Image Denoising & Metric Parameters Improvement using Dictionary Learning and Sparse Coding

Bhagya Prasad Bugge, Bh.S.S.D.S Nagendra Varma, A.Amarnath

Abstract*: *Digital image processing uses efficient computer algorithms for image denoising and to improve the image quality. Noisy image is produced due to various reasons in image acquisition, compression, preprocessing, segmentation etc. Over the last decade, various methods have shown promising results in removing zero mean Gaussian noise from images. Apart from different strategies implemented for noise reduction; this paper proposes a method for reducing noise and to improve metric parameters. Without using pre-chosen set of basis functions to represent the image, this paper discuss about performing image denoising using dictionary learning and sparse representation. Instead of removing coefficients of noise, shrinking sparse coefficients of noise is implemented to eliminate noise and it retains the image quality

Index Terms*: *Denoising, Dictionary learning, Sparse Representation, Shrinkage Map design.

I. INTRODUCTION

The primary objective of noise removal techniques is to extract the original image from a noisy environment. Noisy images are produced during image acquisition, image compression, preprocessing etc. Important problem in image processing is development of image processing algorithm that removes noise while retaining the image structure. Noise prevents the computer vision algorithms to work perfectly. Most of the computer vision algorithms are implemented using like ‘Scale Invariant Feature Transform’ (SIFT), ‘Histogram Of Oriented Gradients’ (HOG) and noise will affect these feature descriptors[1]. Image quality improvement is done by several proposed methods and most of them deal with additive white Gaussian noise.

By using different transformation techniques, image noise can be removed, but image quality may not retain. Instead of using Fourier basis functions to represent corrupted image, dictionary learning is a method for better representation. Dictionary having set of basis signals are used to decompose the signal. Using a particular set of basis signals, an image is uniquely characterized as the linear combination of basis signals. Dictionary learning is performed by K-SVD algorithm[2]. Distinct methods have been suggested and implemented to eliminate the noise. Classical techniques like linear and non linear filtering are used to remove noise, when noise is additive and Gaussian. When we use mean filter there are some limitations like blurring sharp edges and damage of fine image details. And its performance is poor in non-Gaussian and signal dependent noise. The averaging is performed by using the Gaussian smooth model, the anisotropic filtering and neighborhood filtering. The noise removing methods should not damage the original image. Now most noise removal methods damage the fine details and texture. Morphological component analysis and relative total variation are the sophisticated methods to remove the noise textures[1].

Morphological component analysis uses parametric based dictionaries, which indicate basis vectors of DCT & CWT that can discriminate noise and non-noise parts. But, they have certain limitations while handling heavy noise. Another approach is to detect noise using feature descriptor and noise removing via nonlocal filtering or image inpainting. Recent trend is to adopt representation learning approach. It can automatically extract useful features from raw data and is very useful for image restoration.

The existing research has used wavelet transform for noise removing because of its multiresolution and energy compaction properties. An alternative to the wavelet based noise removing method is the bilateral filter introduced by Tomasi & Manduchi, which uses both spatial and intensity information between a pixel and its neighboring pixels unlike the conventional linear filtering where only spatial information is considered. A. Buades, B. Coll, and J.-M. More [3] applied the nonlocal means filter to anticipate each pixel by a weighted average of its neighbouring pixels. X. Liu, X. Wu, J. Zhou, and D. Zhao [4] used trained over-complete dictionary to get much sparser representation for noisy images, and Jie Ren, Jiaying Liu, Mading Li, Wei Bai, and Zongming Guo[5] removed compression noise by soft-thresholding singular values of noisy images.

K. Dabov, A. Foi, V. Katkovnik, and K. Egiazarian [6] proposed a denoising strategy by improving sparse representation in transform

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domain.

II. IMAGE QUALITY ESTIMATION METHODS

Image quality estimation is very widely used for many applications related to medical grounds, security related issues etc. Image parameters can be calculated by either by Objective or Subjective methods. Mainly *peak signal to noise ratio, mean squared error, structural similarity index metric* are used to evaluate the condition of image using full reference objective method (existing objective approach).

