Region Based Robust Single Image Blind Motion Deblurring of Natural Images

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***Abstract*— One of the prime causes of poor image quality in digital imaging is motion blurring. Recovering a clear image from a simple motion blurred image has long been a challenging open problem in digital imaging. The objective of this paper is to recover a motion blurred image due to camera shake or the scene object being in motion. A regularization based approach is proposed to remove motion blurring from the image by regularizing the sparsity of both the original image and motion blur kernel under tight wavelet frame systems. It is based on framelet regularization technique. Framelet technique is implemented to decompose the image into number of framelet coefficient signal. Furthermore, an adapted version of region based framelet method is proposed to efficiently solve the resulting minimization problem. In existing methods, due to inaccurate multiple parameters, the accuracy is low and it is not suitable for non-uniform blur. For non-uniform motion blurring region estimation, adaptive k-means clustering is used. Also according to the region, fast genetic algorithm based optimal framelet method is applied. The experiments on both synthesized images and the real images show that our algorithm can effectively remove complex motion blurring from natural images without requiring any prior information of the motion blur kernel.**

***IndexTerms*—Blur kernel, framelet method, blind deconvolution, motion deblurring, sparse representations.**

I. INTRODUCTION

Recovering a sharp image from a motion blurred image without the knowledge of its blur kernel is known as Blind motion Deblurring .This is an interesting problem in many applications, including video surveillance, medical imaging, and consumer photography, to name but a few.

A motion blur is a common artifact that produces disappointing blurry images with inevitable information loss .It is caused by nature of image sensors that accumulate incoming lights for an amount of time to produce an image. During exposure, if the camera sensor moves a motion blurred image will be obtained. Many aspects of blind motion deblurring have remained unclear until recently [1]-[3]. Technical robustness of highly diverse natural images has not yet received sufficient attention within image processing community.

Image blur due to camera shake is a common problem in consumer level photography. It arises when a long exposure is required and the camera is not held still. As the camera moves, the image formation process integrates into a stream of photographs of the scene taken from slightly different viewpoints.

Removing blur due to camera shake is currently a very active area of research. Given only a single photograph, this blur removal is known as blind deconvolution, i.e., simultaneously recovering both the blur kernel and the deblurred, latent image. Commonly, it is assumed that the blur kernel is spatially invariant; reducing the set of camera motions that may be modeled. Most of the existing methods have produced poor robustness and inaccurate result. To address these problems, this paper proposes a framelet regularization based approach to remove motion blurring from the image by regularizing the sparsity of both the original image and the motion-blur kernel under tight wavelet frame systems.

II. RELATED WORKS

Blind motion deblurring is an interesting subject in the image processing community, but many existing methods suffer from poor robustness towards the wide diversity found in natural images. Image Deblurring has received a lot of attention in the computer vision community. Deblurring is the combination of two tightly coupled sub-problems: PSF estimation and non-blind image deconvolution. These problems have been addressed both independently and jointly [1]. Both are longstanding problems in computer graphics, computer vision, and image processing. Image blur arises from multiple causes. In most recent work, image blur is modeled as the convolution of an unobserved latent image with a single, spatially invariant blur kernel [4, 5, 6 and 7]. Various methods for blind motion deblurring has been mentioned in the next section.

A. EDGE SPECIFIC SCHEME

To remedy the MAP failure, the edge specific scheme relies on the detection and prediction of large scale step edges (LSED). LSED detection-based methods [10], [11], assume that sharp explanations are favored by (2) around step edges (i.e. sharp edges have lower energy than their blurred versions in (2)). However this assumption holds only for a few small windows around LSED. The LSED prediction-based methods [9], [13] firstly restore sharp step edges and then use them to estimate good initial kernel. Since sharpening filters that includes the shock filter can only restore step edges, the LSED prediction-based methods cannot handle images in which the number of LSEDs is small, e.g. highly textured images. However, their method is not robust as it fails to exclude a variety of types of edge to guarantee robust kernel estimation.

