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A Survey on Transformation Technique for Image Filtering & Denoising

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Abstract

Image denoising is a technique of removing or filtering the noise level from the image so that the peak signal to noise ratio increases or error rate decreases. Since various image denoising techniques are implemented for the filtering of images such as using transformation or filters. Here in this paper a complete analysis and survey of all such techniques are implemented and compared so that by analyzing their advantages and limitations a new and efficient technique is implemented in future.

Keywords:—*Gabor Filter, Denoising, wavelet transform, DWT.*

I. INTRODUCTION

The utility of digital images are very much common for all kind of display gadgets. Unfortunately, the input images that are captured by these devices are sometimes not really in good brightness and contrast. Therefore, a process known as digital image enhancement is normally required to increase the quality of these low brightness images. The objective of image enhancement techniques is to improve a quality of an image such that enhanced image is better than the original image. Several image enhancement techniques have been proposed in both spatial and transform domains. In the spatial domain techniques, intensity values of images have been modified whereas in the transform domain techniques, transform domain coefficients are modified, typically, scaled [1].

Image enhancement produces an output image that subjectively looks better than the original image by changing the pixel's intensity of the input image [2]. The reason of image enhancement is to improve the interpretability or perception of information contained in the image for individual viewers, or to make available a improved input for other automated image processing systems. It plays an important role in the use of images in various applications like cancer and tumour detection, medical image processing, radar image processing etc.

There are many image enhancement techniques that have been proposed and developed, the most popular method being Histogram Equalization. This technique is one of the most popular methods for image enhancement due to its simplicity and efficiency. It usually increases the global contrast of the images mostly in cases where the important and useful data of the image is shown by low contrast values. Histogram equalization (HE) [2] is a simple and effective contrast enhancement technique which distributes pixel values uniformly such that enhanced image have linear cumulative histogram. The HE technique is a global operation hence; it does not preserve the image brightness [3].

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Denoising of signals and images is a fundamental task in signal processing. Early approaches, such as Gaussian Gabor filters and anisotropic diffusion [4], denoise the value of a signal $y(x_1)$ at a point x_1 based only on the observed values $y(x_2)$ at neighboring points x_2 spatially close to x_1. To overcome the obvious shortcomings of this locality property, many authors proposed various global and multiscale denoising approaches. Among others, we mention minimization of global energy functionals such as the total-variation functional and Fourier and wavelet denoising methods [5]. Although quite sophisticated, these methods typically do not take into account an important feature of many signals and images, that of repetitive behavior, e.g., the fact that small patterns of the original noise-free signal may appear a large number of times at different spatial locations. For one-dimensional (1-D) signals these properties holds for every periodic or nearly periodic function (such as repetitive neuronal spikes, heart beats, etc.) and for many telegraph type processes. Similarly, identical patches typically appear at many different and possibly spatially distant locations in two-dimensional (2-D) images. The fact that the same noise-free pattern appears multiple instances can obviously be utilized for improved denoising.

Curvelet Transformation

First generation curvelet transform is a multiscale directional transform which has been designed to represent edges and other singularities along curves effectively. It enables directional analysis of images in different scales. Second generation curvelet transform called the discrete curvelet transform (DCvT) has been proposed with less complexity and fast computation. It has two different decompositions namely unequispaced DCvT (UDCvT) and the wrapping DCvT (WDCvT). In UDCvT, the curvelet coefficients are found by irregularly sampling the Fourier coefficients of images. In WDCvT, series of translations and wraparound technique are used [6].

Enhancement based on Wavelet Transformation

Wavelet transform is firstly used to image compression, which is the really predominance in image processing. Later, the WT is also used to detect the edge information, enhancement, fusion, denoise, and so on. For now, there are some different kinds of wavelet can be selected, including Mayer, Daubechies, Symlet and Shannon, etc. For the same signals, different wavelets lead different results because of their different characters on compact, fluency and orthonormal. But, it is still confusing us that how to select the most suitable one in a specific application.

As we know, no matter which kind of WT we used, the low frequency coefficients are corresponding to the main contour of image. On the contrary, the high-frequency coefficients reflect the details and noise. Both of the coefficients are all very useful in promoting image quality. In most of situations, parts of noise can be confined by enhancing coefficients which are belong to low-frequency and low-pass high-frequency. But, the low-pass threshold is not easy to control. If a low-pass threshold filters out most of high-frequency coefficients, much noise will be deleted, and the image will become smoother. But, the image will also become blurring, because many detail characters are also deleted. It means that it is not enough to distinguish noise ingredient from detail ingredient simply according to the frequency of WT. The key of the approach is how to separate two kinds of information effectively [7].

