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Performance Analysis of Median Filtering Techniques for Impulse Denoising

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Abstract:*This exertion proposes comprehensive amalgamation and scrutiny past algorithms using the split-Bregman technique intended forapplications in impulse noise reduction. Desire denoisingisformulated as restraining aLp-regularized Lq-norm data mismatch term. The Lq-norm mismatch arisesowing near the circumstance thatthe racket is sparse. The Lp-norm abuses the prior datathat the image is scarce in a transform sphere. The proposedmeans have been used to reduce salty and pepper noise aswell as accidental valued urge noise. Impulse noise can be classified asfixed valued impulse noise or random valued impulse noise.Fixed valued impulse noise is also called salt and pepper noisein which each noisy pixel have either maximum or minimumintensity value. Highest signal to noise ratiobesides structural correspondence index partake been used to quantitativelyevaluate the salvage results. A comparative revision with presentIRN algorithm recommends the ascendency of purposed process.The decrease is not linear as expected sincethe algorithms are based on split-Bregmantechnique.Our method also yields better results than the popularmedianfiltering techniques used for denoising impulse noise. Clearly reconstruction quality of proposed AP algorithm is better than other algorithmscompared against.*

Keywords:*signal to noise, denoising, impulse noise, pepper noise*

I. Introduction

The field of image processing is broad and contains many interesting applications. Some ofthe common image processing areas are image restoration, compression, and segmentation.Many times, the size of the raw data for the images can require gigabytes of data storage.Researchers have developed routines to compress an image into a reversible form to savestorage space. In this area, there are methods for the compression via wavelets,using general compression schemes that are applicable to any type of file, and methods whichallow some loss of data.

The area of segmentation distinguishes objects from the background in an image. This is particular useful for satellite imagery from an intelligence standpoint. It isalso useful for identification purpose by using facial imagery in a database. Segmentation isused in robotics, where it is important to locate the correct objects to move or manipulate.Another area of image processing is image restoration. In image restoration, a distortedimage is restored to its' original form. This distortion is typically caused by noise in transmission, lens calibration, motion of the camera, or age of the original source of the image.We focus on image restoration in this dissertation.

Within image restoration, there are many tasks that researchers consider. There has beensignificant work on denoising, where noise is removed from the image. This noise could be from transmission problems or due to some atmospheric problem at thetime the image was captured. There is image inpainting, which recovers missing areas froman image. These missing regions may occur because of age of the originalobject that was photographed, or physical defects in the object. Another area in restorationis image deblurring. In this area, the objective is to recover the trueimage given a blurry image. We will focus on image deblurring in this dissertation.There are many models for images. For example, there are wavelet based approaches.

Multi-resolution approaches, which avoid some local minima, wererecently proposed. Good local minima can alsobe found by usingcontinuationschemes, where the regularizing parameter is gradually decreased. In a Bayesian framework, it has been claimed that a MAP estimate of the blur filter (aftermarginalizing out the unknown image) is preferable to a joint MAPestimate of the image and the filter. Most blind and non-blind deblurring methods assume periodicboundary conditions (to allow using FFT-based convolutions), instead of the more realisticunknown boundary conditions(UBC) [5]. This incorrect assumption is a problem in non-blind deblurringandbecomes worse in BID (although it has mostly been ignored), sincethe filter estimate is affected by the inaccuracy of the cyclic model.A simple way to evade the UBC problem is to use the "edgetaper"function, which softens the boundaries of the degraded images, reducing the effect of wrongly assuming periodic boundary conditions;this approach is used, whileemploys a more sophisticated version thereof.

II. Blind Image Deblurring

Blind image deconvolution techniques restore the original sharp image from an observeddegraded image without precise knowledge of a point-spread function (PSF) [43]. Thereare two main approaches to this: 1) first estimate the PSF, and then apply a non-blinddeconvolution method with that PSF; 2) iteratively estimate the PSF and the original sharpimage.For the approach that estimates the PSF first, some traditional methods payed attentionto the frequency zero patterns in a blur kernel. For example, the Fourier transformof a box function as shown is given ash(ωx , ωy) = sinc(Lωx), meaning that ithas periodic zeros at ωx = kπ /L for a non-zero integer k. From, we can expectthat the Fourier transform of the observed image has the same zero pattern if we canignore noise. However, such methods are not practical in the presence of noise. Anotherapproach is to take a set of candidate PSFs, and to choose the one that best explains theobserved image. The selection criteria differ from method to method, such as residualspectralmatchingand generalized cross validation. For the approach that iteratively estimates the PSF and the sharp image, Ayers andDainty proposed to iterate the process of updating the PSF from the estimated sharp image in the Fourier domain, imposing image space constraints on the PSF (non-negativity,for example), updating the sharp image from the PSF in the Fourier domain, and imposing constraints on the sharp image. More recent methods took a conceptuallysimilar approach and estimated a camera shake PSF from a single image by incorporating natural image statistics. Fergus et al. imposed sparseness prior for image derivativedistributions and used an ensemble learning approach to solve the otherwise intractableoptimization problem. Shan et al. introduced a more sophisticated noise model anda local smoothness prior.

