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Modified Image Denoising System Using DWT

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Abstract

In the past few decades, many noise reduction techniques have been developed for removing noise and retaining edge details in images. The process of removing noise from the original image is still a demanding problem for researchers. There have been several algorithms, and each has its assumptions, merits, and demerits. The prime focus of this work is related to the processing of an image before it can be used in applications. The processing is done by denoising of images. In order to achieve this, a combination of denoising algorithms is being used. Image denoising algorithms W.T. (Wavelet transform)and KLT(Karhunen – Loeve transform) is applied on images to remove the noise that is either present in the image during capturing or injected into the image during transmission. The W.T. shows an excellent performance in the denoise field, while KLT shows a good performance in the signal reconstructed ability. Denoising plays a very important role in the field of image processing. It is often done before the image data is to be analyzed. Denoising is mainly used to remove the noise that is present and retains the significant information, regardless of the frequency contents of the signal. De-noising has to be performed to recover useful information. The main purpose of an image-denoising algorithm is to eliminate the unwanted noise level while preserving the important features of an image. PSNR, MSE, and MAXERR parameters are being improved using a combination of image denoising algorithms W.T. (Wavelet transform) and KLT(Karhunen - Loeve transform).

Keywords: *W.T. (Wavelet transform), KLT (Karhunen - Loeve transform), Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT)*

INTRODUCTION

Digital images play an important role in daily life applications such as satellite television, magnetic resonance imaging, computer tomography, and areas of research and technology such as geographical information systems and astronomy. Data sets collected by image sensors are generally contaminated by noise. Imperfect instruments, problems with the data acquisition process, and interfering natural phenomena can all degrade the interest data. Furthermore, noise can be introduced by transmission errors and compression. Thus, delousing is often a necessary and the first step to being taken before the images data is analyzed. It is necessary to apply an efficient delousing technique to compensate for such data corruption.

Image delousing still remains a challenge for researchers because noise removal introduces artefacts and causes blurring of the images. This paper describes different methodologies for noise reduction (or denoising), giving an insight as to which algorithm should be used to find the most reliable estimate of the original image data given its degraded version. Noise modelling in images is greatly affected by capturing instruments, data transmission media, image quantization and discrete sources of radiation. Different algorithms are used depending on the noise model. Most of the natural images are assumed to have additive random noise, which is modelled as a Gaussian. Speckle noise is observed in ultrasound images, whereas Rician noise affects MRI images. The scope of the paper is to focus on noise removal techniques for natural images.

WAVELET TRANSFORM

There are several transforms available like Fourier transform, Hilbert transform, Wavelet transforms, etc. The wavelet transform is better than other transforms because of the following reasons.

- Wavelet transform is better than Fourier transform because it gives frequency representation of raw signal at any given interval of time, but Fourier transform gives only the frequency- amplitude representation of the raw signal, but the time information is lost. So we cannot use the Fourier transform where we need time as well as frequency information at the same time.

- Wavelet transform is better than discrete flourier transform (DFT) as wavelet transform can capture the localized feature, which is the frequency spectrum of a small-time segment. The DFT only offers the global features that will analyze the frequency spectrum. The second point is the computation time which is N for the W.T. and N log N for the DFT. The third dissimilarity that will be given here is that the difference in the energy distribution, with the coefficient as end the energy percentage of the discrete wavelet transform (DWT) descends lightly while the discrete Fourier transform (DFT) descend the increases firstly dramatically.

- Wavelet transform is better than fast Fourier transform (FFT) as individual wavelet functions are localized in time. Fourier sine and cosine functions are not. This localization feature, along with wave lets' localization off frequency, makes many functions and operators using wavelets "sparse" when transformed into the wavelet domain. This sparseness, in turn, results in a number of useful applications such as data compression, detecting features in images, and removing noise from time series.

- Other main advantageous properties of the wavelet transform (to be clarified in the following sections) are:
  Multire Solution: A scale invariant representation.

  Edge Detection: Large wavelet coefficients correspond to image edges.

  Sparsity: The wavelet transform of natural images tends to be sparse.

  Fast Algorithms: The complexity of the fast discrete wavelet transform is a linear function of the number of input samples.

KARHUNEN – LOEVE TRANS FORM (KLT)

Karhunen –Loaves Transform (KLT), which was built on statistical-based properties. The outstanding advantage of KLT is ago odd - correlation. In the MSE (Mean Square Error) sense, it is the best transform, and it has an important position in the data compression technology.

