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Image Denoising Techniques

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Abstract - *Images is becoming increasingly popular in various fields and applications like in field of medical, education etc. Image denoising process refers to the recovery of a digital image that has been tainted by noise. It may be identified during image creation, recording or transmission phase. Advance processing of the image often requires that the noise must be removed or at least should be reduced. Even a small amount of noise can also harmful when looking for high accuracy. In this paper, we aim to provide a review of some of those methods that can be used in image denoising process. This paper summaries the brief description of noise, types of noise, image denoising and also the review of different techniques and their approaches to remove that noise. The purpose of this paper is to provide some brief and useful knowledge of denoising techniques for applications using images to provide an ease of selecting the optimal technique according to their needs.*

Key Words: Noise removing, salt and pepper noise, realistic noise, Gaussian noise, Poisson Noise

1. INTRODUCTION

Visual information that can be transmitted in the form of digital images is becoming a major way of communication in this modern era, but the image found after transmission is often corrupted with noise presence. Noise is the result of faults in images acquisition process that result in pixel values that do not reflect the true intensities of the real scene. The traditional image needs processing before it can be utilized as an input for any decision making. Image denoising includes the management of the image data to develop a high quality image. Different noise models like additive and multiplicative types are used e.g. Gaussian noise, salt and pepper noise, Poisson noise and Real world image noise. Selection of the denoising algorithm is depends on application therefore, it is necessary to have related knowledge about the noise present so as to select the suitable denoising algorithm. The filtering approach has been proved to be the finest when the image is corrupted with salt and pepper noise. The aim of this paper is to focus on noise removal methods for natural images using statistical and non-statistical method.

2. TYPES OF IMAGE NOISE

- Gaussian Noise
- Salt and Pepper Noise
- Speckle Noise
- Poisson Noise
- Real world image noise

Gaussian noise – One of the most arising noises is Gaussian noise. Primary causes of Gaussian noise arise during acquisition e.g. sensor noise produced by poor lighting and/or high temperature, and/or transmission e.g. electronic circuit noise. Gaussian noise characterizes statistical noise having probability density function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. We can also say that, the values that the noise can take on are the Gaussian-distributed. The probability density function of the Gaussian random variable is given by- Where represents the grey level μ the mean value and σ standard deviation. The typical model of this noise is additive, independent at each pixel and independent of the signal intensity, produced mainly by thermal noise. The mean of the every distributed element or pixels of an image that has been affected by Gaussian noise is zero. It means that Gaussian noise equally affects each and every pixel of an image.

Salt-and-pepper noise – Fat-tail distributed or "impulsive" noise is also called as salt-and-pepper noise. Several image containing salt-and-pepper noise may have shady pixels in the bright areas and bright pixels in the dark regions. In salt-and-pepper noise equivalent value for black pixels is 0 and for the white pixels corresponding value is 1. Hence the image that affected by this noise either have extreme low value or have extreme high value for pixels i.e., 0 or 1.Here,Given the probability r with $0 <= r <= 1$ that the pixel is corrupted, we can present salt and-pepper noise in an image by setting a fraction of r/2 randomly selected pixels to the black, and another fraction of r/2 randomly selected pixels to the white. This type of noise can be produced by analog to digital converter errors, bit errors in transmission, etc. Elimination of salt-and-pepper noise can be done by using the dark frame subtraction and interpolating around dark/bright pixels.

Speckle Noise-Speckle noise is the noise that stand up due to the effect of the environmental conditions on the imaging sensors during the image acquisition. This type of noise can be detected in case of medical images, active Radar images and SAR(Synthetic Aperture Radar) images.

Poisson noise- This noise is seen due to statistical nature of the electromagnetic waves such as x-rays, gamma rays and visible lights. The x-ray and gamma ray causes emitted number of photons per unit time. These causes are having the random fluctuation of the photons. The result gathered images have spatial and temporal randomness. In the lighter parts of an image there is a leading noise from an image sensor which is usually produced by statistical quantum fluctuations that this variation in the number of photons sensed at the given exposure level called as photon shot noise. Shot noise monitors a Poisson distribution, which is someway related to Gaussian noise.

