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A survey Paper on Image Denoising Techniques

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Abstract **- Removing noise from the original image is still a challenging problem for researchers. Noise added is not easy to remove from the images. There have been several published algorithms and each approach has its assumptions, advantages, and limitations. This paper presents a review of some significant work in the area of image denoising and finds the one is better for image denoising. After a brief introduction, some popular approaches are classified into different groups and from the introduction we can conclude that the ICA technique is the best technique for image denoising**.

Keywords **- wavelet, PCA, Adaptive PCA, ICA.**

I. INTRODUCTION

Images play an important role in everywhere whether it is in daily life or in applications such as in satellite communication, television, computer tomography, etc. data of images are corrupted by noise and removing of noise plays the main role. There are several techniques from which we can remove the noise such as denoising techniques and they are like wavelet denoising, principle component analysis, Adaptive PCA, sparse code shrinkage method, independent component analysis, etc. there are two basic approaches for image denoising which is like spatial filtering method and transform domain filtering method. All type of techniques are of low pass filter type. Noise is major problem which is to be remove from images; they are like additive or multiplicative in nature. There are various type of noise present in the images such as Gaussian noise, salt and pepper noise, speckle noise, Brownian noise, etc. removing of noise is the challenging problem for the researchers. Selecting appropriate techniques for denoising plays an important role. Filtering in transform domain is more efficient and introduces fewer artifacts. The focus of recent research has been on the higher order statistical method and the non linear transform domain filtering. Denoising technique based on Fourier transform method is localized in frequency domain and the wavelet transform method is localized in frequency and spatial domain but both the methods are not data adaptive. However if the filtering approach is data adaptive it comes out with promising result, and that is the inherent property of ICA techniques. Data adaptivness plays an important role in image denoising process because denoising of images is also dependent on the image which is to be denoised. Here we discussed the denoising techniques.

II. WAVELET DENOISING

This approach focuses on exploiting the multiresolution properties of Wavelet Transform. This technique identifies close correlation of signal at different resolutions by observing the signal across multiple resolutions. This method produces excellent output but is computationally much more complex and expensive. The modeling of the wavelet coefficients can either be deterministic or statistical.

A. Deterministic:

The Deterministic method of modeling involves creating tree structure of wavelet coefficients with every level in the tree representing each scale of transformation and nodes representing the wavelet coefficients. This approach is adopted in. The optimal tree approximation displays a hierarchical interpretation of wavelet decomposition. Wavelet coefficients of singularities have large wavelet coefficients that persist along the branches of tree. Thus if a wavelet coefficient has strong presence at particular node then in case of it being signal, its presence should be more pronounced at its parent nodes. If it is noisy coefficient, for instance spurious blip, then such consistent presence will be missing. Lu et al., tracked wavelet local maxima in scale space, by using a tree structure. Other denoising method based on wavelet coefficient trees is proposed by Donoho.

B. Statistical Modeling of Wavelet Coefficients

This approach focuses on some more interesting and appealing properties of the Wavelet Transform such as multiscale correlation between the wavelet coefficients, local correlation between neighborhood coefficients etc. This approach has an inherent goal of perfecting the exact modeling of image data with use of Wavelet Transform. A good review of statistical properties of wavelet coefficients can be found. The following two techniques exploit the statistical properties of the wavelet coefficients based on a probabilistic model. Wavelets are mathematical functions that analyze data according to scale or resolution. They aid in studying a signal in different windows or at different resolutions. For instance, if the signal is viewed in a large window, gross features can be noticed, but if viewed in a small window, only small features can be noticed. Wavelets provide some advantages over Fourier transforms. For example, they do a good job in approximating signals with sharp spikes or signals having discontinuities. Wavelets can also model speech, music, video and non-stationary stochastic signals. Wavelets can be used in applications such as image compression, turbulence, human vision, radar, earthquake prediction, etc.. The term "wavelets" is used to refer to a set of orthonormal basis functions generated by dilation and translation of scaling function φ and a mother wavelet ψ. The finite scale multiresolution representation of a discrete function can be called as a discrete wavelet transforms [Wa01]. DWT is a fast linear operation on a data vector, whose length is an integer power of 2. This transform is invertible and orthogonal, where the inverse transform expressed as a matrix is the transpose of the transform matrix. The wavelet basis or function, unlike sines and cosines as in Fourier transform, is quite localized in space. But similar to sines and cosines, individual wavelet functions are localized in frequency. Some of the properties of discrete wavelet transforms are listed below [Gr95, Vi99].