II. Background

Improving the quality of the images is the primary target of all image enhancement algorithms. Several image enhancement techniques exist both in spatial as well as transform domains. One of the famous existing techniques includes image enhancement using Curvelet Transform first and then applying histogram equalization. But the results obtained can be still improved more. The DWT provides sufficient information both for analysis and synthesis of the actual signal, with a momentous decrease in the computation time. In DWT, the original image is first high-pass filtered, which provides the three large images, where each describes local changes in brightness in the actual image then it is low-pass filtered and downscaled, which provides an approximation image; this image is then high-pass filtered to produce the three smaller detail images. After that applied low-pass filtered to produce the final approximation image in the upper-left. Once DWT is applied, then the histogram equalization is done to re-assign the intensity value of pixels in the input image such that the output image contains a uniform distribution of intensities. It will also result in higher contrast of previously lower contrast regions and areas thus enhancing the contrast of the image. After implementing the method, we have try to made comparison of proposed method with the already existing technique that uses Curvelet Transform for image brightness preservation based on various evaluation parameters.

III. Literature survey

Discrete Wavelet Transformation

The Discrete Wavelet Transform (DWT) is discrete in time and scale, meaning that the DWT coefficients may have real (floating-point) values, but the time and scale values used to index these coefficients are integers. A signal is decomposed by DWT into one or more levels of resolution (also called octaves), A one-dimensional, one-octave DWT. It includes the analysis (wavelet transform) on the left side and the synthesis (inverse wavelet transform) on the right side. The low-pass filter produces the average signal, while the high pass filter produces the detail signal. In multi-resolution analysis, the average signal at one level is sent to another set of filters, which produces the average and detail signals at the next octave [8]. The detail signals are kept, but the higher octave averages can be discarded, since they can be re-computed during the inverse transform. Each channel's outputs have only half the input's amount of data (plus a few coefficients due to the filter). Thus, the wavelet representation is approximately the same size as the original. The DWT can be 1-Dimensional, 2-D, 3-D, etc. depending on the signal's dimensions [9].

The 2-D transform is simply an application of the 1-D DWT in the horizontal and vertical directions [10], at least for the separable case. The non-separable 2-D transform works differently from the one shown, since it computes the transform based on a 2-D sample of the input convolved with a matrix, but the results are the same. The separable idea can be extended to the 3-D DWT.

1-D Wavelet Architecture

One-dimensional architectures can be classified into many types, the main ones are: space multiplexed, systolic array, time multiplexed, folded, and digit-serial. There are techniques for improving these designs, which include lattice, pipelining/register networking, combined DWT and IDWT, and approximating results. However, each improvement involves a certain tradeoff: for example, lattice uses less space at the expense of a slower speed. Examples of each category will be discussed below. Architectures are often designed with applications in mind. For 1 -D transforms, applications may include denoising a nuclear magnetic resonance (NMR) signal, compressing seismic information [10], and identifying noisy FM signals [11].

According to Kim [12], one drawback of the histogram equalization can be found on the fact that the brightness of an image can be altered after the histogram equalization, just because of to the flattening property of the histogram equalization. Therefore, it is hardly utilized in consumable electronic products such as TV where preserving original input brightness may necessary in order not to introduce unnecessary visual deterioration [12]. Kim proposed a technique whereby the input histogram is divided into two sub-histograms on the basis of its mean value. The main motive behind this technique was to preserve the brightness of the image while enhancing its contrast.

Wan et. al. [13] proposed Dualistic sub-image histogram equalization (DSIHE). They also does the same thing that BBHE does but the criterion for separation of histograms is median value. They also proposed another technique namely Recursive Mean Separate Histogram Equalization (RMSHE) [14], where the histogram is recursively partitioned based on local mean values and the number of sub-histograms (2^r) is given by user.

Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) technique was proposed by Chen and Ramli [15]. In this technique the histogram is partitioned based on a threshold level which is equivalent to minimized difference between the input mean and output mean. In case of preserving the brightness of original image this method is better than BBHE and DSIHE.

Wang et. al. [16] proposed a technique called Brightness Preserving Histogram Equalization with Maximum Entropy (BPHEME). The idea behind their technique was to find the target histogram that maximizes the entropy, keeping in view that brightness of original image is preserved, and then apply histogram transformations to transform the original histogram to the targeted one. The results showed that this technique is better than BBHE, DSIHE and MMBEBHE Multi-histogram equalization (MMLSEMHE) methods were proposed by Menott et. al. [17]. According to them, though bi-HE methods preserve the brightness of the original image but, the output image may not look as natural as the original image. They proposed a technique which on one hand preserves the brightness of the input image and on the other hand generated images with natural appearances. Later in the same year, Ibrahim et. al. proposed their method for preserving brightness entitled preserving dynamic histogram equalization (BPDHE) [18], in which the histogram is first subjected to 1-D Gaussian filter and then it is sub-partitioned into a number of sub-histograms based on its local maximums. Each sub-histogram is then equalized separately.