Realistic noise: Most of the previous image denoising methods focus on the additive white Gaussian noise i.e AWGN. Though, the real-world noisy image denoising problem with the proceeding of the computer vision methods. In mandate to stimulate the study on this problem while applying the parallel real-world image denoising datasets, we can build the new standard dataset that contains widespread real-world noisy images of the diverse natural scenes. These images are taken by different cameras under the different camera settings. We estimate the different denoising approaches on our new dataset as well as the previous datasets. Broad experimental results prove that the recently proposed techniques designed especially for realistic noise removal based on the sparse or low rank theories to achieve improved denoising performance and they are more robust than the other competing methods.

3. IMAGE DENOISING

The problem of image denoising can be demonstrated as follows:
Y =x+ny = x+n (1)

where , x is the unknown clean image, y is the observed noisy image, and n represents additive white Gaussian noise (AWGN) with standard deviation σn, which can be estimated in everyday requests by various approaches, such as median absolute deviation, block-based estimation , and principle component analysis (PCA)-based methods. The aim of noise reduction is to cut the noise in natural images while reducing the loss of original features and then improving the signal to noise ratio (SNR).

The main tasks for image denoising are as follows:

- flat regions must be smooth,
- edges should be protected without blurring images,
- textures of image should be preserved, and
- New pieces must not be generated.

To solve the clear image x from the Equation (1) is an ill-posed problem that we cannot get the single solution from the image model with noise present. To gain a good estimate image x^x^, image denoising has been well-studied in the field of the image processing over the earlier several years. Here image denoising techniques can be roughly categorized as dictionary learning based methods, nonlocal self-similarity based methods, sparsity based methods and A Trilateral Weighted Sparse Coding Scheme for Real-World Image Denoising.

4. DENOISING METHODS

Dictionary learning based methods

We can address the image denoising problem, where homogeneous Gaussian additive noise and zero-mean white is to be removed from the present image. The scheme taken is based on the sparse and redundant demonstrations over the trained dictionaries. Using the K-SVD algorithm, we can obtain a dictionary that will describe the image content efficiently. Two training choices can be measured: using the tainted image itself, or training on a corpus of high-grade image database. As the K-SVD is limited for handling slight image patches, we range its distribution to arbitrary image sizes by relating the global image prior that services the sparsity over the patches in each and every place of a image. We can display how such Bayesian treatment can leads to the simple and effective denoising algorithm. This leads to the state of the art denoising performance; equivalent and many times surpassing newly published leading alternative denoising ways.

Sparse representations of signals have shown considerable attention in current years. The assumptions that the natural signals i.e. images confess a sparse decomposition above the dismissed dictionary leads to the efficient algorithms for conducting the sources of data. In specific, the scheme of well adapted dictionaries for images has been a major issue. The K-SVD has been recently proposed for such task and presented to perform very well for the various grayscale image processing tasks. Here we show the problem of the learning dictionaries for colored images and extend the K-SVD-based grayscale images denoising algorithm. This work sets forward methods for managing the missing information and non homogeneous noise, paving the way to state of the art results in applications such as color image denoising.

Nonlocal self-similarity based methods

Nonlocal image representation or SSC(Simultaneous sparse coding) has presented great potential in many low level visualization tasks, primary to several state of the art image restoration methods, including BM3D and LSSC. Though, it still wants a physically suitable explanation about why a SSC is the well model than the conventional sparse coding for a class of natural images. While, the problem of sparsity optimization, specially when the tangled with a dictionary learning, is computationally tough to solve. In this we take a low-rank method toward SSC and offer a conceptually simple clarification from a bilateral variance estimation outlook, i.e. the singular-value breakdown of linked packed patches can be seen as pooling both the local and nonlocal data for assessing signal variances. Such perspective motivates us to develop the new class of the image restoration algorithms which called spatially adaptive iterative singular-value thresholding (SAIST). For the noisy data, SAIST simplifies the famous BayesShrink from local to the nonlocal models for the incomplete data, SAIST also extends prior deterministic annealing based result to the sparsity optimization through a incorporating idea of dictionary learning. In addition to the computational efficiency and conceptual simplicity SAIST has attained highly competent objective performance compared to the several state of the art techniques in image denoising and completion trials. The subjective quality results compared with those, which obtained by the existing methods, specially at high noise levels and with the large volume of missing data.