KLT has four characteristics:

1. **De-correlation:** After transforming the weight if vector Signal Yun related.

2. **Energy concentration:** After the transform of the N-dimensional vector signal, the maximum variance is in the former of M lower sub-vector.

3. **Under measuring of the MSE:** The distortion is less than other transforms. It is the sum of the sub-vectors which were omitted.

4. No quick algorithm and the different signal sample collection has different transformation matrices.(it is the shortcoming of KLT)

KLT is chosen over other transforms as:

- DCT, which is short of Discrete Cosine Transform, it is very similar with DFT (Discrete Fourier Transform) but it only uses real numbers. Both KLT and DCT are used in image processing. For the DCT, especially the DCT – II is always used to lossless data compression for signal and image. It has an "energy concentration" property: most of the signal information tends to be concentrated in a few low–frequency components of the DCT, approaching the KLT for signals based on certain limits of Markov process. Then the side - correlation gets close to KLT. So the DCT is almost as good as KLT for a1st order Markov process.

- There is no fast algorithm in KLT, which is a big barrier in practical application. The DCT has a fast algorithm. Then the DCT can achieve much faster compression than the KLT, while the DCT lead correlatively lagged gradation of compression quality at the same compression ratio compared to the KLT.

- A fast Fourier transform (FFT) is an efficient algorithm to compute the discrete Fourier transform (DFT) and its inverse. The FFT has been applied widely, such as digital signal processing, solving partial differential equations to algorithms for quick multiplication of large integers, and soon. Beyond the FFT, the KLT is used to extract weak signals from noise plus data compression. Both KLT and FFT are used to image processing and signal processing.

- The KLT is a mathematical tool superior to the FFT in that it accuracy applies to any finite bandwidth, rather than applying to infinitely small bandwidth only (i.e. to monochromatic signals) as the FFT does. Also, the KLT applies to both stationary and non-stationary processes, but the FFT works only for stationary inputs to chastic processes. The KLT is defined for any finite time interval, but the FFT is plagued by "window" problems. For the KLT it needs a shigh computational burden because of no "fast" KLT. Compared with FFT, it is a fast algorithm than FFT.

- KLT is built on statistical-based properties. The W.T. is based on waveform transform. They are based on a different foundation. The outstanding advantage of KLT is a good correlation. For the W.T., the basic method is used to denoising and analyze signal.

The KLT and W.T. are always used in image processing. In this paper, KLT is focused on the reconstruction ability. And the Wavelet is focused on delousing ability.

TYPES OF NOISES

Noise is undesired information that degrades the image. In the image denoising process, information of the type of noise present in the original image plays a significant role. Most images can be corrupted with noise modelled with either a uniform, Gaussian, or salt and pepper distribution. Another type of noise is speckle noise which is multiplicative. Noise is present in an image either in an additive or multiplicative form.

Rule for additive noise

$$W(x, y) = s(x, y) + n(x, y)$$

Rule for multiplicative noise

$$W(x, y) = s(x, y)\times n(x, y)$$

Where (x,y) is the original signal, n(x,y) is the noise introduced into the signal to produce a noisy image w(x,y), and (x,y) is the pixel location. The above image algebra is done at a pixel level. Image addition also has applications in image morphing. Image multiplication means the brightness of the image is varied.

The digital image acquisition process transforms an optical image into a continuous electrical signal that is, sampled. In every step of the process, there are fluctuations caused by natural phenomena, adding random value to the exact brightness value for a given pixel.

Gaussian Noise

Gaussian noise is evenly distributed in the signal. That means every pixel in the noisy image is the sum of the random Gaussian distributed noise value and true pixel value. This type of noise has a Gaussian distribution, which has a probability distribution function given by,

$$F(g) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-(g-m)^2/2\sigma^2} ,$$

Where g represents the grey level, m is the mean of the function, and σ is the standard deviation in the noise.

Salt and Pepper Noise

Salt and pepper noise is an impulse type of noise that is also referred to as intensity spikes. It is caused generally due to errors in the data transmission. It has only two possible values that are a and b. The probability of each is typically less than 0.1.

Corrupted pixels can be set alternatively to the minimum or to the maximum value, giving the image a "salt and pepper" like appearance. Pixels remain unchanged for unaffected. For an 8-bit image, the value of pepper noise is 0, and for salt noise, 255. Salt and pepper noise is mainly caused by malfunctioning of pixel elements in the sensors of cameras, faulty memory locations, or timing errors of the digitization process.

