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Non-linear Filter for Digital Image De-noising

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Abstract: - *This paper presents an outline for removing noise in digital images. We see that the real time images are get more corrupted while acquisition, processing and transmission. As we deal 98% of our daily work on real time application data. So to suppress noise and elimination of noise from real time images is a research area for the developers, that how to predict noise and to remove that one noise from the image. As the real time images deals with spatial domain area. So in this paper we present a non-liner filter that may used to detect and remove the noise from digital images. The proposed filter is implemented in MatLab. There are so many filters available in literature, some are used to remove substitutive noise and some for additive noise but no filter is used to reduce noise from real time images. So we give a spatial filter for digital image de-noising used for real time applications.*

Keywords: Digital Noise, digital image, filters, mean filter, spatial-domain filter.

I. Introduction

As a cost efficient rotate, image processing methods have been exploited through the years to improve the quality of digital images. Uncompressed pictures or video require very high data rates [1] [2]. The transmission or storage of this data may be impractical, or even impossible for many applications. However, there is significant redundancy both in video and pictures, allowing compression of data. Yet, compression ratios above a certain level are achieved at the outlay of some loss of detail in the image or video. The amount of compression is determined by the bandwidth requirements for the particular application.

De-noising -based coding is used extensively in image processing systems. In low bit rate applications, this scheme gives rise to blocking artifacts which strictly reduce the visual quality of the image. Reducing blocking artifacts is essential to render the compressed visual data acceptable to the viewer. Various de-noising methods have been proposed in the literature to reduce blurring effects. Many of these methods are based on the post-processing idea. In other words, Noise introduced in an image is usually classified as substitutive (impulsive noise: e.g., salt & pepper noise, random-valued impulse noise, etc.) and additive (e.g., additive white Gaussian noise) noise. The impulsive noise of low and moderate noise densities can be removed easily by simple de-noising schemes. The simple median filter [4] works very nicely for suppressing impulsive noise of low density. However, many efficient filters have been developed for removal of impulsive noise of moderate and high noise densities.

II. Type of Digital image noise

Depending on applications, there are various types of imaging systems. X-ray, Gamma ray, ultraviolet, and ultrasonic imaging systems are used in biomedical instrumentation. In astronomy, the ultraviolet, infrared and radio imaging systems are used. Sonic imaging is performed for geological exploration. Microwave imaging is employed for radar applications. But, the most commonly known imaging systems are visible light imaging. Such systems are employed for applications like remote sensing, microscopy, measurements, consumer electronics, entertainment electronics, etc. In any type of image there are two types of noise that may cause an image to be blurring and degrade.

A. Salt & peepers' noise

Salt and pepper noise is a form of noise typically seen on images. It represents itself as randomly occurring white and black pixels. An effective noise reduction method for this type of noise involves the usage of a median filter or a contra harmonic mean filter. Salt and pepper noise creeps into images in situations where quick transients, such as faulty switching, take place [21].

B. Gaussian noise

Gaussian noise is statistical noise that has its probability density function equal to that of the normal distribution, which is also known as the Gaussian distribution. In other words, the values that the noise can take on are Gaussian-distributed. A special case is white Gaussian noise [20], in which the values at any pairs of times are statistically independent (and uncorrelated). In applications, Gaussian noise is most commonly used as additive white noise to yield additive white Gaussian noise.

III. Classification of image de-noising filters

There are two basic approaches to image de-noising, spatial filtering methods and transform domain filtering methods.

A. Spatial filtering

A traditional way to remove noise from image data is to employ spatial filters. Spatial filters can be further classified into non-linear and linear filters.

1. Non-Linear Filters: With non-linear filters, the noise is removed without any attempts to explicitly identify it. Spatial filters employ a low pass filtering on groups of pixels with the assumption that the noise occupies the higher region of frequency spectrum. Generally spatial filters remove noise to a reasonable extent but at the cost of blurring images which in turn makes the edges in pictures invisible. In recent years, a variety of nonlinear median type filters such as weighted median [5], rank conditioned rank selection [6], and relaxed median [14] have been developed to overcome this drawback.

