ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940

International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 2, February 2014

Detection and Removal of Distorted Regions in Remote Sensing Images

Anandhi.A[1], Nivedha.V[2], Prithi.K[3]

Assistant professor, Computer Science, Christ College of Engineering and Technology,

Pondicherry, India[1]

Student, computer Science, Christ College of Engineering and Technology, Pondicherry, India[2,3]

Abstract: In sensor imaging, an existing open challenge problem is to restore a clear image from a sole remote sensor image. In our proposed system, we concentrate mainly on how to restore a motion distortion image which is caused due to satellite tracking. We have proposed a regularization based approach, which removes motion distortion from the sole image by carefully regularizing the sparsity of both the real image and the noise distorted image under a tight wavelet frame systems. Moreover, we have adapted a model of the Split Bregman method that effectively answers the occurrence of minimization issues in the system. The implementation of our proposed algorithm on both the original image and synthesized image proves that complex motion distortion is effectively removed from the satellite images and it does not require any information about the kernel in advance.

Keywords: image processing, satellite images, split bregman method, regularization etc.

I. INTRODUCTION

Satellite imagery consists of photographs of the earth and its surroundings which is taken through an artificial satellite revolving around the earth. Normalizing such satellite images for cloud, sensor and haze induced defects within satellite image and overlaying two dimensional satellite images on three dimensional surface of earth is called satellite image processing. Distortion is considered to be prime reason for poor image quality in satellite imaging. When a satellite captures an image, it represents not just the scene at a single instant of time, rather the scene over a period of time. If the camera or objects in a scene are moving fast over such period of exposure time, the objects will be blurred along the direction of relative motion between camera and object.

Another possible reason for motion distortion is camera shake, especially while using long shutter speed under low lighting condition or taking images with telephoto lens. Many research works were conducted to get clear image from motion blurred image using motion deblurring methods. In most works, the motion blur which is resulted due to camera shake is designed by a spatial-invariant convolution process, i.e., the discrete convolution operator, is the original image to recover, is the observed blurry image, is the blur kernel (or point spread function), and is the noise. Image deconvolution problem occurs when the actual image is recovered from observed image. Generally, image deconvolution problem is categorized into two types, 1.If the blur kernel is given as a prior, recovering the original image becomes a nonblind deconvolution problem. Nonblind deconvolution [1], [3]-[7] is known as an ill-conditioned inverse problem as a small perturbation of may cause the direct solution from being heavily distorted. In the past, there have been extensive research literatures on the robust nonblind deconvolution algorithm. 2. If the blur kernel is also unknown, how to reverse the effect of convolution by on the blurred image is then a blind deconvolution problem. In general, blind deconvolution is a very challenging ill-conditioned and ill-posed inverse problem because it is not only sensitive to image noise but also under constrained with infinitely many solutions. Removing motion blurring from images is a typical blind deconvolution problem, as the relative motion between the camera and the scene varies for individual images. Thus we have proposed an efficient method to recover motion-blurred image, the rest of the paper is organized as follows; the introduction is followed by the literature survey in section II. Section III describes the existing mechanisms for processing distorted satellite images. Section IV consists of our proposed system with its explanation and advantages followed by conclusion in section V.

II. LITERATURE SURVEY

Split Bregman methods have been experimented to be the efficient tools for resolving all variation norm minimization problems, which starts from partial differential equation based image restoration namely image denoising and magnetic resonance imaging reconstruction from sparse samples. In this system, the convergence of the split Bregman iterations is showed, in which the number of inner iterations is said to be one. Obviously, we show that these split Bregman iterations is able to resolve minimization problems caused due to the experimental approach for image restoration in the literature.

These split Bregman iterations is widely used to the experiment based image restoration approach whose analysis operator is derived from the tight framelet showed in [1]. This produces a set of new frame based image restoration algorithms that has almost got various topics in image restorations, such as image denoising, deblurring, in painting, and cartoon-texture image decomposition. Various numerical simulation results are provided.

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 2, February 2014

The class of l1-regularized optimization problems has received more attention nowadays because of the arrival of compressed sensing," which permits images and signals to be redesigned from small amounts of data. In spite of these present importance, many l1-regularized problems still seems difficult to solve, or needs techniques which is really problem-specific. In this paper [2], it is visualized that Bregman iteration can be used to solve a large amount of constrained optimization problems. With the use of this technique, we propose a “Split Bregman" method, which can solve a broad stream of l1-regularized problems. This technique is used to the ROF functional for image denoising, and to a compressed sensing problem that usually comes in Magnetic Resonance Imaging.