Hossain et. al. [19] proposed a technique called Minimum Mean Brightness Error Dynamic Histogram Equalization (MMBEDHE) whereby, the input image is divided into a number of sub-images and then the classical HE is applied to each of them. The absolute average error using this technique was calculated to be very less as compared to since then existing techniques [19]. In the same year, Xie et. al. [20] came up with their technique for image enhancement known as "An Adaptive Image Enhancement Technique Based on Image Characteristic". In this technique, the actual or original image is primary subjected to Laplace Filter which is a spatial high-pass filter. Based on its output, the first-order classifying of the image is done. Here the image is smoothened using low-pass filter and the edges are sharpened using high-pass filter. At the end, HE is applied to it [20].

Continuing with the research Demirel et. al. [21] proposed a new method for enhancement of satellite images contrast called Satellite Image Contrast Enhancement Using Discrete Wavelet Transform and Singular Value Decomposition. Their method was based on Discrete Wavelet Transform (DWT) and singular-value decomposition. They first applied DWT to input image to divide it into four frequency sub-bands, then used singular value decomposition and then again applied inverse DWT to reconstruct the image.

Dabov et al. [22] proposed a novel image denoising strategy based on an enhancement sparse representation in transform-domain. The enhancement of sparsity is achieved by grouping similar 2-D image fragments e.g., blocks into 3-D data arrays which is called as groups. Collaborative filtering is a special procedure developed to deal with these 3-D groups. The filter is realized with three successive steps: 3-D transformation of a collection reduction of the transform range, and inverse 3-D transformation.

Ning [23] proposed a very efficient algorithm for image denoising based on wavelets and multifractals for singularity detection. By modeling the intensity surface of a noisy image as statistically self-similar multifractal process and taking advantage of the multiresolution analysis with wavelet transform to exploit the local statistical self-similarity at different scales, the point-wise singularity power value distinguishing the local singularity at each extent was computed. By thresholding the singularity strength, wavelet coefficients at each extent were classified into two categories: the edge-related and regular wavelet coefficients and the irregular wavelet coefficients. The irregular wavelet coefficients were denoised using an approximate minimum mean-squared error (MMSE) evaluation technique, at the same time as the edge-relayed and usual wavelet coefficients were smoothed using the fuzzy weighted mean (FWM) filter preserving the edges and details when reducing noise.

The framelet is an improvement upon the critically sampled DWT with important additional properties: (1) It employs one scaling function and two distinct wavelets, which are designed to be offset from one an additional by one half, (2) The double-density DWT is over-complete by a factor of two, and (3) It is nearly shift-invariant. In two dimensions, this transform outperforms the standard DWT in expressions of denoising; on the other hand, there is opportunity for improvement because not all of the wavelets are directional. Specifically, although the double-density DWT utilizes more wavelets, some lack a principal spatial orientation, which checks them from being able to separate those directions.

Here author has[24] propose new approach point of reference estimation based on Gabor filters, as an alternative of the predictable approach. As the usual direction estimation is launched on the minimization of high-frequency coefficients, it is efficient for uncorrupted images but does not effort fine within corrupted images. In actual fact, the local image features may be disturbed by the noise. Then the way explained by the minimization may not exactly keep up a correspondence to the authentic orientation additionally, the noise cannot be eradicated efficiently in view of the fact that the noise energy for the most part high frequency is dense into the low-pass subband also. The schoolwork of a directional lifting transform for wavelet frames. A non subsampled lifting arrangement is developed to sustain the translation invariance as it is a significant belonging in image denoising. Then, the directionality of the lifting-based tight frame is unambiguously talk about, go after by a specific translation invariant directional framelet transform (TIDFT). The TIDFT has two framelets ψ1, ψ2 with become extinction moments of arrange two and one correspondingly, which are able to detect singularities in a given bearing set. It provides an efficient and sparse representation for images surrounding rich textures along with properties of fast accomplishment and just the thing reconstruction. So the investigational consequences give you an idea about that the TIDFT do better than some other frame-based denoising process, such as contourlet and shearlet, and is viable to the modern denoising move towards.

IV. CONCLUSION

The various techniques implemented for the image denoising using filtering and transformation techniques is efficient in terms of PSNR and error rate, but there must be an efficient technique implemented in future for the better filtering as compared to the existing techniques.

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