2. Linear Filters: A mean filter is the optimal linear filter for Gaussian noise in the sense of mean square error. Linear filters too tend to blur sharp edges, destroy lines and other fine image details, and perform poorly in the presence of signal-dependent noise. The wiener filtering method requires the information about the spectra of the noise and the original signal and it works well only if the underlying signal is smooth. Wiener method implements spatial smoothing and its model complexity control correspond to choosing the window size. To overcome the weakness of the Wiener filtering, and Johnstone proposed the wavelet based de-noising scheme in [12].

B. Transform Filtering

The transform domain filtering methods can be subdivided according to the choice of the basic functions. The basic functions can be further classified as data adaptive and non-adaptive. Non-adaptive transforms are discussed first since they are more popular.

Efficient suppression of noise in an image is a very important issue. De-noising finds extensive applications in many fields of image processing. Image de-noising is usually required to be performed before display or further processing like texture analysis [10] [12], object recognition [13] [18], image segmentation [9], etc. Conventional techniques of image de-noising using linear and nonlinear techniques have already been reported and sufficient literature is available in this area [19].

Recently, various nonlinear and adaptive filters have been suggested for the purpose. The objectives of these schemes are to reduce noise as well as to retain the edges and fine details of the original image in the restored image as much as possible. However, both the objectives

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conflict each other and the reported schemes are not able to perform satisfactorily in both aspects. Hence, still various research workers are actively engaged in developing better filtering schemes using latest signal processing techniques.

IV. The proposed spatial-domain digital image filter

In Spatial-domain filter (proposed), first we prepare an algorithm for image de-noising and then compare this filter with performance measures such as MSE, MAE and time complexity with existing filters.

A. Proposed filter

Image de-noising is a common procedure in digital image processing aiming at the suppression of different type of noises that might have corrupted an image during its acquisition or transmission. This procedure is traditionally performed in the spatial-domain or transform-domain by filtering. In spatial-domain filtering, the filtering operation is performed on image pixels directly. The main idea behind the spatial-domain filtering is to convolve a mask with the whole image. The mask is a small sub-image of any arbitrary size (e.g., 3×3, etc.). Other common names for mask are: window, template and kernel. An alternative way to suppress additive noise is to perform filtering process in the transform-domain. In order to do this, the image to be processed must be transformed into the frequency domain using a 2-D image transform.

The detailed algorithm for the (Proposed) Spatial domain filter is given as follows.

1. Assume D (i, j) is a moving window centered at pixel d(i, j) with a window size of 2k + 1 (where k is an integer). In this case, the window size is equal in both dimensions and has to be an odd number, such as 3, 5, 7, etc. To calculate the local mean and local standard deviation, it is necessary to first obtain the sum S(i, j) of all the N(i, j) pixel values in the moving window.

$$S(i,j) = \sum_{m=i-k}^{i+k} \sum_{n=i-k}^{j+k} d(m,n) \quad \ldots (1)$$

$$N(i,j) = (2k+1)^2 \quad \ldots\ldots\ldots\ldots (2)$$

2. The local mean μ(i, j) of the moving window D is then computed as

$$\mu(i,j) = \frac{S(i,j)}{N(i,j)} \quad \ldots\ldots\ldots\ldots\ldots (3)$$

and the local standard deviation σ(i, j) is calculated as

$$\sigma(i,j) = \frac{\sqrt{\sum_{m=i-k}^{i+k} \sum_{n=i-k}^{i+k} (d(i,j) - \mu(i,j))^2}}{N(i,j)} \quad \ldots\ldots\ldots\ldots (4)$$

3. The range of valid pixel values can thus be determined by the above local statistics and a user-defined multiplier M. The lower bound LB (i, j) and upper bound UB (i, j) are defined as

$$LB(i,j) = \mu(i,j) - M\,\sigma(i,j) \quad \ldots\ldots (5)$$

$$UB(i,j) = \mu(i,j) + M\,\sigma(i,j) \quad \ldots (6)$$

4. If the central pixel l(i, j) at the mask moving window L equals 0 (i.e., labeled as speckle), then only the original central pixel value d(i, j) is replaced by the local adaptive median r(i, j) of the local window, which is the median of all the values of the pixels that are labeled as valid, excluding speckle pixels. The local adaptive median r(i,j) is calculated as

$$r(i,j) = \text{median}\,(d(m,n)) \quad \ldots\ldots\ldots (7)$$

Where

$$l(m,n) = 1 \text{ and } i - k \le m, n \le i + k. \quad \ldots\ldots\ldots\ldots (8)$$

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert. The human visual system (HVS) is so complicated that it is not yet modeled properly. Therefore, in addition to objective evaluation, the image must be observed by a human expert to judge its quality.