Patch based image processing has attained a great realization in low level visualization such as image denoising. In detailed, the use of image NSS (nonlocal self-similarity) prior refers to the point that a local patch often has many nonlocal parallel patches so that it crossways the images, that has been expressively enhanced the denoising presentation. Though, in most of existing approaches only the NSS of the input tainted image is the demoralized, while how to develop the NSS of a clean natural images is still an open problem. Here we offer a patch cluster based NSS prior learning pattern to learn the clear NSS prototypes from the natural images for the high performance denoising. Patch Groups can be removed from working out images by placing the nonlocal parallel patches into a groups, and the Patch Group based Gaussian Mixture Model i.e. PG-GMM learning algorithm is developed to learn the NSS prior. We show that, owe to the learned Patch Group based Gaussian Mixture Model, a simple weighted sparse coding model, which has a closed form solution, can be used to perform the image denoising efficiently, resulting in high Peak Signal to Noise Ratio measure, fast speed, and particularly the best visual class among all the rival approaches.

Sparsity based methods

We offer a novel image denoising approach based on the improved sparse representation in the transform domain. The enhancement of the sparsity is always attained by the grouping related 2D image blocks into the 3D data arrays which we can also call as groups. Collective altering is a special technique developed to deal with the 3D groups. We understand that using this step: 3D transformation of a group is reduction of the transform spectrum & inverse of the3D transformation. The result of it is a 3D estimation that holds the equally altered grouped image blocks. By reducing the noise, the combined altering exposes even the nest details shared by grouped segments and at the same time it will preserves the important unique features of each separate block. The altered blocks are then returned to their original locations. Because these blocks are overlying for each and every pixel that can obtain many different estimates which need to be shared. Aggregation is a particular averaging process which is exploited to take the advantage of this idleness. A significant development is obtained by especially developed collaborative Wiener altering. An algorithm based on this novel denoising approach and this efficient implementation are accessible in full detail an extension to color image denoising is also established. The investigational outcomes authenticate that this computationally accessible algorithm understands state of the art denoising presentation in terms of the both particular visual quality and peak signal to noise ratio [7]
We suggest an actual color image denoising technique that activities filtering in greatly sparse local 3D transform domain in each and every channel of luminance chrominance color space. For each image segments in each channel the 3D array is shaped by assembling collected blocks parallel to it, the process that we call grouping. The high comparison between grouped segments in each 3D array qualifies the extremely sparse demonstration of the true signal in a 3D transmute domain and therefore a succeeding shrinkage of transform spectra results in operative noise reduction. The individuality of planned technique is a application of a grouping constraint on which the chrominance by reprocessing accurately the same grouping as for the luminance. The results prove the efficiency of the suggested grouping constraint and shows that the developed denoising algorithm attains state of the art presentation in terms of both visual quality&PSNR.[8]

A Trilateral Weighted Sparse Coding Scheme for Real-World Image Denoising

Most of the image denoising approaches assumes that the corrupted noise be AWGN (Additive White Gaussian Noise). Though, the natural noise in real world noisy images is much more difficult than Additive White Gaussian Noise, and it is hard to be demonstrated by simple logical deliveries. As a result many state of the art denoising approaches in fiction become much less actual when applied to real world noisy images taken by CMOS or CCD cameras. In this we improve a TWSC (trilateral weighted sparse coding) system for healthy real world image denoising. Explicitly, here we introduce three weight matrices into the data and regularization terms of the sparse coding framework to describe the measurements of the realistic noise and image priors. Trilateral weighted sparse coding can be re-formulated as a linear equality controlled problem and can be resolved by irregular direction technique of multipliers. The existence and individuality of the solution and junction of the planned algorithm can be analyzed. Wide spread trials prove that the planned TWSC system overtakes state of the art denoising approaches on eliminating natural noise.

4. CONCLUSION

In this paper we provide some brief and useful knowledge of denoising techniques for applications using images to provide an ease of selecting the optimal technique according to their needs. We can say that the trilateral weighted sparse coding scheme is best for finding the natural noise from images and other techniques are useful for identifying Salt n Pepper noise, Gaussian Noise and other noise. This paper gives brief discussion of types of noise and also different techniques for denoising.

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