III. Proposed Method

Figshows four stages in a generic processing flow of image deblurring. We firstcapture an image, and then segment the image into regions each of which can be assumedto have a uniform blur. After that, for each local region, we estimate the blur kernel andfinally use it to deconvolve the image. Some methods may perform segmentation and blurestimation simultaneously. Some may iterate blur estimation

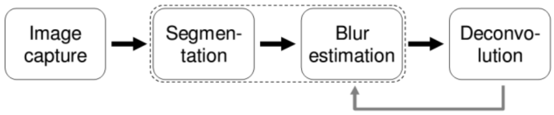

Fig 1.0: Processing flow of image deblurring

Table 1.1 summarizes the relationship between the proposed method and some of theprevious work for three of the above four stages and for the three blur types, namelydefocus, motion, and camera shake blur. We set aside the image capture stage becauseit is trivial for methods purely based on an image processing approach, and for methodsinvolving optics modifications, the (modified) image capture stage can facilitate one, two,or all of the succeeding three stages depending on the methods. Therefore, the table hastwo rows for each blur type, one for methods involving optics modifications, and the otherfor pure image processing methods.

While a method for segmenting and identifying 1D motion blur (e.g., horizontal motions)in a single image is reported in the literature, it still seems difficult to handle general2D (i.e., in-plane) motions in a pure image processing framework. Chapter 4proposesto move the camera image sensor circularly about the optical axis during exposure, sothat the attenuation of high frequency image content due to motion blur can be prevented,facilitating deconvolution. This is an extension of motion-invariant photographysothat it can handle 2D linear object motion, although that leaves the segmentation stage anopenproblem.The most closely related work to the proposed approach includes coded exposure photography and motion-invariant photography .

The motion-invariant strategy best preserves high frequencies for target object motionrange, but it does not generalize to motion directions other than the one it assumes. Thecoded exposure strategy can handle any direction, and its performance only graduallydecreases for faster object motion. Our circular motion strategy can treat any directionand speed up to some assumed limit, and it achieves better high frequency preservationfor target object speed than the coded exposure strategy in terms of deconvolution noise.Similar to the motion-invariant strategy, the circular motion strategy degrades static sceneparts due to sensor motion, but it can partially track moving objects so that they arerecognizable even before deconvolution. Unlike the other strategies, the circular motionstrategy has no 180◦motion ambiguity in PSF estimation; it can distinguish rightwardobject motion from leftward one.

IV. Outputs

Visually compares reconstruction quality of Previous and Present algorithms with IRN algorithm. It is visually clearthat reconstruction quality for hyperspectral and multispectralimage is better for proposed algorithms and competitive onLena image.

Fig 1.1 Original Image

Fig 1.2 Noisy Image

Fig 1.3 Recovered Image

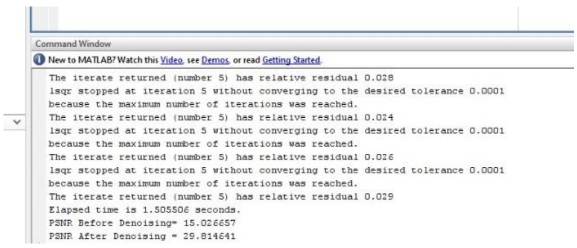

Fig 1.4 Debug Widow Showing PSNR Before & After Denoising

V. Conclusion

The field of blind image deconvolution is critical as well as challenging problem.The thesis has been worked out considering only spatial-invariant type of blur toreduce the problem complexity. But spatial-invariant blur fails to model the blur inmost of the practical case[24]. The noise effect is considered zero which is normallyimpractical. The irreducible demand of psf for unambiguous deconvolution is anotherlimitation. The ground truth image used is grayscale and is synthetically blurred.The degree of ringing suppression of our deconvolutionmethod depends on the choice of parameter w, which is related to the image noise level.We would like to consider determining the parameter automatically based on noise estimation methods. Proposed synthesis and analysis prior algorithms are able toreduce both salt and pepper noise and random value impulsenoise from color, multispectral, and hyperspectral images. Thealgorithms can be applied on each band individually todenoiseall the bands. Quantitative and qualitative results suggeststhat the algorithms are competitive or better than existingalgorithm in terms of PSNR, Structural similarity and visualquality. The capability of the current algorithm is limited toeach spectral band separately. It does not account for interband correlation. In future, we look forward to extend thesedenoising methods for multiple bands by taking into accountthe spectral correlations.

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