Blur removal is a vital issue in signal and image processing. The blurring matrices we get by using the zero boundary condition in respect to assuming dark background outside the scene are Toeplitz matrices for dimensional problems and block Toeplitz block matrices for dimensional cases. They are technically strong to invert specially in the block case. When the periodic boundary condition is used the matrices become block circulated and can be equalized in parallel by discrete Fourier transform matrices. The use of the Neumann boundary condition is considered [4], corresponding to a reaction of the original scene at the boundary. The resulting matrices are block Toeplitz plus Hankel matrices. It is showed that for symmetric blurring functions these blurring matrices can always be diagnosed by discrete cosine transform matrices. So the cost of inversion is comparatively lower than that of using the zero or periodic boundary conditions. We also show that the use of the Neumann boundary condition provides an hassle free way of knowing the regularization parameter when the generalized cross-validation is used. When the blurring function is nonsymmetrical we show that the optimal cosine transform pre conditioner of the blurring matrix is equal to the blurring matrix generated by the symmetric part of the blurring function. Numerical results are given to explain the efficiency of using Neumann boundary condition.

III. CURRENT WORKS

Last few decades, we had extensive research works on single-image blind deconvolution. Past works on blind deblurring usually uses a single image and depicts a prior parametric form of the blur kernel, like a linear motion-blur kernel model .These parametric motion-blur kernel models can be obtained by estimating only a few parameters, but they are usually simplified for practical motion blurring. In order to avoid more general motion blurring from images, some probabilistic priors on natural images’ edge distributions are proposed to derive the blur kernel .Demerits of these methods are either that the assumed probabilistic priors does not look realistic for natural images or that it requires certain user interactions to obtain an accurate estimation. It is evident that there are active research works on multi-image-based blind motion deblurring methods as multiple images provides plenty of information of the scene and leads to an easier configuration for precise estimation of blur kernels. The other way is to formulate the blind deconvolution as a joint minimization problem to estimate both the blur kernel and the clear image in parallel.

At present, Change Detection (CD) and its differences have been the popular choices of the regularization term in present to solve most of the blind deblurring. These CD-based blind deconvolution techniques results in good performance on eluding certain types of blurrings on specific types of images, such as out-of-focus blurring on medical images and satellite images. However, CD regularization is not the optimal choice for removing motion blurring because CD regularization penalizes, for example the total length of the edges for piecewise constant functions. As a result, the support of the resulting blur kernel tends to be a disk or several isolated disks. A highly designed CD based model [9], with good performances on removing modest motion blurring from images excluding rich textures. However, it is based on the precise input of some prior information of the blur kernel. The main drawback of the CD-based regularization for nature images is that CD-based regularizations do not preserve or withhold the details and textures very well on the regions of complex structures because of the likely staircase effects.

The user inputs are important in running the segmentation process in order to obtain exact results. Normally, interactive-based segmentation methods are initiated by exploiting the user inputs with a set of strokes, lines, scribbles, or curves for generating labeled pixels for object and background termed as seeds. Then, on the basis of these seeds, the segmentation process is proceeded further, for example, adaptive weight distances spline regression and maximal-similarity-based region merging. Practically, the more user interactions we have, the more accurate is the result, but at last, the level of interaction is usually referred to be simple and minimal. In remote sensing, user-based interaction method is basically developed to tackle supervised classification problems. The basic idea of these semiautomatic methods known as “active learning” is that, starting from a small and suboptimal training kit, extra samples, considered important, are selected in some way from a vast amount of unlabeled data (learning set). Further, these samples are named by the user and then added to the training set. The entire procedure is continued till a stopping criterion is satisfied.

Drawbacks

a) The pixels under these markers are used for practicing a support vector machine (SVM) classifier in the same way to supervise remote-sensing image classification.
b) Aftermath practices, the pixels in the image are firstly classified with SVM as change and no change. It is a known fact that the experiment of image pixels under spatial independent assumption might lead to inconsistencies because of various reasons, which consists, for example, the co registration noise.

ISSN (Online) : 2278-1021
ISSN (Print) : 2319-5940
International Journal of Advanced Research in Computer and Communication Engineering
Vol. 3, Issue 2, February 2014

IV. OUR PROPOSED CONCEPT

We put forward a new optimization method to remove complex shift blurring from a single image by introducing new sparsity-based regularization terms on both images and motion-blur kernels. Our approach is likely the recent works on both nonblind image deconvolution and blind motion deblurring. Two nonblind image deconvolution algorithms in and are both based on the observation that images normally have sparse representations or approximations in some redundant transform domain, e.g., wavelet and framelet transforms. Given the blur kernel, is solved in and by seeking a sparse solution in the corresponding transformed domain.