B. NON-EDGE SPECIFIC SCHEME

The non-edge specific scheme does not rely on the recovery of one specific kind of edge. This consequently avoids the weakness exhibited by the edge specific scheme. One approach is to seek an image measurement that favors sharp explanations [15] (i.e. sharper images achieve lower measurement scores).But it is extremely hard for a measurement to work well for thousands of natural images, let alone for millions of examples. Another approach is to marginalizing the sparse prior distribution. A more robust solution [8] is the marginalization method, which solves k by maximizing p(x/y).

C. NON-EDGE SPECIFIC ADAPTIVE SCHEME (NEAS)

The NEAS is an elegant combination of the marginalization method and the LSED prediction method. NEAS inherits the advantages of the non-edge specific scheme since it does not rely on the recovery of specific image edges. Meanwhile, NEAS adopts a adaptive prior, leading to the capability of handling the variation of sparse image priors that exists in natural images in an adaptive manner. Consequently, NEAS achieves a high degree of robustness and a good performance across a wide variety of natural images. This method focuses entirely on the issue of algorithm robustness to image diversity. Other issues such as blur formulation and optimization are not at the center of this research. And only spatially uniform blurs are considered in this method. Space-variant blur models can be found in [12], [14].

III. PROPOSED SYSTEM

A regularization based approach is proposed in this paper to remove motion blurring. It is based on framelet regularization technique. Framelet technique is implemented to decompose the image in to number of framelet coefficient signal. Furthermore, an adapted version of region based framelet method is proposed to efficiently solve the resulting minimization problem. Framelet-transform is similar to wavelet transforms but has some differences.

Framelets have two or more high frequency filter banks, which produce more subbands in decomposition. This can achieve better time frequency localization [16] ability in image processing. There is redundancy between the Framelet subbands, which means change in coefficients of one band can be compensated by other subbands coefficients. Coefficient in one subband has correlation with coefficients in the other sub band. This means that changes on one coefficient can be compensated by its related coefficient in reconstruction stage which produces less noise in the original image

The genetic algorithm is a population-based iterative optimization method. In Genetic algorithm, deciding on a coding is the critical part of the algorithm design. Genetic algorithms include the genetic representation and the evolution process. Genetic algorithm is used in framelet filter to optimize the parameter value and to select the best value; this algorithm also finds the optimal filter coefficients.

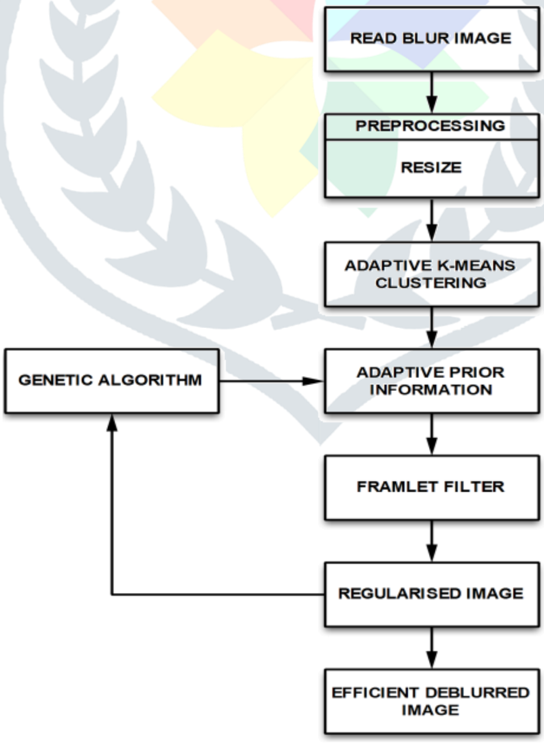

Fig 1: Block diagram of the proposed Method

Preprocessing is a common name for operations with images at the lowest level of abstraction; both input and output are intensity images. The aim for preprocessing is an improvement of the image data that suppresses unwanted distortions or enhances some image features important for further processing. If the aim of preprocessing is to correct some degradation in the image, the nature of a priori information is important: knowledge about the nature of the degradation; knowledge about the properties of the acquisition device and conditions under which the image was obtained.

Clustering can be considered the most important unsupervised learning problem; so, as every other problem of this kind; it deals with finding a structure in a collection of unlabeled data. A loose definition of clustering could be "the process of organizing objects into groups whose members are similar in some way". A cluster is therefore a collection of objects which are "similar" between them and are "dissimilar" to the objects belonging to other clusters. The goal of clustering is to determine the intrinsic grouping in a set of unlabeled data.

