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"IMPROVED IMAGE DENOISING BASED ON AN HYBRID APPROACH OF WAVELET AND PCA''

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Abstract

Removing noise from the original signal is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. The problem of image denoising can be solving by using hybrid approach of Principal component analysis and wavelet. Principal component analysis (PCA) is nothing but an orthogonal transformation that seeks the directions of maximum variance in the transformation that seeks the directions of maximum variance in the data and is commonly used to reduce the dimensionality of the data. Wavelet determines a threshold as well as neighbouring window size for every sub band using its lengths. Wavelets give a superior performance in image denoising due to properties such as sparsity and multiresolution structure. With Wavelet Transform gaining popularity in the last two decades various algorithms for denoising in wavelet domain were introduced. So here hybrid method for image denoising is introduced.

INTRODUCTION

Digital images play an important role both in daily life applications such as satellite television, magnetic resonance imaging, computer tomography as well as in 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 data of interest. Furthermore, noise can be introduced by transmission errors and compression. Thus, denoising is often a necessary and the first step to be taken before the images data is analyzed. It is necessary to apply an efficient denoising technique to compensate for such data corruption. Image denoising still remains a challenge for researchers because noise removal introduces artifacts and cause blurring of the images.

Original image Noisy image

Noise can be systematically introduced into an image during acquisition and transmission. A fundamental problem of image processing is to effectively remove noise from an image while keeping its features intact.

The nature of the problem depends on the type of noise added to the image. Fortunately, two noise models can adequately represent most noise added to images: additive Gaussian noise and impulse noise. Additive Gaussian noise is characterized by adding to each image pixel a value from a zero-mean Gaussian distribution. Such noise is usually introduced during image acquisition. The zero-mean property of the distribution allows such noise to be removed by locally averaging pixel values. Ideally, removing Gaussian noise would involve smoothing inside the distinct regions of an image without degrading the sharpness of their edges. Classical linear filters, such as the Gaussian filter, smooth noise efficiently but blur-edges significantly.

The essence of these methods is to use local measures of an image to quantitatively detect edges and to smooth them less than the rest of the image. Impulse noise is characterized by replacing a portion of an image's pixel values with random values, leaving the reminder unchanged. Such noise can be introduced due to transmission errors. The most noticeable and least acceptable pixels in the noisy image are then those whose intensities are much different from their neighbours. The Gaussian noise removal methods mentioned above cannot adequately remove such noise because they interpret the noise pixels as edges to be preserved. Wavelet analysis and Principal component analysis has been demonstrated to be powerful methods for performing image noise reduction Performance of denoising algorithms is measured using quantitative performance measures such as peak signal-to-noise ratio (PSNR), signal-to-noise ratio (SNR) as well as in terms of visual quality of the images. Many of the current techniques assume the noise model to be Gaussian. In reality, this assumption may not always hold true due to the varied nature and sources of noise. An ideal denoising procedure requires a priorknowledge of the noise, whereas a practical procedure may not have the required information about the variance of the noise or the noise model.

Thus, most of the algorithms assume known variance of the noise and the noise model to compare the performance with different algorithms. Gaussian Noise with different variance values is added in the natural images to test the performance of the algorithm. Not all researchers use high value of variance to test the performance of the algorithm when the noise is comparable to the signal strength. Use of FFT in filtering has been restricted due to its limitations in providing sparse representation of data. Wavelet Transform is the best suited for performance because of its properties like sparsity, multiresolution and multiscale nature. In addition to performance, issues of computational complexity must also be considered. Thresholding techniques used with the Discrete Wavelet Transform are the simplest to implementWavelet analysis has been demonstrated to be one of the powerful methods for performing image noise reduction. The procedure for noise reduction is applied on the wavelet coefficients obtained after applying the wavelet transform to the image at different scales. The motivation for using the wavelet transform is that it is good for energy compaction since the small and large coefficients are more likely due to noise and important image features, respectively. The small coefficients can be thresholded without affecting the significant features of the image. In its most basic form, each coefficient is thresholded by comparing against a value, called threshold. If the coefficient is smaller than the threshold, it is set to zero; otherwise it is kept either as it is or modified. The inverse wavelet transform on the resultant image leads to reconstruction of the image with essential characteristics.

