Performance Analysis of Median Filtering Techniques for Impulse Denoising

Anusha Seepana, K. Madhavi

Abstract: This exertion proposes comprehensive amalgamation and scrutiny past algorithms using the split-Bregman technique intended for applications in impulse noise reduction. Desire denoising is formulated as restraining aLp-regularized Lq-norm data mismatch term. The Lq-mismatch arises owing near the circumstance that the racket is sparse. The Lp-norm abuses the prior data that the image is scarce in a transform sphere. The proposed means have been used to reduce salt and pepper noise as well as accidental valued urge noise. Impulse noise can be classified as fixed valued impulse noise or random valued impulse noise. Fixed valued impulse noise is also called salt and pepper noise in which each noisy pixel have either maximum or minimum intensity value. Highest signal to noise ratio besides structural correspondence index partake been used to quantitatively evaluate the salvage results. A comparative revision with present IRN algorithm recommends the ascendency of purposed process. The decrease is not linear as expected since the algorithms are based on split-Bregman technique. Our method also yields better results than the popular median filtering techniques used for denoising impulse noise. Clearly reconstruction quality of proposed AP algorithm is better than other algorithms compared 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 of the 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 save storage 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 which allow 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 is also useful for identification purpose by using facial imagery in a database. Segmentation issued 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 distorted image 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 been significant work on denoising, where noise is removed from the image. This noise could be from transmission problems or due to some atmospheric problem at the time the image was captured. There is image inpainting, which recovers missing areas from an image. These missing regions may occur because of age of the original object that was photographed, or physical defects in the object. Another area in restoration is image deblurring. In this area, the objective is to recover the true image 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, were recently proposed. Good local minima can also be found by using continuations schemes, where the regularizing parameter is gradually decreased. In a Bayesian framework, it has been claimed that a MAP estimate of the blur filter (after marginalizing out the unknown image) is preferable to a joint MAP estimate of the image and the filter. Most blind and non-blind deblurring methods assume periodic boundary conditions (to allow using FFT-based convolutions), instead of the more realistic unknown boundary conditions (UBC) [5]. This incorrect assumption is a problem in non-blind deblurring and becomes worse in BID (although it has mostly been ignored), since the 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, while employs a more sophisticated version thereof.
II. Blind Image Deblurring

Blind image deconvolution techniques restore the original sharp image from an observed degraded image without precise knowledge of a point-spread function (PSF) [43]. There are two main approaches to this: 1) first estimate the PSF, and then apply a non-blind deconvolution method with that PSF; 2) iteratively estimate the PSF and the original sharp image. For the approach that estimates the PSF first, some traditional methods pay attention to the frequency zero patterns in a blur kernel. For example, the Fourier transform of a box function as shown is given as $h(x, y) = \text{sinc}(\omega_0 x/L)$, meaning that it has periodic zeros at $\omega = k\pi /L$ for a non-zero integer $k$. From this, we can expect that the Fourier transform of the observed image has the same zero pattern if we can ignore noise. However, such methods are not practical in the presence of noise. Another approach is to take a set of candidate PSFs, and to choose the one that best explains the observed image. The selection criteria differ from method to method, such as residual-spectral-matching and generalized cross validation. For the approach that iteratively estimates the PSF and the sharp image, Ayers and Dainty 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 conceptually similar approach and estimated a camera shake PSF from a single image by incorporating natural image statistics. Fergus et al. imposed sparseness prior for image derivatives distributions and used an ensemble learning approach to solve the otherwise intractable optimization problem. Shan et al. introduced a more sophisticated noise model and a local smoothness prior.

III. Proposed Method

Fig 1.0 shows four stages in a generic processing flow of image deblurring. We first capture an image, and then segment the image into regions each of which can be assumed to have a uniform blur. After that, for each local region, we estimate the blur kernel and finally use it to deconvolve the image. Some methods may perform segmentation and blur estimation simultaneously. Some may iterate blur estimation.

Table 1.1 summarizes the relationship between the proposed method and some of the previous work for three of the above four stages and for the three blur types, namely defocus, motion, and camera shake blur. We set aside the image capture stage because it is trivial for methods purely based on an image processing approach, and for methods involving 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 has two rows for each blur type, one for methods involving optics modifications, and the other for 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 general 2D (i.e., in-plane) motions in a pure image processing framework. Chapter 4 proposes to move the camera image sensor circularly about the optical axis during exposure, so that the attenuation of high frequency image content due to motion blur can be prevented, facilitating deconvolution. This is an extension of motion-invariant photography so that it can handle 2D linear object motion, although that leaves the segmentation stage an open problem. 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 motion range, but it does not generalize to motion directions other than the one it assumes. The coded exposure strategy can handle any direction, and its performance only gradually decreases for faster object motion. Our circular motion strategy can treat any direction and speed up to some assumed limit, and it achieves better high frequency preservation for 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 scene parts due to sensor motion, but it can partially track moving objects so that they are recognizable even before deconvolution. Unlike the other strategies, the circular motion strategy has no 180° motion ambiguity in PSF estimation; it can distinguish rightward object motion from leftward one.

IV. Outputs

Visually compares reconstruction quality of Previous and Present algorithms with IRN algorithm. It is visually clear that reconstruction quality for hyperspectral and multispectral image is better for proposed algorithms and competitive on Lena image.

DOI: 10.9790/2834-1102018184 www.iosrjournals.org 82 | Page
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 to reduce the problem complexity. But spatial-invariant blur fails to model the blur in most of the practical cases [24]. The noise effect is considered zero which is normally impractical. The irreducible demand of psf for unambiguous deconvolution is another limitation. The ground truth image used is grayscale and is synthetically blurred. The degree of ringing suppression of our deconvolution method 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 to reduce both salt and pepper noise and random value impulse noise from color, multispectral, and hyperspectral images. The algorithms can be applied on each band individually to denoise all the bands. Quantitative and qualitative results suggest that the algorithms are competitive or better than existing algorithm in terms of PSNR, Structural similarity and visual quality. The capability of the current
algorithm is limited to each spectral band separately. It does not account for interband correlation. In future, we look forward to extend these denoising methods for multiple bands by taking into account the spectral correlations.

References