INDEPENDENT COMPONENT ANALYSIS BASED NOISE REDUCTION TECHNIQUES IN IMAGES

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ABSTRACT— Image denoising involves the manipulation of the image data to produce a visually high quality image. Denoising of natural images is the fundamental and challenging research problem of Image processing. Fourier transform method is localized in frequency domain where the Wavelet transform method is localized in both frequency and spatial domain but both the above methods are not data adaptive. This thesis reviews the existing denoising algorithms, such as principal component analysis (PCA), Adaptive principal component analysis, and independent component analysis (ICA), and performs their comparative study with their parameters. Different types of noise can be removed by using these techniques, but in our project we use the Gaussian noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. Independent Component Analysis (ICA) is a higher order statistical tool for the analysis of multidimensional data with inherent data adaptiveness property. The noise is considered as Gaussian random variable and the image data is considered as non-Gaussian random variable. Specifically the Natural images are considered for research as they provide the basic knowledge for understanding and modelling of human vision system and development of computer vision systems. Independent component analysis (ICA) is powerful tool by comparing it with the principal component analysis (PCA) and Adaptive principal component analysis. This project reviews significant existing denoising methods and concludes with the tabular Summary of denoising methods and their parameters. A quantitative measure of comparison is provided by the signal to noise ratio of the image.

Categories and Subject Descriptors:

Image Processing and Computer Vision

Keywords:

Image denoising, independent component analysis, wavelet

1. INTRODUCTION

Visual information transmitted in the form of digital images is becoming a major method of communication in the modern age, but the image obtained after transmission is often corrupted with noise. The received image needs processing before it can be used in applications. Image denoising involves the manipulation of the image data to produce a visually high quality image. This thesis reviews the existing denoising algorithms, such as filtering approach, wavelet based approach, and multifractal approach, and performs their comparative study. Different noise models including additive and multiplicative types are used. They include Gaussian noise, salt and pepper noise, speckle noise and Brownian noise. Selection of the denoising algorithm is application dependent. Hence, it is necessary to have knowledge about the noise present in the image so as to select the appropriate denoising algorithm. The filtering approach has been proved to be the best when the image is corrupted with salt and pepper noise. The wavelet based approach finds applications in denoising images corrupted with Gaussian noise. In the case where the noise characteristics are complex, the multifractal approach can be used. A quantitative measure of comparison is provided by the signal to noise ratio of the image. A very large portion of digital image processing is devoted to image restoration. This includes research in algorithm development and routine goal oriented image processing.[10] Image restoration is the removal or reduction of degradations that are incurred while the image is being obtained. Degradation comes from blurring as well as noise due to electronic and photometric sources. Blurring is a form of bandwidth reduction of the image caused by the imperfect image formation process such as relative motion between the camera and the original scene or by an optical system that is out of focus. When aerial photographs are produced for remote sensing purposes, blurs are introduced by atmospheric turbulence, aberrations in the optical system and relative motion between camera and ground. In addition to these blurring effects, the recorded image is corrupted by noises too. A noise is introduced in the transmission medium due to a noisy channel, errors during the measurement process and during quantization of the data for digital storage. Each element in the imaging chain such as lenses, film, digitizer, etc. contributes to the degradation. [13]

2. ALGORITHMS AND DETAILS ON METHODS:-

2.1 Principal Component Analysis

The central idea of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first *few* retain most of the variation present in *all* of the original variables. [7]

2.2 Adaptive principal component analysis:-

These techniques are based on learning approach to obtain sequentially principal component vectors. Some works in PCA are reported using Hebbian or anti-Hebbian learning and gradient-based learning. There are several reports that are successful in using PCA for data reduction and detection. Most of the works are software-based due to the complication of the hardware requirements. [14]

A large percentage of the image denoising algorithms assume an orthogonal basis decomposition of the signal. While this may be an efficient way to decompose the image for compression purposes, several authors have shown that an over-complete representation of the signal is superior for image denoising. The main advantage of over-complete expansion is summarized as a suppression of the Gibbs phenomena. In the Translation- Invariant denoising algorithm is achieved by shifting the signal multiple times, denoising each shifted signal separately (using orthogonal decompositions for each shift), shifting back and then averaging the results. When denoising shifted versions of the signal, edge artifacts occur at different locations. When the signals are shifted back and averaged these edge artifacts are averaged as well. The authors showed that a uniform thresholding in a Translation Invariant denoising does well in eliminating some of the edge artifacts seen in orthogonal wavelet denoising. The authors extend the idea of by simultaneously processing all the shifted versions to obtain more accurate statistical models for signal components. The work extends the idea of wavelet thresholding to an adaptive wavelet thresholding method based on context modelling. Each wavelet coefficient is modelled as a random variable of a generalized Gaussian distribution with an unknown parameter. Experimentally, their adaptive thresholding using shift-invariant non-sub sampled wavelet transform (SI Adapt Shrink) is one of the best denoising algorithms.