Alternative type of regularization techniques for blind deconvolution is using number of sparsity-based priors to regularize images, kernels, or both of them. Considering a smooth blur kernel, a quasi-maximum-likelihood approach is proposed to deconvolute both sparse images and nature images, which are sparsified through a sparsifying kernel learned from training data. As the sparsity based prior on the kernel, which assumes that the kernel can be shown by a weighed combination of Gaussian-type basis functions with weights satisfying a heavy-tailed student's distribution. The regularization on image is also based on the assumption that the image variations make a heavy-tailed student's -distribution.

The following are the Process models we adopted for processing the image at a compression rate.

a) Image preprocessing
b) Image Filtering
c) Distortion detection
d) Removal of misidentified Distortion
e) Distortion filling

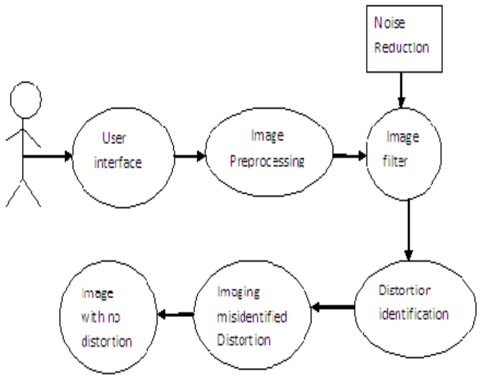

Fig. 2. Overall structure

a. Image preprocessing

To know how image files are stored and their file formats, and perform basic steps like reading, writing and motion an image on screen. It gets the input as images. The input images are in two dimensional.

b. Image Filtering

In this section, this gives importance mainly to detect in the given input image consists of blur and some distortion in the particular image. These noises and distractions are detected. Filtering is done which transform the changes in pixel intensity values or having poor contrast, etc.Image filtering is done for the enhancement and smoothing of given input images.

c. Distortion Detection

The basic characteristics of distortion are that they have lengthened structural characteristics. Distortion-detection is carried out a grayscale morphological filter that changes the input grayscale image into another grayscale output image where pixels with a large gray value are potential blur or blur-like elements. Thus distortion detection, which produces output gray scale image, is used to identify the distortions in the image given as input.

d. Removal of misidentified Distortion

Apply thresholding to separate distortion from the rest of the image. Thresholding is same as segmentation. Manual interaction is required in this module. A binary image will be created showing only the blur regions.

e. Distortion Filing

Use trimmed mean filter to remove the blur. That is, we are placing threshold binary image over result image, to notice blurs and smooth the blur portion of original image using the pixels from the regions around the blurs.

V. CONCLUSION

Our proposed system uses two interactive segmentation methods to restore a clear image from distorted satellite image. This method is believed to work better and efficient than anyother existing mechanisms. Our future work may include mechanisms to increase the resolution of the resultant image.

REFERENCES

[1] J.-F. Cai, S. Osher, and Z. Shen, "Split Bregman method and frame based image restoration," Multiscale model. Simul., vol. 8, no. 2, pp. 337–369, 2009.
[2] T. Goldstein and S. Osher, "The split bregman method for l1-regularized problems," SIAM J. Imaging Sci., vol. 2, no. 2, pp. 323–343,2009.
[3] H. C. Andrews and B. R. Hunt, Digital image restoration. Englewood Cliffs, NJ: Prentice-Hall, 1977.
[4] M. K. Ng, R. H. Chan, and W. Tang, "A fast algorithm for deblurring models with neumann boundary condition," SIAM J. Sci. Comput., vol. 21, no. 3, pp. 851–866, 2000.
[5] T. F. Chan and J. Shen, Image processing and analysis, ser. Variational, PDE, wavelet, and stochastic methods. Philadelphia, PA: Society for Industrial and Applied Mathematics (SIAM), 2005.
[6] A. Chai and Z. Shen, "Deconvlolution: A wavelet frame approach," Numer. Math., vol. 106, pp. 529–587, 2007.
[7] Y. Lou, X. Zhang, S. Osher, and A. Bertozzi, "Image recovery via nonlocal operators," Journal of Scientific Computing, vol. 42, no. 2, pp. 185–197, 2010.
[8] J.-F. Cai, H. Ji, C. Liu, and Z. Shen, "Blind motion deblurring using multiple images," Journal of Computational Physics, vol. 228, no. 14, pp. 5057–5071, 2009.
[9] Haikel Hichri,Yakoub Bazi, Naif Alajlan and Salim Malek, "Interactive Segmentation for Change Detection in Multispectral Remote-Sensing Images," Geoscience and Remote Sensing Letters, IEEE (Volume:10 , Issue: 2)
[10] Jian-Feng Cai, Hui Ji, Chaoqiang Liu and Zuowei Shen, "Framelet based blind motion deblurring from a single image" in Image Processing, IEEE Transactions on (Volume:21 , Issue: 2)