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Quasi-Monte Carlo Method for the Reduction of Computation Time to Denoise Image Corrupted By Salt and Pepper Noise

Reka Durai[1]
M.Phil Research Scholar,
PG & Research Dept. of Comp. Science,
Gobi Arts & Science College(Autonomous),
Gobichettipalayam, Erode,
Tamilnadu, India.

Dr.V.Thiagarasu[2]
Associate Professor of Comp. Science,
PG & Research Dept. of Comp. Science
Gobi Arts & Science College(Autonomous),
Gobichettipalayam, Erode,
Tamilnadu, India.

Abstract: In image processing, restoration and noise reduction are expected to improve the quality of the image and the performance of quantitative image analysis. Adaptive median filtering techniques and the non-local means filtering algorithm are used to denoise image, corrupted by salt and pepper noise. Adaptive median filtering involves a two stage process, when the number of computations is very high and hence the simulation time increases with increase in the size of the corrupted image. To overcome this problem to introduce a quasi-Monte Carlo method, this is in contrast to the regular Monte Carlo method or Monte Carlo integration, which are based on sequences of pseudorandom numbers. QMCNLM speeds up the classical NLM by computing a small subset of image patch distances, which are randomly selected according to a designed sampling pattern. In Experimental result, QMCNLM provides better results when compared with the NLM.

Keywords: Non-local means filter, QMCNLM, adaptive median filter, salt and pepper noise.

I. INTRODUCTION

Image Processing is a technique to enhance raw images received from cameras/sensors placed on satellites, space probes and aircrafts or pictures taken in normal day-to-day life for various applications. Various techniques have been developed in Image Processing during the last four to five decades [1][2]. Most of the techniques are developed for enhancing images obtained from unmanned spacecrafts, space probes and military reconnaissance flights. Image Processing systems are becoming popular due to easy availability of powerful personnel computers, large size memory devices, graphics software etc.

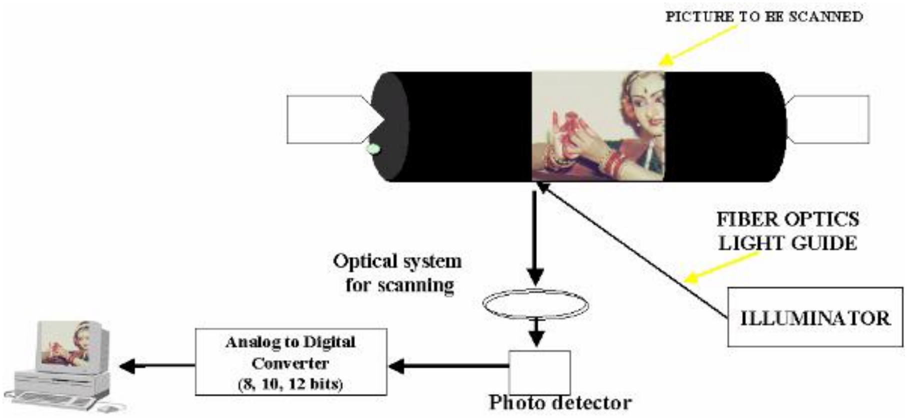

Fig 1 Image Scanner-Digitizer Diagram

The image will be converted to digital form using a scanner – digitizer and then process it. In Fig. 1. shows image scanner-digitizer diagram. It is defined as the subjecting numerical representations of objects to a series of operations in order to obtain a desired result [4]. It starts with one image and produces a modified version of the same. It is therefore a process that takes an image into another. The term digital image processing generally refers to processing of a two-dimensional picture by a digital computer.

In a broader context, it implies digital processing of any two-dimensional data. A digital image is an array of real numbers represented by a finite number of bits. The principle advantage of Digital Image Processing methods is its versatility, repeatability and the preservation of original data precision.

II. Related Work

In the literature, Impulse noise is caused by malfunctioning pixels in camera sensors, faulty memory locations in hardware, or transmission in a noisy channel. Two common types of impulse noise are the salt-and-pepper noise and the random-valued noise [3]. For images corrupted by salt-and pepper noise (respectively random-valued noise), the noisy pixels can take only the maximum and the minimum values (respectively any random value) in the dynamic range. There are many works on the restoration of images corrupted by impulse noise.

The median filter was once the most popular nonlinear filter for removing impulse noise, because of its good denoising power and computational efficiency [2]. However, when the noise level is over 50%, some details and edges of the original image are smeared by the filter.

III. Proposed System

In proposed system, Quasi- Monte Carlo method is proposed for reducing the computation complexity of the classical NLM. The proposed method speeds up the classical NLM by computing a small subset of image patch distances, which are randomly selected according to sequences of pseudorandom numbers [14]. Quasi- Monte Carlo method approximates the s-dimensional integral and chooses the vector. Quasi-Monte Carlo uses a low-discrepancy sequence such as the Halton sequence, the Sobol sequence, or the Faure sequence. The advantage of using low-discrepancy sequences is a faster rate of convergence [8]. Quasi-Monte Carlo has a rate of convergence close to O (1/N). Experimental result of proposed system provides lesser computation time when compare with the existing system.

Advantages

- Less computation time is required when denoising.
- The advantage of using low-discrepancy sequences is a faster rate of convergence.

Fig 2 Original Image


Fig 3 Add noise in it

Salt and Pepper Noise

In this module, Intensive simulations were carried out using several monochrome images, from which a 256x256 image is chosen for demonstration [5]. The test image is corrupted by fixed value salt and pepper noise with noise variance varying from 1 to 10 [13]. Fig.3. shows salt and pepper noise in the original image (Fig. 2).