A) Objective method: The Objective method is a process of estimating image quality using computer based algorithm. It generates result of image quality automatically without the help of an observer.

B) Subjective method: The process of estimating image quality using human observer is known as subjective method of image quality estimation

III. NOISE MODELS

Noise influences the images during image procurement, compression and while transmitting[7]. Noise produces objectionable effects such as unreal edges, unseen lines, comers, blurred objects and disturbs background scenes. To reduce these unwanted effects, earlier knowledge of noise model is necessary for further processing. We consider that the noise is independent of spatial coordinates and that is uncorrelated with respect to image itself[7]. Some influential noise functions are:

A) *Gaussian noise*:

The probability density function of Gaussian random variable, x, is given by

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

B) *Rayleigh noise:*

The probability density function of Rayleigh noise is given by

$$f(x) = \begin{cases} \frac{2}{b}(x-a)e^{-(x-a)^2/b} & \text{for } x \geq a \\ 0 & \text{for } x < a \end{cases}$$

C) *Gamma noise*:

The probability density function of the Gamma noise is given by

$$f(x) = \begin{cases} \frac{a^b x^{b-1}}{(b-1)!} e^{-ax} & \text{for } x \geq a \\ 0 & \text{for } x < a \end{cases}$$

Where the parameters are such that a > 0, b is a positive integer.

D) *Exponential noise*:

The probability density function of the exponential noise is given by

$$f(x) = \begin{cases} ae^{-ax} & \text{for } x \geq a \\ 0 & \text{for } x < a \end{cases}$$

E) *Uniform noise*:

The probability density function of the uniform noise is given by

$$f(x) = \begin{cases} \frac{1}{m-n} & \text{if } n \leq x \leq m \\ 0 & \text{otherwise} \end{cases}$$

F) *Impulse noise* (salt & pepper noise)

The probability density function of the uniform noise is given by

$$f(x) = \begin{cases} I_a & \text{for } x = a \\ I_b & \text{for } x = b \\ 0 & \text{otherwise} \end{cases}$$

Data-drop-out and *spike* noise are also the terms used to represent impulse noise.

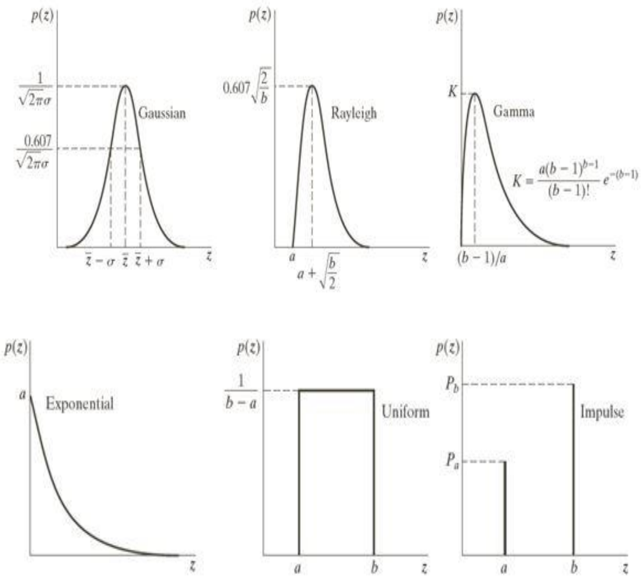

Figure.1: Noise Models

IV. NOISE REMOVING FILTERS

Spatial filtering is the best approach of preference in situations when only additive random noise is present. Some spatial filters to remove noise are given below[7].

