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RECOVERY OF SINGLE IMAGE FROM MULTIPLE BLURRY SATELITE IMAGES

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Abstract --

It is addressed the problem of obtaining a single image from multiple fuzzy images of the same scene. The blur and picture are defined by a group of sparse domains in order to recover a blind image using blind deconvolution. It is used to make use of both local and non-local data. The joint blind deconvolution method solves blur estimation and image recovery using multiple images. The reweighted data is generated to improve the recovery efficiency, with the weight determined by the estimation error. In addition, the block matching method is studied in order to minimize unnecessary noise effects in a sparse representation, and it is used to locate similar patches. The new estimation improves performance significantly, and the image is extracted using a split Bregman iteration algorithm and a super resolution algorithm. It also contains actual and synthetic images to illustrate the algorithm's effectiveness. As a consequence, our method can recover a single image from a set of blurred images.

Keywords — Blind deconvolution, multiple image blind deblurring, group sparse.

I. INTRODUCTION

In many imaging scenarios, capturing high-quality images is a top priority. The users can accomplish this aim by taking advantage of significant hardware advancements (eg., the increasing resolution of the camera sensor). Taking several images of the same scene and selecting the best as output based on the image's threshold value to achieve a high-quality image in this scenario.

Deblurring and denosing, two well-known image problems, have been extensively studied with the aid of subsequent processing steps, such as object recognition and feature extraction, which heavily rely on the input of a clear image. The main goal is to recover a higher-quality picture from a blur image polluted by noise, blur, and other variables.

To reconstruct the original image x from its degraded observed version y, image restoration has been extensively studied. It can be expressed in the following way:

$$y = Hx + n,$$

where y represents the captured image, H represents an unknown spatial blur kernel, n represents additive Gaussian White noise, and x represents the original image In terms of the number of images available for reconstruction, single image and multiple image reconstruction are used. In the case of single image restoration, the deblurring method may be blind or non-blind. Using two motion blurred images for multiple image deblurring that is superior to that used for a single image throughout multiple image reconstruction.

II. RELATED WORK

For a review of the extensive literature in this field. Existing methods traditionally used a robust algorithm to estimate a single latent image from a series of blur images.[1] They use a Bayesian-inspired penalty feature to enter an unknown latent image with blur and noise in this paper.[3] This will only present applicable state-of-the-art algorithms and will be limited in certain ways. It can accommodate a variable number of degraded observations, limiting the number of observations in general. When it is necessary, high-quality images control the estimation in this paper.Another method is to solve the image denoising problem with the k-SVD algorithm.[2]

From a single picture, high quality motion deblurring this approach used a unified probabilistic model of both blur kernel estimation and unblurred image restoration to compute a deblurred image. The key drawback of this study is that even minor kernel errors or image noise can result in significant artifacts.[5]

Blind image deconvolution is performed by D.Kundur and D.Hatzinakos (2014). This paper gave a summary of the main approaches to the issue of blind image deconvolution. The main disadvantage of this paper is its increased numerical complexity. As a result, we proposed the system to overcome the limitations listed above by using the following algorithm to recover a single image.[4]

III. ALGORITHM

The Super resolution algorithm and the split Bregman iteration algorithm are the two primary algorithms in our approach. The super resolution algorithm reconstructs a high-resolution image from a low-resolution one, and it is primarily used to improve image resolution. Split Bregman Iteration was the previous method that was used. Furthermore, this paper employs a super resolution algorithm. In this method, group sparse regularization is applied to both the kernel and the image to improve recovery efficiency. Reweighted data fidelity is developed and used to minimize unnecessary noise in group sparse.

Another algorithm, joint deblurring approach, was used in the existing procedure, and it was a more complex two-step interactive mechanism in which each step is solved using well-known algorithms (SBI algorithm and super resolution algorithm). Super resolution refers to a group of techniques for improving the resolution of an image system. They're used to create high-resolution images from lower-resolution images captured in the same scene.

When compared to previous methods, the proposed joint estimation approach provides a major improvement in image recovery efficiency. The images generated by algorithms 1 and 2 are still polluted by unwanted noise a.