Adaptive prior information learned from a single image to highly diverse natural images leads to significant variation of performance over different natural images. A more robust solution is the marginalization method, which solves k (kernel) by maximizing p (x/y).It has been proved that this leads to the true solution under the condition that the size of x is much larger than the size of k according to Bayesian estimation theory. However, this is based on the assumption that the prior ρ (x) is the same for all natural images. In fact, the deviation of ρ(x) among natural images leads to significant performance variation of the marginalization method over different natural images

IV. EXPERIMENTAL RESULTS AND IMPLEMENTATION RESULTS

This section analyzes the fundamental causes of poor robustness and inaccurate multiple parameters of the existing blind motion deblurring techniques. The analysis is based on experiments carried out on a huge image set, Image Net, which offers a comprehensive coverage of natural images from the real world.

The sparse prior ρ(x) within differently sized local windows in a natural image is observed and how many of them favor the sharp version shows the average percentage of the windows sized at 25× 25 that favor the sharp versions within the 20 category bins. It shows that this percentage is quite small for highly textured images (<0. 15%). Further, the blurred versions are favored almost at natural images. It features 12 sub trees, containing a total of 1.2 million high quality images spread over 5247 categories Analysis has been performed on the images under this categorization. The experiments needed to artificially blur all of the 1.2 million images from Image Net using different blur kernels, creating pairs of blurred and sharp images. Second step of the project is to identify the non-uniform region. Estimate the histogram and local peaks mentioned as red color in Figure 3. Generating blurred images using artificial kernels is a common practice in much blind motion deblurring research. Since the true motion blur kernel is unknown, different artificial kernels are often used to mimic the real motion blur. First we use an image histogram to get the number of different regions. In most images, there are too many local maxima of image histograms, for consistency we have rescaled the range h as 1≤h (l) 256. All red circle points in Figure 3 are local maxima. However, we need to find only significant local maxima since those maxima are necessary to discriminate regions.

To extract the significant local maxima, we first search for an interval, including the global maximum of an original histogram, and then fix the interval. We call such a fixed interval a Cluster. Next, we remove the cluster, gained from the previous searching process, from the original histogram to find another new cluster. We then search for the new cluster of the reduced histogram and repeat this process until we have the desired result. Since the histogram changes every iteration, which is precisely the reduced version of the original histogram, the global maximum also adaptively changes every iteration. We therefore call such a maximum as adaptive global maximum that corresponds to one of the significant local maxima of the original histogram. This whole process is a series of clustering a gray level interval [1, L] into several subintervals so that the original histogram has the adaptive global maximum over each subinterval. Thus, we call this process the AGMC process.

The goal of this process is to divide the interval [1, L] into subintervals $I_i = [a_i, b_i]$ where each subinterval I_i is a cluster containing the i^{th} adaptive global maximum, which is the global maximum of the i^{th} histogram. We would however need to remove very small histogram values that are usually useless in the detection of regions. To find a cluster that is a subinterval with an adaptive global maximum at each iteration, we fix k=2, and repetitively implement the standard k-means clustering. The standard k-means clustering method is a process to solve the minimization problem. We resolve those problems by fixing k=2 , setting the initial two centers as starting index of I and ending index of I (I is the domain of histogram), and repeating the k-means clustering in the following way. Note that, in our method, the two-means clustering is applied to the reduced histograms and the original histogram. Thus, the starting and the ending indexes are changeable, not fixed as 1 and 256. Once we implement the two-means clustering, the histogram is divided into two clusters I_1 and I_2 since k=2 is chosen. Then, we have two maxima, i.e., one is obtained in $I_1$and the other is obtained in I_2. It is clear that if the maximum value of the histogram in one cluster I_1 is larger than the maximum value of the histogram in the other cluster I_2, then cluster I_1 contains the global maximum of the histogram. This gives the first rule.

