different values of weighting parameter (γ). It is evident from this table that image quality degrades as value of weighting parameter (γ) increases.

Table 4.5: Quantitative Measures for Text Image

Sr #	Weighting Parameter (γ)	SSIM	PSNR (dB)	Artifact Power (AP)
1	1.2	0.8959	36.3154	0.0124
2	3.2	0.8487	35.0232	0.0212
3	4.2	0.8531	35.2794	0.0205
4	5.2	0.8213	35.0288	0.0258

4.1 Comparative Analysis

Experimental results obtained on different data-sets are compared with previous image de-blurring techniques. Figure 4.6 shows the comparative results on natural, face, text and low illumination images.

Blur Image | Xu | Pan | Jinshan | Proposed

Blur Image | Xu | Pan | Jinshan | Proposed

Blur Image | Xu | Hu | Jinshan | Proposed

Fig. 4.6: De-blurred Image Quality Comparison

Image quality of de-blurred images are analyzed based on the quantitative measures e.g SSIM, PSNR. Table 4.6, 4.7, 4.8 and 4.9 depicts the de-blurred image quality comparison of proposed technique with the previous techniques on face, low illumination, natural and text images. In [21] Xu proposed de-blurring technique that was based on the L_0 Sparse Representation. This method performs better for the natural images. Jinshan [22-24] methods of image de-blur were based on L_0 Regularized Intensity that was specifically proposed to de-blur text images. The proposed method is based on the dark channel prior that performs favorably on all type of datasets.

Table 4.6: Comparative Results on Face Images

Method	Ref	SSIM	PSNR
Xu	[21]	0.9354	35.6534
Pan	[25]	0.9428	36.7439
Jinshan	[26]	0.9767	39.6317
Proposed	-	0.9671	38.3167

Table 4.7: Comparative Results on Low Illumination Images

Method	Ref	SSIM	PSNR
Xu	[21]	0.8593	34.1267
Jinshan	[26]	0.8792	35.6539
Hu	[27]	0.8652	34.9962
Proposed	-	0.8959	36.3154

Table 4.8: Comparative Results on Natural Images

Method	Ref	SSIM	PSNR
Xu	[21]	0.9876	41.0346
Jinshan	[26]	0.9836	40.8379
Cho	[28]	0.9650	38.7347
Proposed	-	0.9858	40.9252

Chapter-5

Conclusion

5. Conclusion

A blind image de blurring technique based on dark channel prior has been proposed. Input image is preprocessed to effectively remove the noise effects. Discrete wavelet transform is employed to reduce the dimensions of images. The algorithm is based on the proposition that in blurred image dark pixels are averaged with neighboring high intensity pixels. As a result convolution intensity of dark pixels increases and proposed method is proved both theoretically and empirically. Two properties are derived from the proposed technique. First that averaging of low intensity pixels with high intensity pixels increases the area of dark pixels in blurred image. Secondly, non-zero elements of blurred image will be greater than that of clear image. Dark channel of image is computed and minimized using Lo regularization. To handle Lo regularization half quadratic splitting optimization approach is used. As a result latent image is estimated. FFT is used for the estimation of blur kernel. Both the estimated latent image and estimated blur kernel are convolved and subsequently difference between the resultant with blurred image is computed. Experimental results reveal that quality of de-blurred images using proposed model is comparable to the state of the art dark channel prior techniques whereas computational efficiency is improved.

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