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Image Denoising and Blind Deconvolution by Non-uniform Method

B.Kalaiyarasi[1], S.Kalpana[2]
II-M.E(CS)[1], AP / ECE[2], Dhanalakshmi Srinivasan Engineering College, Perambalur.

Abstract — Image processing allows a much wider range of algorithms to be applied to the input data and can avoid problems such as the build-up of noise and signal distortion during processing of images. Iterative deblurring algorithm used in the existing technique mainly removes the blur caused during camera shake using the depth map but it does not focus on the noise present in the image. This paper presents a survey on different image filtering techniques. Image filtering is a crucial part of vision processing as it can remove noise from noisy images. There are many filtering techniques to filter an image. Here both linear and non-linear filters are employed for noise removal and sharpness enhancement. In this work four types of noise (Gaussian noise , Salt & Pepper noise, Speckle noise and Poisson noise) is used and image de-noising performed for different noise by Wiener filter, Median filter, Bilateral filter and Alpha trimmed mean filter. Decision based median filtering algorithm and alpha-trimmed mean filter algorithm gives promising results over salt and pepper noise. Further we have compared the different results on the basis of PSNR and MSE values of the restored image. Finally the conclusion is formulated. Thus we can reduce computational cost and prevent over-fitting.

Index Terms— Adaptive Bilateral Filter (ABF), Blind Deconvolution, Image denoising, Non-uniform method, Sharpness enhancement

I. INTRODUCTION

Images are produced to record or display useful information. Due to imperfections in the imaging and capturing process, however, the recorded image invariably represents a degraded version of the original scene. The undoing of these imperfections is crucial to many of the subsequent image processing tasks. There exists a wide range of different degradations that need to be taken into account, covering for instance noise, geometrical degradations (pin cushion distortion), illumination and color imperfections (under/over-exposure, saturation), and blur.

For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed. Blind deconvolution can be performed iteratively, whereby each iteration improves the estimation of the PSF and the scene, or non-iteratively, where one application of the algorithm, based on exterior information, extracts the PSF. A good estimate of the PSF is helpful for quicker convergence but not necessary. Blind deconvolution has several challenging aspects: modeling the image formation process, formulating tractable priors based on natural image statistics, and devising efficient methods for optimization.

In terms of noise removal, the conventional linear filter works well in smooth regions, but significantly blurs the edge structures of an image. A lot of researches have been done on edge-preserving noise removal. One of the major endeavors in this area has been to utilize the rank order information [2, 3]. Due to a lack of the sense of spatial ordering, rank order filters generally do not suppress Gaussian noise optimally. In more recent years, a new approach to edge preserving de-noising was proposed by Tomachi et al [4] and Smith et al [5].

NON-UNIFORM METHOD:

The works on camera shake removal fall into two main streams according to the assumption on blur kernels: spatially uniform and non-uniform. The former methods formulate image blur as a 2D convolution process, and perform deconvolution on a single blurred image, multiple images, captured at different settings such as long-exposure/short exposure image pair or an image set deteriorated by different blur kernel. The uniform methods assume that all the pixels are blurred with the same blur kernel, but this assumption does not hold because the image blur at a specific position is highly correlated with both camera motion and corresponding scene depth, i.e., spatially varying. Therefore, more and more researchers focus their attentions on non-uniform motion blur recently.

II. EXISTING METHOD

To deal with the non-uniform blur caused by an arbitrary camera motion, both scene structure and high-dimensional motion need to be considered. Here, we use a depth aware projective blur model considering scene depth and describe motion with 6 DoF explicitly. To the best of our knowledge, state-of-the-art blind deblurring approaches can only handle camera motion of no higher than 3 DoF, which limits the capacity of these algorithms for dealing with the image of large-depth-range scenes deteriorated by 6D camera motion.

To overcome this problem, Temporal Sampling Motion Function (TSMF) and Probabilistic Motion Density Function (PMDF) are proposed to reduce variable number and improve the convergence respectively.