(a) DWT is a fast linear operation, which can be applied on data vectors having length as integer power of 2.
(b) DWT is invertible and orthogonal. Note that the scaling function φ and the wavelet function ψ are orthogonal to each other in L2(0, 1), i.e., $<\varphi,\psi>=0$.
(c) The wavelet basis is quite localized in space and frequency.
(d) The coefficients satisfy some constraints
(e) The wavelet coefficients of a fractional Brownian motion (fBm) supports Stationarity, i.e., $g\, j\,(k) = g\, j\,(0), \forall\, k$.
(f) Wavelet coefficients exhibit Gaussianity: where σψ is a constant depending on ψ and *H*, the Hurst parameter for fBm. This property aids wavelets in the removal of Gaussian noise from images.
(g) The wavelet coefficients are almost decorrelated, where *N* refers to the number of vanishing moments.

Principle component analysis:

Principal Component Analysis (PCA) is an exploratory tool designed by Karl Pearson in 1901 to identify unknown trends in a multidimensional data set X. The algorithm was introduced to psychologists in 1933 by H. Hotelling; hence sometimes it is called Hotelling's Transform. However, today we know that implementing PCA is the equivalent of applying Singular Value Decomposition (SVD) on the covariance matrix of a data set (2, 3). By providing a tutorial on PCA using SVD, students are familiarized with both matrix decomposition techniques. When there is need to dimension reduction (reduce the no. of variables) and further analyze the relationship between different variables (quantity); we can use PCA to solve this kind of problems. Principal components are the direction of greatest variability (covariance) in the data, then the next orthogonal (uncorrelated) direction of the greatest variability. So first remove all the variability along the first component, and then find the next direction of greatest variability and so on……………. Principal component analysis(PCA) is a linear data adaptive type of transform technique which is also known as Hotelling transform .In this transform linear subspace fit for the given data is to be calculated i.e. optimizing for the minimum mean square distance between the data points and their projection on the subspace . If it is assumed that the dimension of the data is m and the dimension of the transform subspace is n, then it is required to find the orthogonal vector wi ,where (i=1,2,3…. n). The principal components are found by optimizing the direction of maximum data variance under the constraint of the orthogonality to previously found direction.

III. Adaptive PCA

Principal Component Analysis (PCA) is a second order statistical approach, which has been used to extract the features of data set or perform data reduction (compression). Specially, when data set is, redundant and overwhelming large, PCA is very effective linear technique as a preprocessing step to extract data features and to cluster data for classification. It can play as optimal linear transform known as Kahunen- Louvre (LK) for data compression. To obtain the principal component vectors, traditionally the covariance matrix is calculated then eigen values are obtained, and corresponding to each eigen value, a component (eigen) vector is found. This procedure is complicated and computationally intensive thereby making it restrictive to apply for real world applications such as data compression and data extraction. Moreover, the PCA hardware implementation for real time application becomes even more challenging. To get over the hurdles from the traditional PCA technique, the simple sequential PCA techniques are introduced. These techniques are based on learning approach to obtain equentially 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.

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 modeling. Each wavelet coefficient is modeled 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 (SIAdaptShrink) is one of the best denoising algorithms.

IV. 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.

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. In the independent component analysis method all the pixels in the image are work independently means they work their own and they are not dependent on the neighbors pixel value. So it gives the best result while finding in the denoising techniques.

Conclusion

PCA is a second order blind source separation method based on the covariance of the data and mainly used for the dimensional reduction and whitening of the data for the further processing. But as we taken the adaptive principle component analysis the centering of the reconstructed data is more suitable than that of principle component analysis. But same as that of principle component analysis there is also some limitation to reconstruct the data so we take the another method which is independent component analysis, in that method all component work their independently, so that it gives maximum result to reconstruct the data. Therefore we can say that ICA is the powerful tool to denoise the image.

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