IV. IMAGE FILTERING ALGORITHMS

Non Local Means Filter

The approach of Non-local means filter was introduced by Buades in 2005 based on non-local averaging of all pixels in the image. The method was based on denoising an image corrupted by white gaussian noise with zero mean and variance [6]. If compared with other well-known denoising techniques, such as the Gaussian smoothing model, the anisotropic diffusion model, the total variation denoising, the neighbourhood filters and an elegant variant, the Wiener local empirical filter, the translation invariant wavelet thresholding, the non-local means method noise looks more like white noise [7].

Non Local Means filtering is based on estimating each pixel intensity from the information provided from the entire image and hence it exploits the redundancy caused due to the presence of similar patterns and features in the image. In this method, the restored gray value of each pixel is obtained by the weighted average of the gray values of all pixels in the image. The weight assigned is proportional to the similarity between the local neighbourhood of the pixel under consideration and the neighbourhood corresponding to other pixels in the image [15]. Given a discrete noisy image ν = {ν(i)} for a pixel *I* the estimated value of NL[*v*](*i*) is computed as weighted average of all the pixels i.e.:

$$NL[v](i) = \sum_{j\in I} w(i,j).v(j)$$

where the family of weights {w(i, j)}j depend on the similarity between the pixels i and j. The similarity between two pixels i and j depends on the similarity of the intensity gray level vectors ν(Ni) and ν(Nj), where Nk denotes a square neighbourhood of fixed size and centred at a pixel k. The similarity is measured as a decreasing function of the weighted Euclidean distance, $\| \nu(Ni) - \nu(Nj) \|^2_{2,a}$, where a > 0 is the standard deviation of the Gaussian kernel.

The pixels with a similar grey level neighbourhood to ν(Ni) have larger weights in the average. These weights are defined as

$$W(i,j) = \frac{1}{z(i)} e^{\frac{\|v(Ni)-v(Nj)\|^2_{2a}}{h^2}}$$

where Z(i) is the normalizing constant and the parameter h acts as a degree of filtering. It controls the decay of the exponential function and therefore the decay of the weights as a function of the Euclidean distances. Fig. 4. shows the result of Non Local Means filter.

Fig 4 Result by Non Local Means filter

Quasi-Monte Carlo Non-Local Means For Filtering

In this method, m is used to denote the number of pixels in the noisy image, and n the number patches in the reference set X [9].We use upper-case letters, such as X, Y, Z, to represent random variables, and lower-case letters, such as x, y, z, to represent deterministic variables [11]. Finally, for notational simplicity in presenting our theoretical analysis, assume that all pixel intensity values have been normalized to the range [0, 1]. Given a set of random samples from χ, approximate the numerator and denominator by two random variables [10][12].

$$A(p) = \frac{1}{n}\sum_{j=1}^{n} \frac{x_j w_j}{p_j} I_j \text{ and } B(p) = \frac{1}{n}\sum_{j=1}^{n} \frac{w_j}{p_j} I_j$$

where the argument p emphasizes the fact that the distributions of A and B are determined by the sampling pattern p. Fig. 5. shows the result of Quasi - Monte Carlo Method**.**

Fig 5 Result by Quasi - Monte Carlo Method

V. Result and Discussion

The proposed approach is has been evaluated on publicly available standard images. The size of images is in 512 X512 X8. The main objective criterion of the proposed method is to denoise with image with Quality preservation. PSNR which is employed to estimate the quality of marked decrypted image. To quantify achieved performance, the following criteria's have been considered. The embedding rate expressed in bpp (bit of message per pixel of image).

PSNR

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not. PSNR is most easily defined via the mean squared error (*MSE*).

$$\mathrm{PSNR} = 10^{\log_{10}}\left(\frac{NM(2^{d}-1)^2}{\sum_{i,j=1,1}^{N,M}(I(i,j)-I_w[(i,j)]^2}\right)$$

Where d is depth of an image and M are the image dimensions.

Mean Square Error (MSE)

The mean square error (MSE) has been the dominant quantitative performance metric in the field of image processing. It remains the standard criterion for the assessment of image quality and fidelity. MSE is parameter free and inexpensive to compute, with a complexity of only one multiply and two additions per sample. It is also memory less and the squared error can be evaluated at each sample, independent of other samples.

$$\mathrm{MSE}=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j)-\hat{I}(i,j)]^2$$

Where M and N are the total number of pixels in the horizontal and the vertical dimensions of the image. I and Î denote the original and filtered image.

MAXERR

MAXERR is the maximum absolute squared deviation of the data, X, from the approximation, XAPP where XAPP is a real-valued signal or image approximation with a size equal to that of the input data, X.

L2RAT

L2RAT is the ratio of the squared norm of the signal or image approximation, XAPP, to the input signal or image, X.

VI. Conclusion And Future Work

The present work proposes Quasi-Monte Carlo non-local means for filtering the salt and pepper noise affected image. For lower values of noise variance, the existing filters like median filter and adaptive median filter can denoise salt and pepper noise, but fail to remove noise effectively as the noise variance increase. The present work proposes a method to handle salt and pepper noise even at higher variances. In addition to denoising it reduces the computational complexity when the noise in the image is increased. Experimental result of proposed system shows better result when compare with existing system.

The problem of estimating a discontinuous surface from noisy data is not dealt in present work. The procedure need to be explored further that can therefore remove noise correctly in continuity regions of the surface, and preserve discontinuities at the same time. In future, the present work can be explored for identifying different noises and preserves the edge information while denoising.

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