Speckle Noise

Speckle noise is multiplicative noise. This type of noise occurs mostly in all coherent imaging systems such as acoustics, laser, acoustics and SAR (Synthetic Aperture Radar) imagery. The Source of this noise is attributed to the random interference between the coherent returns. A fully developed speckle noise has the characteristic of multiplicative noise.

Brownian Noise

Brownian noise is under the category of fractal or 1/f noises. The mathematical model for 1/f noise is the fractional Brownian motion. Brownian motion is a non-stationary stochastic process that follows a normal distribution. Brownian noise is a special case of 1/f noise. It can be obtained by integrating white noise.

Poisson Noise

Many images like those from radiography have noise that satisfies a Poisson distribution. The magnitude of Poisson noise varies across an image, and it depends on the image intensity, making removing such noise very hard.

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Poisson images occur in situations where the image acquisition is performed using the detection of particles (e.g), counting photons being emitted from a radioactive source is applied in medical imaging like SPECT and PET therefore Poisson noise reduction is an essential problem. Poisson noise is generated from the data in place of adding artificial noise to the data. For example, if a pixel in an unsigned integer input has the value 10, then the corresponding output pixel will be generated from a Poisson distribution with a mean 10.

PARAMETERS UNDER CONSIDERATION

The term peak signal-to-noise ratio (PSNR) is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Because many signals have a very wide dynamic range (ratio between the largest and smallest possible values of a changeable quantity), the PSNR is usually expressed in terms of the logarithmic decibel scale.

Image enhancement or improving the visual quality of a digital image can be subjective. Saying that one method provides a better quality image could vary from person to person. For this reason, it is necessary to establish quantitative/empirical measures to compare the effects of image enhancement algorithms on image quality.

Using the same set of tests images, different image enhancement algorithms can be compared systematically to identify whether a particular algorithm produces better results. The metric under investigation is the peak-signal-to-noise ratio. If we can show that an algorithm or set of algorithms can enhance a degraded known image to more closely resemble the original, then we can more accurately conclude that it is a better algorithm.

For the following implementation, let us assume we are dealing with a standard 2D array of data or matrix. The dimensions of the correct image matrix and the dimensions of the degraded image matrix must be identical.

The mathematical representation of the PSNR is as follows:

$$PSNR = 20\log_{10}\left(\frac{MAX_f}{\sqrt{MSE}}\right)$$

Where the MSE (Mean Square Error) is

$$MSE = \frac{1}{mn}\sum_{0}^{m-1}\sum_{0}^{n-1}\|f(i,j) - g(i,j)\|^2$$

f represents the matrix data of our original image

g represents the matrix data of our degraded image in question

m represents the numbers of rows of pixels of the images, and I represent the index of that row

N represents the number of columns of pixels of the image, and j represents the index of that column.

Max is the maximum signal value that exists in our original "known to be good" image Maximum squared error (MAXERR) is the maximum absolute squared deviation of the data from the approximation.

PROPOSED SYSTEM

The proposed system is a joint algorithm that combines the W.T. with the KLT. The W.T. shows an excellent performance in the depose field, while KLT shows a good performance in the signal reconstructed ability.

Role of KLT in the algorithm: KLT is mainly used to compute the covariance cicatrix and the use it to rebuild after denoising by W.T. The PCA In this part will compute the covariance matrix. The process is to transform a given data set X of dimension M to an alternative data set Y of smaller dimension L, where Y is the KLT of matrix X.

Role of W.T. in the algorithm: W.T. is used for noising the image by using wavelet threshold. Firstly, transform the image into a double data vector matrix. And then delouse on the horizon, diagonal, vertical vector. The principle to denoise is that ge to ut the high frequency through controlling the value of the threshold. According to different signals, the threshold will not change. Only the data ate acupoint will not be the same while computation. And at last, they will give a result of the signal by using integral.

Use the inverse W.T. to rebuild the signal. But in this part, their construction work will be done by KLT.

One advantage of this algorithm is that the PSNR, MSE and Maximum squared error (MAXERR) gets improved. Another marked advantage of this algorithm is that we can descend the dimensions of the image, and the dimensions of the image in the three directions (horizontal, vertical, diagonal) can also be descended.