B. Image Metrics

The quality of an image is examined by objective evaluation as well as subjective evaluation. For subjective evaluation, the image has to be observed by a human expert. The human visual system (HVS) is so complicated that it is not yet modeled properly. Therefore, in addition to objective evaluation, the image must be observed by a human expert to judge its quality.

There are various metrics used for objective evaluation of an image. Some of them are mean squared error (MSE), root mean squared error (RMSE), mean absolute error (MAE) and peak signal to noise ratio (PSNR).

Let the original noise-free image, noisy image, and the filtered image be represented by f (x, y), g(x, y), and fˆ (x, y), respectively. Here, x and y represent the discrete spatial coordinates of the digital images. Let the images be of size M×N pixels, i.e. x=1,2,3,…,M, and y=1,2,3,…,N. Then, MSE and RMSE are defined as:

$$\mathrm{MSE} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[\hat{f}(x,y) - f(x,y)]^2}{\mathrm{MxN}} \quad \ldots\ldots (1)$$

$$\mathrm{RMSE} = \sqrt{MSE} \quad \ldots\ldots\ldots (2)$$

The MAE is defined as:

$$\mathrm{MAE} = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}[\hat{f}(x,y) - f(x,y)]}{\mathrm{MxN}} \quad \ldots\ldots\ldots (3)$$

The PSNR is defined in logarithmic scale, in dB. It is a ratio of peak signal power to noise power. Since the MSE represents the noise power and the peak signal power is unity in case of normalized image signal, the image metric PSNR is defined as:

$$\mathrm{PSNR} = 10\log_{10}\left(\frac{1}{\mathrm{MSE}}\right)\ \mathrm{dB} \quad \ldots\ldots\ldots (4)$$

The MSE, MAE and PSNR indices are used to compare the proposed with the exiting filters such as mean filter, kaun filter and the 4th order differential equation.

V. Results

The performances of the proposed filter are compared with existing spatial-domain filters. The objective evaluation metrics: peak-signal-to-noise ratio (PSNR), root mean-squared error (RMSE), mean absolute error (MAE), and execution time/Time complexity (TE/TC) are considered for comparing their filtering performances. The developed filter is compared against some well-known filters available in literature. The proposed spatial-domain filter is simulated on test images: Lena of size 512×512 pixels each corrupted with salt and peppers noise of standard deviation σ= 0.1,0.2,0.3,0.4 & 0.5

A. For Salt & peppers noise with standard deviation σ= 0.5

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Ranjeet Kaur et al, Int. J. Comp. Tech. Appl., Vol 2 (6), 1761-1767

“Figure 1: The original Lena image”

“Figure 2: The (Salt & peppers) standard deviation σ=0.5 noisy image”

“Figure 3: Filtered image using fourth order differential equation filter”

“Figure 4: Filtered image using Kaun filter”

“Figure 5: Filtered image using mean filter”

“Figure 6: Filtered image using proposed filter.”

VI. Conclusion

We develop a spatial-domain filter for digital image de-noising using MatLab. The proposed filter is compared with the existing spatial-domain filters: *mean filter, kaun filter, and fourth order differential filter*. To check the filtering performance of the proposed filter as

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Ranjeet Kaur et al, Int. J. Comp. Tech. Appl., Vol 2 (6), 1761-1767

well as the existing filters, the objective evaluation metrics: *peak-signal-to-noise ratio* (PSNR), *root mean-squared error* (RMSE), *mean absolute error* (MAE), and *execution time/Time complexity* (TE/TC) are considered for comparing their filtering performances. To give a concise presentation of all simulation results so as to have a precise comparative study, the performance measures of the proposed filter as well as some high-performing existing filters are shown in figures.

VII. Future work

Some new directions of research in the field of image de-noising are not yet fully explored. There is adequate scope to develop very effectual filters in the directions such as: very few filters are developed based on blind techniques. Independent component analysis can be a very good candidate for blind de-noising. We can implement such kind of filters on RGB images too. The widow size of different filters can be made adaptive for efficient de-nosing. The shape of the window can also be varied and made adaptive to develop very effective filters.

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