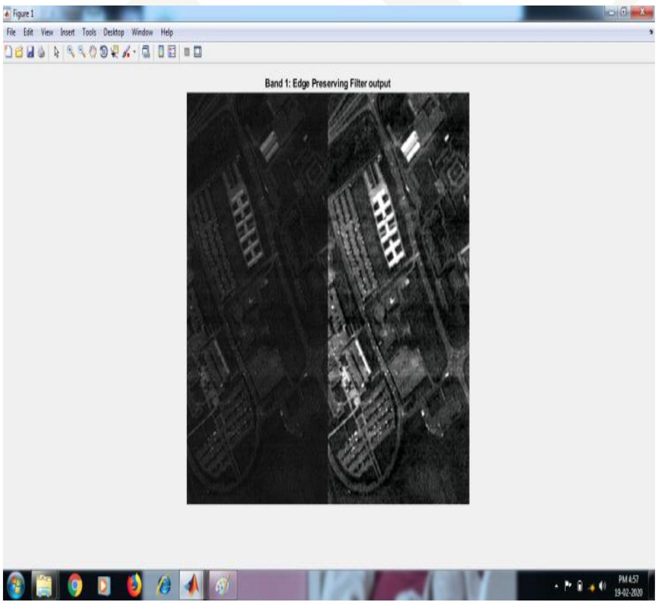

Figure: Band 1, Edge Preserving Filter output

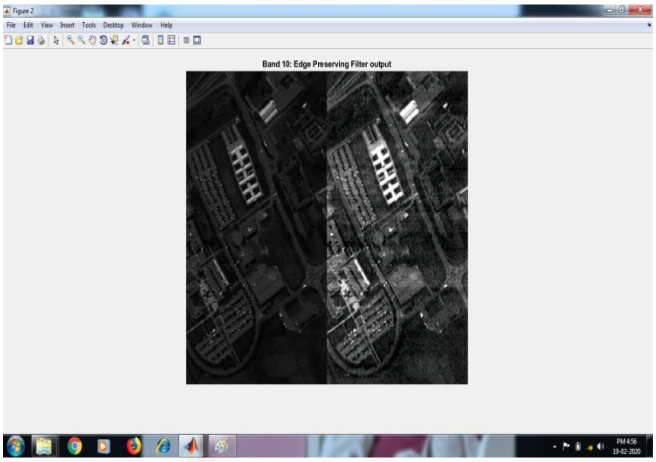

Figure 2: Band 10, Edge Preserving Filter output

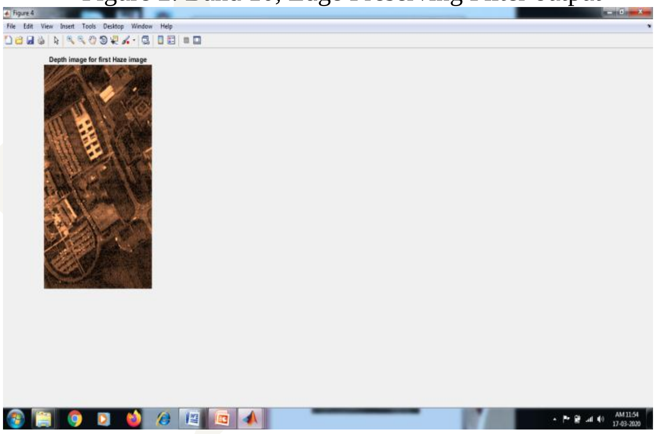

Figure 3: Depth Image for first Maze Image

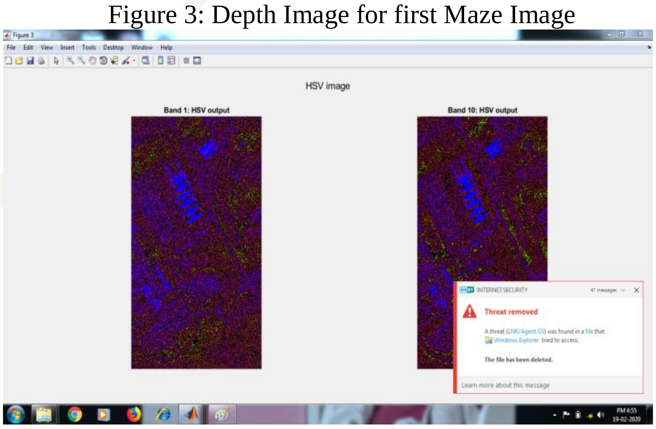

Figure 4: HSV Image

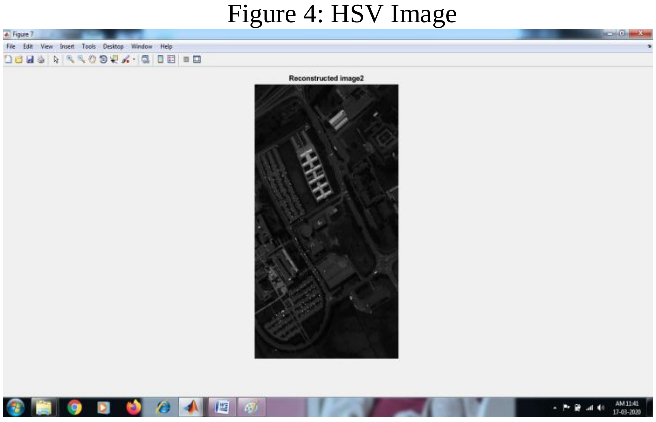

Figure 5: Reconstructed Image 2

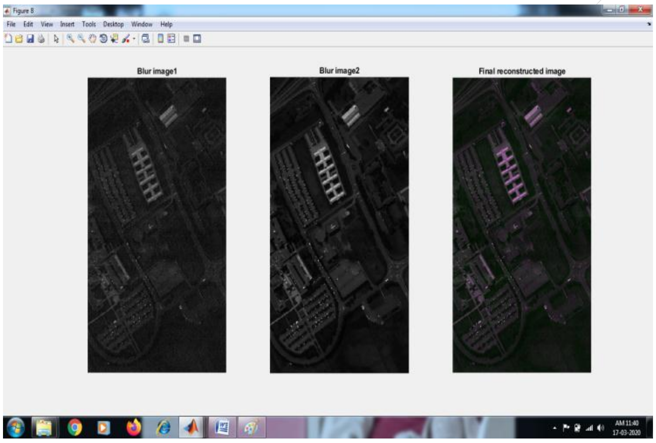

Figure 6: Final Reconstructed Image

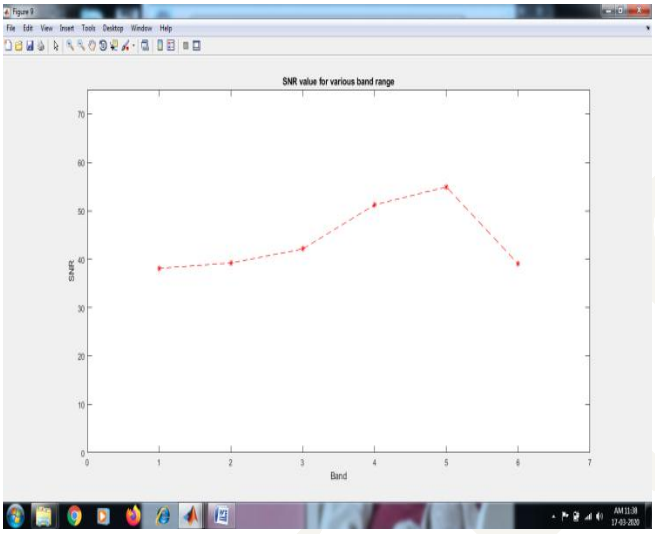

Figure 7: SNR value for various Band Image

IV. CONCLUSION

The Split Bregmen formulation is a quick way to solve nearly any l1 regularization problem. For several issues, they were able to effectively parallelize. The sparse domain represents kernel and sparse, and this paper proposes a new joint blind estimation method to help in the recovery of latent image from multiple fuzzy noisy images. The findings show that joint estimation improves the efficiency of image recovery as compared to the previous image.

V. REFERENCE

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