SIMULATION RESULTS

The proposed algorithm is verified under two conditions firstly when SNR=5dBand secondly, when SNR=10dB.

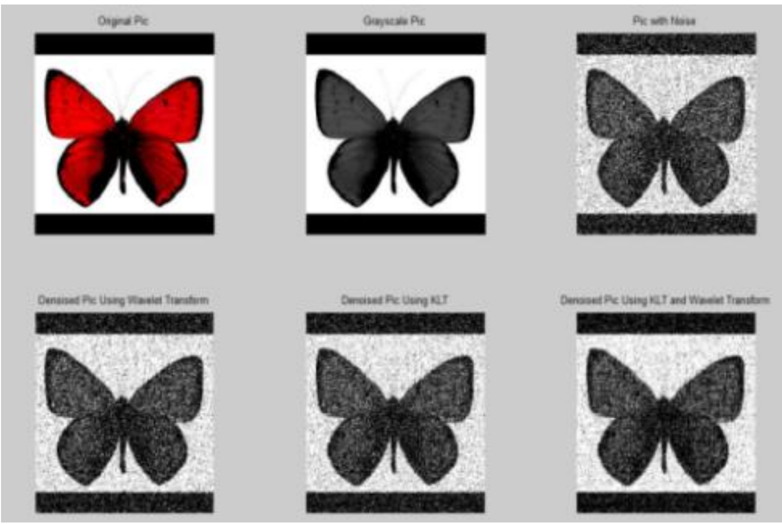

Figure 1: Simulation results of proposed algorithm (SNR=5dB).

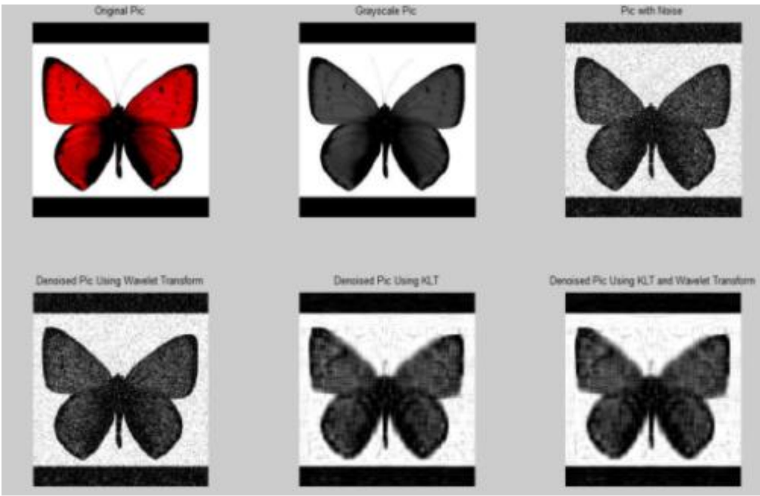

Figure 2: Simulation results of proposed algorithm (SNR=10dB).

The simulation results show the original image, grayscale image, image with white Gaussian noise, denoised images using Wavelet transform alone, KLT alone and with the proposed algorithm.

The simulation results show the original image, grayscale image, image with white Gaussian noise, denoised images using

Wavelet transform alone, KLT alone and with the proposed algorithm.

Table 1 Analysis of Parameters Using Different Algorithms.

S. NO.	SNR	PARAMETERS	WITH WT	WITH KLT	WITH PROPOSED ALGORITHM
1.	5 dB	PSNR	58.5461	58.6093	60.8935
		MSE	0.0909	0.0896	0.0529
		MAXERR	1.3630	1.3449	0.9535
2.	10 dB	PSNR	63.5667	67.7402	67.9733
		MSE	0.0286	0.0109	0.0104
		MAXERR	0.7411	0.7150	0.6894

Table 1 shows the values of PSNR, MSE, and MAXERR obtained using different algorithms. From the table analysis, it can be concluded that the parameters are improved using the proposed algorithm in comparison to W.T. and KLT alone.

CONCLUSION

The purpose of this dissertation work is to develop an efficient image delousing system based on W.T. (Wavelet transform) and KLT (Karhunen - Loeve transform). W.T. has been widely used; KLT is not as popular as W.T., there as on caused by its different mathematical structure. The parameters PSNR, MSE and MAXERR are compared for SNR values of 5dB and 10dB for an image affected by white Gaussian noise. The results show that the proposed system is more efficient than the W.T. and KLT alone.

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