There exist various methods for wavelet thresholding which rely on the choice of a threshold value such as VisuShrink, SureShrink and BayesShrink. The VisuShrinkhas a limitation of not dealing with minimizing the mean squared error, The Sure- Shrink threshold depends upon Stein's Unbiased Risk Estimator (SURE). It minimizes the mean squared error that takes the combination of the universal thresh- old and the SURE threshold. The BayesShrink is a data-driven adaptive image denoising method.

So by combining the both methods of noise removal i.e. wavelet transform and Principal component analysis and then analyzing the result on several images, can make conclusion that the proposed approach gives a better visual quality image.In this, first eliminating image noise by using Wavelet transforms, and then applying PCA to get the optimized denoising outputs.

LITERATURE SURVEY

PCA was invented in 1901 by Karl Pearson. Now it is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done by Eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix, usually after mean centering (and normalizing) the data matrix for each attribute. The results of a PCA are usually discussed in terms of component scores, sometimes called factor scores (the transformed variable values corresponding to a particular data point), and loadings (the weight by which each standardized original variable should be multiplied to get the component score)In the history of mathematics, wavelet analysis shows many different origins. Much of the work was performed in the 1930s, Before 1930, the main branch of mathematics leading to wavelets began with Joseph Fourier (1807) .The first mention of wavelets appeared in an appendix to the thesis of A. Haar (1909).

[1] This paper proposes a denoising technique by using a new statistical approach, principal component analysis with local pixel grouping (LPG).In this paper, author introduces PCA as a method of identifying patterns in data, and expressing the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analyzing data. The other main benefit of PCA is that once you have found these patterns in the data, and you compress the data, ie. by reducing the number of dimensions, without much loss of information**.** PCA is a de-correlation technique and it is mainly used in pattern recognition and dimensionality reduction and etc. By transforming the original dataset into PCA domain and preserving only the several most significant principal components, the noise and trivial information can be removed. A PCA-based scheme was proposed for image denoising by using a moving window to calculate the local statistics, from which the local PCA transformation matrix was estimated. The proposed algorithm has two stages, in the the first stage it gives an initial estimation of the image by removing most of the noise and the second stage will further refine the output of the first stage. The second stage has the same type of procedure except for the parameter of noise level. Since the noise in the first stage is significantly reduced, the LPG accuracy will be much improved in the second stage so that the final denoising result is visually much better.

[2]In this paper wavelet thresholding evaluated the performance using the quality measure PSNR which is calculated as:

PSNR (in db10)=10* $log_{10}(255)^2$/MSE, Where MSE is the mean squared error between the original image and reconstructed image.

Here there is a comparison between the performance of different denoising schemes that include Visushrink, Neigh hrink and Modineigh Shrink. In these approch different window sizes of 2 × 2, 3 × 3, 5 × 5, and 7 × 7 are taken. The noise levels have been taken as 10, 20, 30, 50, 75, and 100. The images considered in experiments are standard images that include Lena, Barbara, and Gold hill each of size 512 × 512 .The wavelet transform used is Daubechies least asymmetric compactly supported wavelet with eight vanishing moments. According to this paper wavelet transform performed four times in order to obtain four scales of decomposition.

In this paper graphs for PSNRvs noise level for the VisuShrink, Neigh Shrink, ModNeiSh and wavelet thresholding methods for Lena image are shown in for window sizes 2 × 2, 3 × 3, 5 × 5 and 7 × 7, respectively. It is proven that wavelet thresholding method performs better than the VisuShrink, Neigh Shrink, ModNeiSh methods for all window sizes. The only case when wavelet thresholding method performs no better than these methods is for window size of 7 × 7 and noise level up to 20. In fact, for higher values of noise, the performance of all methods converges. The reason is that all the methods, remove almost same number of co-efficient. Similar results were obtained for other images also.