A) *Arithmetic mean filter*:

It smoothes local variations in an image and noise is reduced.

$$f(x,y) = \frac{1}{mn}\left[\sum_{(s,t)\in S_{xy}} \frac{1}{g(s,t)}\right]$$

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B) *Geometric mean filter:*

$$f(x,y) = \frac{mn}{\left[\sum_{(s,t)\in S_{xy}} \frac{1}{g(s,t)}\right]}$$

This filter works well for salt noise, but fails for pepper noise. It is well suited for Gaussian noise.

C) *Median Filter*:

The value of a picture element is replaced by the median of the picture element values in the neighborhood of that element.

$$f(x,y) = \underset{(s,t)\in S_{xy}}{median}\{g(s,t)\}$$

This filter has nice noise reduction ability and it effectively eliminates unipolar and bipolar impulse noise.

Here we take a look at two adaptive filters whose performance varies depending on statistical aspects of the image inside the filter boundary defined by the m x n rectangular window. These filters performance is exceptional to the filters discussed so far. But, these filters improvements will increase the filters complexity.

i) Adaptive local noise reduction filter

ii) Adaptive median filter

Median filter performs well only if the impulse spatial density is small. Adaptive median filter can supervise the large noise probabilities. Additionally, it retains the detail while smoothing non impulse noise.

V. DICTIONARY LEARNING AND SPARSE CODING

Orthogonal and bi-orthogonal sets of basis signals were very useful by reason of their mathematical simplicity. But, the shortcoming of these sets of basis signals is their bounded expressiveness-ultimately overshadow their directness. This force to the evolution of advanced set of basis signals, having more number of basis signals than the dimensions of the signal, which shows a wider range of signal phenomena.

We consider the set, S= $[s_1\ s_2\ ....s_L]$ ϵ R^{N*L} , where the column constitutes the basis signals, and $L \geq N$.

Representing a signal x ϵ R^N using this set, where signal is represented as linear combination of the basis signals, [8]

$X = S\,\Psi_s$ (1)

$\Psi_s = \arg\min C(\Psi)$ subject to $X = D\Psi$ (2)

Practical choices of $C(\Psi)$ promote the sparsity of the representation. Solving the equation (2) is referred to as sparse coding.

Sparse and redundant representation modelling of data assumes an ability to describe signals as linear combinations of a few basis signals from a pre-specified set of signals. Sparse representation is to find a sparse vector.

$$\alpha \in R^m$$

Such that x ≈ D α, where α is regarded as sparse code.

Let S= $[s_1\ s_2\ ....s_L]$ ϵ R^m be a set of normalised "basis vectors". Instead of using pre-chosen set of basis functions, we propose to learn the set of signals, i.e. dictionary learning.

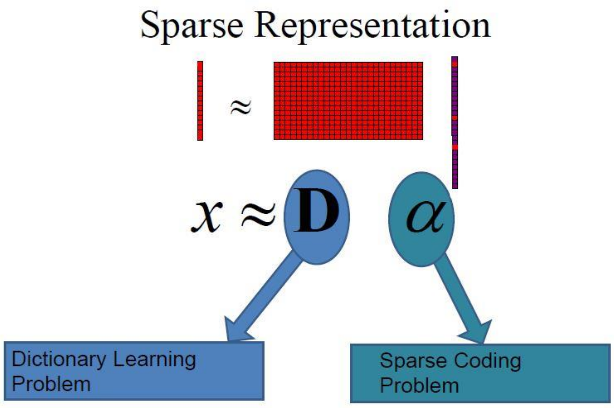

Figure 2: Sparse Representation

Sparse representation is the modelling of data and ability to characterize signals as linear combinations of a few signals from a pre-defined set [8].

In general, the choice of a convenient signal set can be done using one of two ways:

(i) Building a sparsifying signal set depending on a mathematical model of the data, or

(ii) Learning a signal set to execute best on a training set.

Patch clustering has been used to evaluation of the noise in the corrupted image.

VI. PROPOSED WORK

The main objective is to remove the noise associated with a picture. In this case, we assume the noise is Gaussian and then try to filter the noise.