2.2.1 Denoising algorithm:-

Starting with a noisy image, the complete denoising algorithm is:

1. Estimate the noise variance,σ^2

2. Partition the image into overlapping patches as shown on the left side of Fig. 1. Each patch, depicted on the right side of Fig. 1, contains a *train region*, a *denoise region* and an *overlap region*. The *overlap region* is included in the *denoise region*, which is included in the *train region*.

3. Fix the dimension,$\boldsymbol{N^2}$ of the training vectors and generate S. The training vectors are N × N patches, reordered in a $\boldsymbol{N}^2$ long vector, and the training set S is the collection of all the possible N ×N patches included in the *train region*. To be consistent, the number of training vectors in S is M. The dimension of S, the matrix formed by ordering the vectors in S as column vectors, is $\boldsymbol{N^2} \times$ M.

4. The PC basis functions are the eigenvectors of $\mathbf{Q}$ =$(ss^t)^{-1}$, which are also the principal components of S.

5. For l = 1…..$\boldsymbol{N^2}$ And i = 1: : :M finds the PC coefficients y_i^l by taking projections of the training vectors in S onto the PC basis functions.

6. For l = 1…..$\boldsymbol{N}^2$ estimate the variance of the PC coefficients using equation (8).

7. Denoise the PC coefficients using equation (7) and reconstruct the denoised training vectors in S. Since the training vectors in S overlap, average out the results in regions of overlap after the denoised training vectors are put back into the *train region*. In the middle of the *train region* each pixel is estimated N2 times, while on the boundary, it may be estimated only once. Choose the *denoise region* such that each pixel is estimated N2 times. This step resembles the over-complete basis denoising algorithm of [3]. The training vectors are formed from a moving window, which is similar to shifting the signal. In this sense the denoising algorithm has a built-in shift invariant feature. [2]

8. If the *denoise region* is too large, blocking artifacts in the denoised image can become a problem, even though the PSNR values are still good. To average out the blocking artifacts between different denoised regions, add an *overlap region*.

2.3 Independent component analysis:-

Recently a new method called Independent Component Analysis (ICA) has gained wide spread attention. The ICA method was successfully implemented in denoising Non-Gaussian data. One exceptional merit of using ICA is it's assumption of signal to be Non-Gaussian which helps to denoise images with Non-Gaussian as well as Gaussian distribution. Independent component analysis (ICA) is a method for finding underlying factors or components from multivariate (multidimensional) statistical data. What distinguishes ICA from other methods is that it looks for components that are both *statistically independent*, and *nongaussian*. Here we briefly introduce the basic concepts, applications, and estimation principles of ICA. [11]

Independent component analysis (ICA) is a statistical and computational technique for revealing hidden factors that underlie sets of random variables, measurements, or signals. ICA defines a generative model for the observed multivariate data, which is typically given as a large database of samples. In the model, the data variables are assumed to be linear or nonlinear mixtures of some unknown latent variables, and the mixing system is also unknown. The latent variables are assumed nongaussian and mutually independent and they are called the independent components of the observed data. These independent components, also called sources or factors, can be found by ICA.

3. RESULTS:-

The Codes are written for PCA, Adaptive PCA, and ICA. These codes are simulated, synthesized and implemented in Matlab. The results of simulation are reported here. The images which are obtained are as follows:-