1) TSMF: Traditional blind deblurring methods use the probability density function of motion parameter to describe
the camera motion by sampling uniformly in parameter space and giving each sample a weight to describe the fraction of time the camera spent on this discretized pose. As the parameter dimension increases, the needed sample size increases drastically and induces high computational cost. TSMF is proposed to describe camera motion by sampling camera poses in time-domain and each sample needs at most 6 parameters to describe the camera pose at this moment.

2) PMDF: PMDF is adopted to constrain the motion parameters and thus improves convergence of optimization. In computation aspect, we propose to compute PMDF by a robust voting framework from low-dimensional blur kernels, which can be estimated from local image patches. In practice, we describe the PMDF in a probabilistic manner instead of an exact optimum to raise the robustness to estimation error of low-dimensional blur kernels.

This paper firstly describes the adopted imaging model and parametrization (TSMF) and then gives the two steps of our algorithm respectively:

1) Compute PMDF
   a) Split image into patches and estimate their 2D local blur kernels
   b) Calculate the confidence of 2D local blur kernels

c) Project 2D local blur kernels back to 6D parameter space and estimate PMDF by robust voting
2) PMDF guided camera shake removal
a) Add PMDF to objective function as a constraint
b) Iteratively optimize TSMF and sharp image

In summary, the proposed model is advantageous over the
Previous methods in multiple aspects:

(i) Depth and 6-DoF camera motion are both explored explicitly to address arbitrary motion blur for large depth range scene

(ii) Camera motion is modeled completely with 6 DoF, and TSMF is proposed to reduce the scale of the problem effectively

(iii) PMDF is proposed to impose unified constraints to spatially varying blur, and it can be computed effectively from low-dimensional local kernel estimation under a robust voting scheme.

III. PROPOSED METHOD

In ABF every sample is replaced by a weighted average of its neighbors (as in the WLS).These weights reflect two forces

1. How close are the neighbor and the center sample, so that larger weight to closer samples,
2. How similar are the neighbor and the center sample larger weight to similar samples.

All the weights should be normalized to preserve the local mean.

$$\hat{X}[k] = \frac{\sum_{n=-N}^{N} W[k,n]Y[k-n]}{\sum_{n=-N}^{N} W[k,n]} \qquad (1)$$

Kernel properties:

- Per each sample, we can define a 'Kernel' that averages its neighborhood

$$\frac{\left[W[k,-N],....W[k,-1],\ W[k,0],W[k,+1],W[k,+N]\right]}{\sum_{n=-N}^{N} W[k,n]} \qquad (2)$$

- This kernel changes from sample to sample!
- The sum of the kernel entries is 1 due to the normalization,
- The center entry in the kernel is the largest,

Subject to the above, the kernel can take any form (as opposed to filters which are monotonically decreasing).

1) *Parameterization:*

If N is the limit of 2D kerne size, which can be set according to the blur level of image, the projection of high-dimensional camera motion in 2D kernel space should be no
larger than N. When the camera motion during exposure is slight, uniformly discretizing each parameter will lead to a near uniform sampling in 2D blur kernel space, i.e. the interval in 2D blur kernel domain between

projections of two adjacent samples is approximately one pixel as well. To be on the safe side, set 1.2*N* discretization levels along each dimension.

2) *Back-Projection:*

The 2D local blur kernels can be regarded as the 2D projection of 6D camera motion. Inversely, for a certain 2D local blur kernel, there are a set of samples meeting the projection. The so-called back-projection step is trying to calculate this set and their corresponding weights for a certain local blur kernel.