Rule 1) Choose a cluster

$$I^* = \begin{cases} I_1, \text{ if } \max_{l \in I_1} h(l) > \max_{l \in I_2} h(l) \\ I_2, \text{ otherwise} \end{cases}$$

Then, we again perform the two-means clustering over the chosen cluster and repeat this process until Rule 2 holds

Rule 2) $| \arg_{l \in I_1} \max h(l) - \arg_{l \in I_2} \max h(l) | < \sigma$

Parameter σ designates the least difference in intensities of distinct regions, which guarantees that the regions with similar intensities are not split for some large σ. If σ is very small, we can even separate regions with similar intensities. With the smaller σ, we get the larger number of regions. Since we desire to get only the significant local maxima of the original histogram, we have to stop the AGMC procedure if Rule 3 holds.

Rule 3) $\max h^i < \omega \text{ mean } (h^0)$

where h^i is the i^{th} histogram, which is the reduced histogram after the (i-1) iterations, and h^0 is the original histogram. Rule 3 signifies that h^i is too small compared with the original histogram and such an h^i is usually useless in the detection of regions. This prevents us from finding small local maxima.Figure 4 shows the image obtained after performing adaptive k-means clustering on the blurred gray image.

Fig.2. Original image after adding PSF and noise

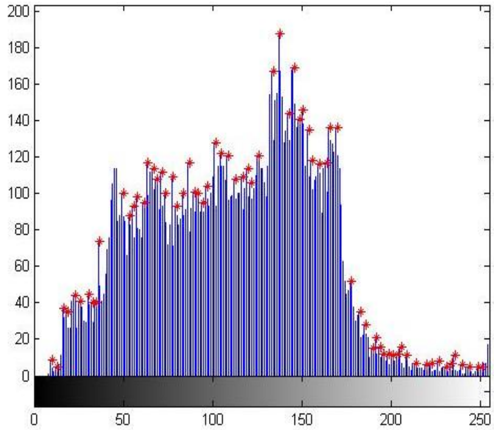

Fig.3. Estimate the histogram and local peaks

Fig.4. Adaptive K-means clustering

Fig.5. Adaptive framelet based deblurred image

Framelet technique is implemented to decompose the image in to number of framelet coefficient signal. Framelet filter divide the frequency in to multiple times. Furthermore, an adapted version of region based framelet method is proposed to efficiently solve the resulting minimization problem. Genetic algorithms are used to framelet filter to optimize the parameter value and to select the best value. This algorithm also finds the optimal filter coefficients. The results obtained were compared with the existing approaches. In comparison, the results from genetic algorithm based optimal framelet method are satisfactory.

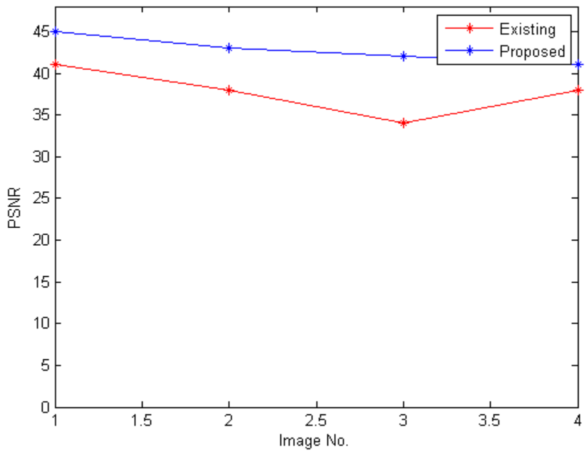

Fig.6. Performance of PSNR Value

V. CONCLUSION

Blind motion deblurring is a chronic inverse problem in the image processing community. This project discusses a critical issue – the robustness to image diversity, which has been neglected for many years. In existing method requires multiple images however proposed method need only single images. The PSNR value and the robustness are relatively high in proposed method due to the usage of framelet domain and genetic algorithm respectively. We conclude that the sources of the sensitivity to image diversity in many of the existing methods originate from the failure to handle edge variation. For non-uniform motion blurring region estimation, adaptive k-means clustering is used. Also according to the region fast genetic algorithm based optimal framelet method is applied. We use statistics to adaptively key to enhance the robustness. Based on this, framelet regularization technique is proposed as a novel blind motion deblurring method. The experiments on both synthesized images and the real images show that our algorithm can effectively remove complex motion blurring from natural images without requiring any prior information of the motion blur kernel. Experiments on a large set of images have shown that it produces high-quality results.

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