3.1 noisy image and the image (JPG) obtained by the Adaptive PCA:-

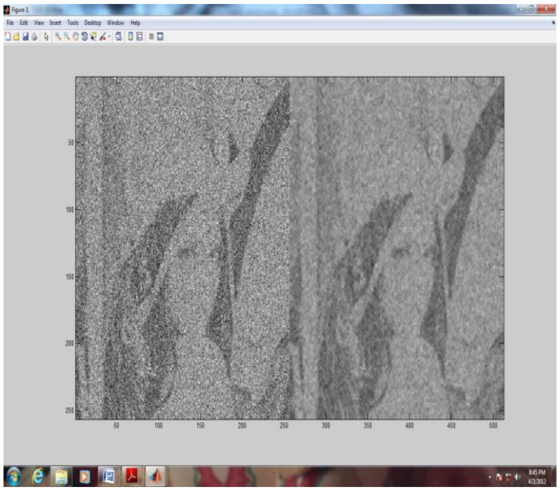

Fig 3.1: Noisy image and image (JPG) obtained by PCA:-

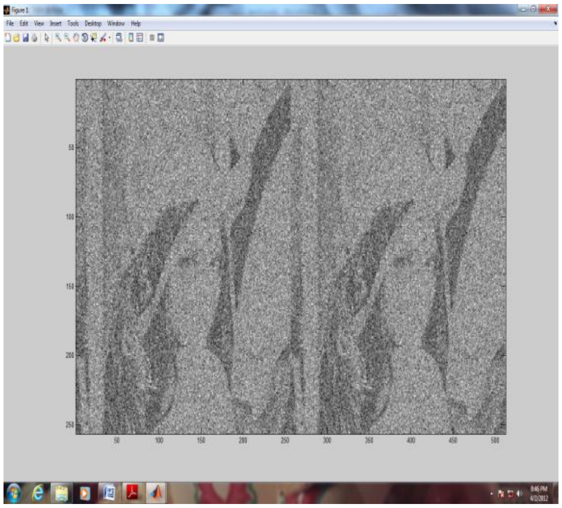

Fig 3.2: Noisy image + denoised image (JPG) by Adaptive PCA

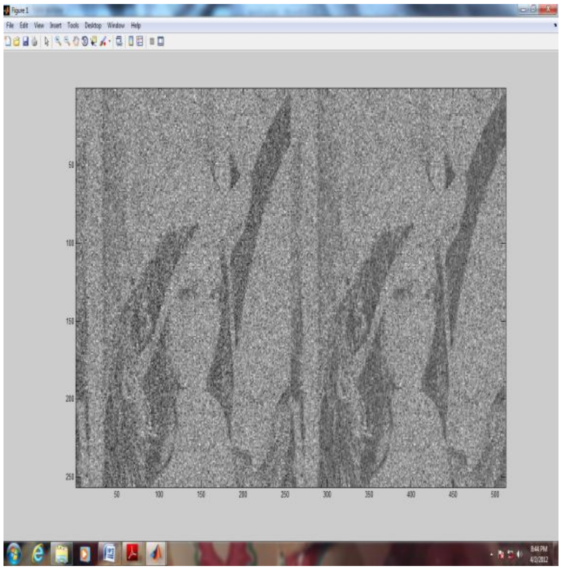

Fig 3.3: Noisy image and image (JPG) obtained by ICA:-

Same image is process on gif & bmp image table of results are as follows

METHODS	Signal to noise ratio		
	JPG Image	Gif Image	Bmp Image
Original image + noisy image	6.816146	6.841642	6.842876
Local PCA	6.936651	6.962064	6.967201
Adaptive PCA	7.379763	8.099423	7.809952
Local ICA	13.704733	13.751627	13.696066

The parameters of these three methods are as follows:

parameters		PCA		Adaptive PCA		ICA	
		Max. value	Min. value	Max. value	Min. value	Max. value	Min. value
1.	**correlation**	**0.0872**	**0.0728**	**0.0375**	**0.0277**	**0.0946**	**0.0791**
2.	**entropy**	**0.3080**	**0.3072**	**0.0247**	**0.0246**	**0.2215**	**0.2202**
3.	**sum variance**	**236.1883**	**236.1265**	**254.7307**	**254.7283**	**242.2625**	**242.1672**

4. CONCLUSION

The signal to noise ratio of an image under study is 8.5db. Principal component analysis will achieved an improve value of signal to noise ratio as 8.69db. Adaptive PCA has proven to show an enhanced value of signal to noise ratio upto 11.01db. Adaptive PCA has shown an improvement in noise reduction. Furthermore with independent component analysis with local maxima algorithm we could achieve a further enhancement value upto 15.18db of signal to noise ratio for the image under study. For various type of image format we get the different signal to noise ratio, and by comparing the signal to noise ratio and parameter table we can conclude that ICA is the best tool for the image denoising. The improvement of signal to noise ratio proves that ICA is powerful tool for denoising of an image.

Some preliminary studies have been made about the effectiveness of Independent Component Analysis. So we can conclude that ICA-based methods give, at least for their application, significantly better results than PCA. The superiority of ICA over PCA is also implicit in the use of PCA as a pre-processing step.

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