[3] In this paper, a new method is developed i.e. Wavelet Embedded Anisotropic Diffusion (WEAD), and applied it to denoise images corrupted with additive Gaussian noise. The intention behind this method is to reduce the convergence time of anisotropic diffusion and thereby increase its performance. In the method BayesShrink is used along with anisotropic diffusion to get a better performance than stand alone Anisotropic diffusion or BayesShrink In the Bayesian Shrinkage of the nonlinearly diffused signal is taken. The intention to develop this method is to decrease the convergence time of the anisotropic diffusion. It is understood that the convergence time for denoising is directionally proportional to the image noise level. In the case of anisotropic diffusion, as iteration continues, the noise

level in image decreases (till it reaches the convergence point), but in a slow manner. But in the case of Bayesian shrinkage, it just cut the frequencies above the threshold and that in a single step. An iterative Bayesian Shrinkage will not incur any change in the detail coefficients from the first one. In the proposed algorithm, here the threshold for Bayesian shrinkage is recalculated each time after anisotropic diffusion, and as a result of two successive noise reduction step, it approaches the convergence point much faster than anisotropic diffusion. As the convergence time decreases, image blurring can be restricted, and as a result image quality increases

[4]In this paper, denoising based on time-shift Principal Component Analysis (PCA). PCA is a linear transformation that "rotates" a set of data of dimension K, expressing each as a sum of K one-dimensional components ("principal components") that are (a) mutually orthogonal to each other, and (b) ordered in terms of variance from large to small. The total variance (or power) is conserved. Components are ordered with decreasing variance, and therefore as much variance as possible is "packed" into the first components. If the data set is of lower dimensionality than the space, i.e. it fits within a "hyper plane", later components may be discarded without loss. PCA is thus useful for dimensionality reduction. PCA is often used as an ingredient in denoising algorithms. Here we use PCA in combination with subspace projection to synthesize, for each reference/target channel pair, a filter that maximizes the proportion of noise that can be suppressed. The goal is to provide a simple and effective means for reducing the impact of environmental noise on data recorded from MEG or other noise-sensitive techniques. The TSPCA algorithm is remarkably effective in removing environmental magnetic noise from MEG recordings, and it seems that the same method should work well for other physiological recording techniques, such as EEG, local field potentials, etc. A necessary condition for applying TSPCA is the availability of reference channels sensitive only to noise. The original feature of TSPCA is that it can handle a convolutive mismatch between target and reference channels, as well as various forms of nonlinearity. The

ability to effectively suppress high-levels of environmental noise is crucial to the deployment of MEG systems in health applications, as high-quality shielding is expensive and bulky. For a given environment it can lead to better quality data, and for scientific investigations it reduces the need for long experiments, involving multiple presentation of the same stimulus. Noise immunity is also an important step towards practical brain-machine interfaces.

PROPOSED ALGORITHM

1) Perform multiscale decomposition on the image corrupted by Gaussian noise.

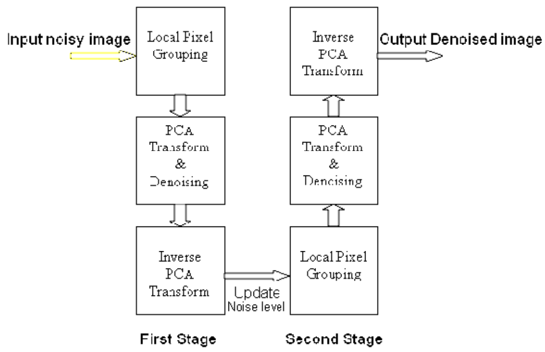
2) Estimate the robust median using the following:

3) For each level, compute T**NEW** as a threshold using

4) For each sub band (except the low pass residual), apply Neigh Shrink method to obtain the noiseless wavelet coefficients.

5) Perform the inverse wavelet transform on the modified coefficients to obtain the denoised estimate image

6)Apply image to first stage



TOOL AVAILABLE

Matlab software

Images in MATLAB and the Image Processing Toolbox

The basic data structure in MATLAB is the array,an ordered set of real or complex elements. This object is naturally suited to the representation of images, real-valued ordered sets of color or intensity data. MATLAB stores most images as two-dimensional arrays, in which each element of the matrix corresponds to a single pixel in the displayed image.

For example, an image composed of 200 rows and 300 columns of different colored dots would be stored in MATLAB as a 200-by-300 matrix. Some images, such as true color images, require a three-dimensional array, where the first plane in the third dimension represents the red pixel intensities, the second plane represents the green pixel intensities, and the third plane represents the blue pixel intensities. This convention makes working with images in MATLAB similar to working with any other type of matrix data, and makes the full power of MATLAB available for image processing applications.

CONCLUSION

In this paper, we have presented an intelligentapproach based on Wavelet and principal component analysis for noise denoising. Experimental results ofproposed intelligent denoising algorithm exhibithigh performance in PSNR and visual effect inimages even in presence of high ratio of noise.

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