3) Robust Voting:

In this step, the PMDF is computed by a weighted voting process. For each sample in high-dimensional parameter space, its probability density can be estimated by considering the contamination from bad hypotheses (i.e. outliers of 2D local blur kernels estimated by uniform method), we propose a robust voting method to compute PMDF. As is well known, median filter is widely used in robust estimation for its desirable ability in suppressing the effects from bad hypotheses, but it cannot deal with the white noise with short-tailed distribution. Therefore, we adopt order based bilateral weighted voting which combines median filter and Gaussian filter to achieve good performance under both bad hypotheses and short-tailed noise of good hypotheses

OUTPUT RESULTS:

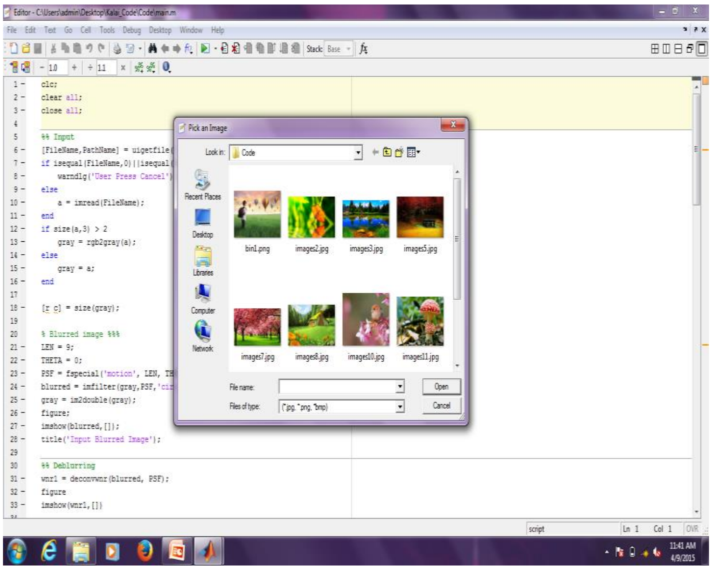

Fig.1a Input Data

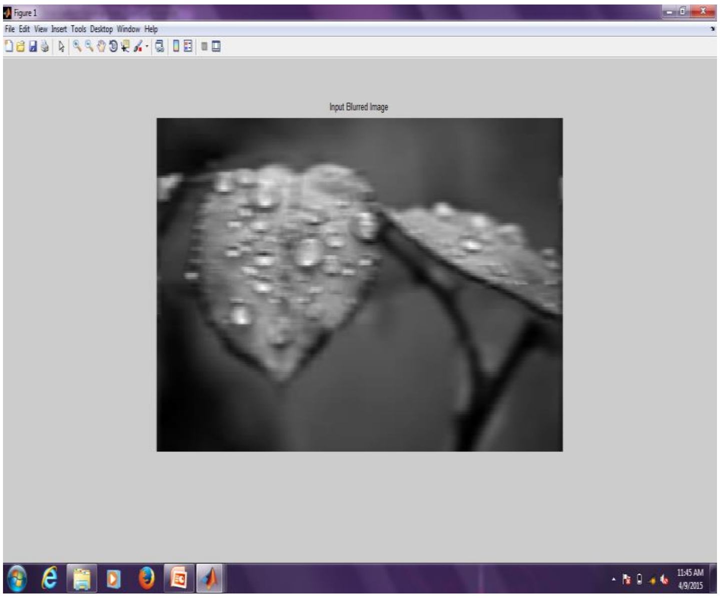

Fig.1b Input Blurred Image

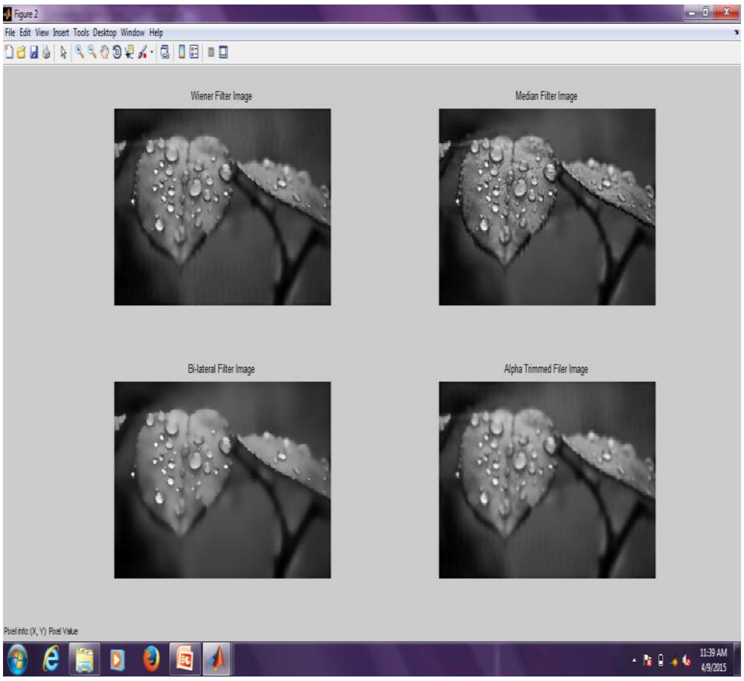

Fig.1c Restored Images (4 filter types)

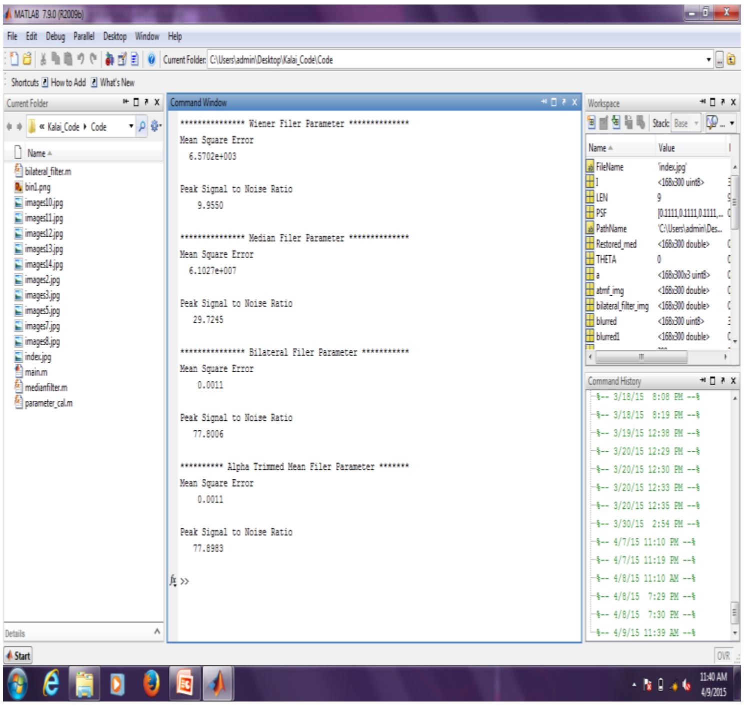

Fig.1d PSNR and MSE values (4filter types)

IV .CONCLUSION

The comparative study of various denoising techniques for digital images shows that bilateral and alpha-trimmed filters outperform the other standard spatial domain filters. Although all the spatial filters perform well on digital images but they have some constraints regarding resolution degradation. These filters operate by smoothing over a fixed window and it produces artifacts around the object and sometimes causes over smoothing thus causing blurring of image. In this paper four types of noises (Salt and Pepper, Gaussian, Speckle and Poisson noise) had been added to the original clean image. It is observed that all noise causes degradation in the image quality which results in loss of information. The denoising of degraded image is performed using Wiener, Median filter, Bilateral and Alpha-Trimmed mean filter. From the simulation results it's confirmed that Median filter works well for Salt and Pepper noise than Wiener filter whereas Wiener filter works well for removing Poisson and speckle noise compared to Median filter.

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Kalaiyarasi received the B.E degree in Electronics and Communication Engineering from Anna University, India in 2013. She is currently pursuing M.E degree in Communication Systems, Anna University, India. Her research interests mainly include image processing and computational photography.

Kalpana received the B.E degree in Electronics and Communication Engineering from Anna University, India and the M.E degree in Communication Systems, Anna University, India. She is currently working as an assistant professor in the department of ECE, Dhanalakshmi Srinivasan Engineering College, Perambalur. Her research interests mainly include digital communication, image processing and computational photography.