In this paper, a patch clustering has been used to estimate the noise and then to filter it. The work done in this method has been descripted as in following steps;

Step 1:

The first step is to divide the input image into several pieces based on the correlation between the pixels of the image. The patch clustering is a method that makes some clusters from an image based on the similarity between the data. In this case the correlation between the data is used to define the similarity.

Step 2:

The next step is to compress the noise. In this stage, a shrinkage technique is used to generate a shrinkage map for the image. Then the soft-thresholding method is handled.

Step 3:

In the next step, the image will reconstruct by using below equation and we can find the estimation of the image. By comparing this estimated image and the original image, we can detect the noise. For this part, some various methods like support vector machine (SVM) or deep convolutional neural network (DCNN) can be used.

$$\hat{X}_i = U_i S_i^{(T)} V_i$$

Step 4:

The final step is the stage that the noise should be

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removed. In this case, based on the noise that is detected in the previous step, the algorithm is starting to eliminate the noise from the original image. Finally, we can see the image after de-noising.

If a Gaussian noise with sigma=0.001 and zero mean has been added to the original image. As can be seen after the process, the final image has better quality and this is because of filtering the noise.

Figure 3: Error Map

Figure.3 & Figure.4 are the generated error map and shrinkage map respectively. Error map gives information between noisy image and original image. Shrinkage map gives information about the shrinking of sparse coefficients of noise parts of corrupted image. After multiple iterations, we get the final shrinkage map as shown in Figure 5, consisting very small amount of coefficients of noise.

Figure 4: Shrinkage Map

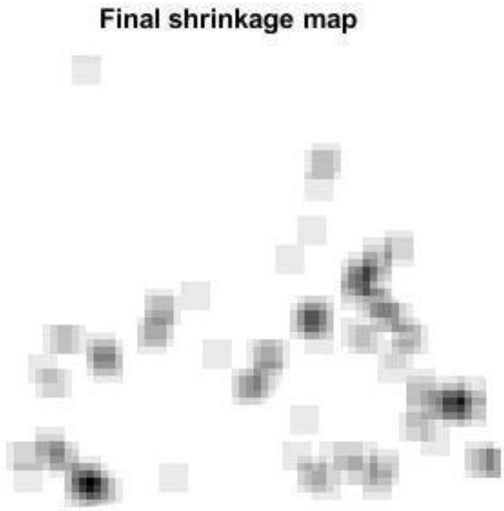

Figure 5: Final Shrinkage Map

VII. RESULTS

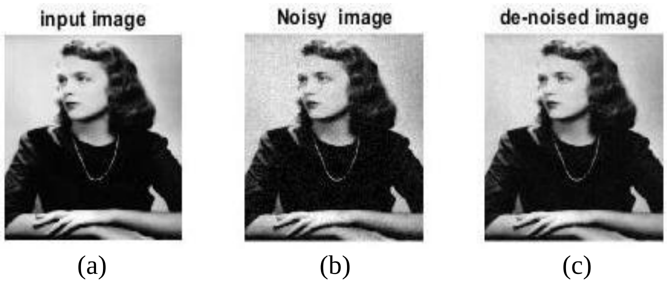

Figure 6: (a) input image, (b) input image after adding Gaussian noise, and (c) image after removing the noise

Table I shows the comparison of noisy and denoised image metric parameters. As shown, the '*PSNR'* (*peak signal to noise ratio*) increased after filtering the noise. Also, the '*CNR'* (*contrast to noise ratio*) is decreased that shows the energy of the noise has been reduced. The '*EPI'* (*edge preservation in*dex) shows the visibility of the image and as is shown the visibility of the image increased. '*SSIM'* (*structural similarity index metric*) is also high for denoised image.

Table 1. Analyzing metric parameters of noisy image and denoised image

RESULTS		
Metric parameter	Noisy image	Denoised image
PSNR	24.85	29.29
CNR	61.22	47.75
SSIM	0.67	1.00
EPI	0.62	0.87

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