Image De-noising based on Non Local Means (NLM) using Curvelet transformation

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Abstract— **Image denoising is being a governing field in image processing. Image denoising is applied before any image processing and information extraction algorithm on image. In this paper Non Local Means (NLM) algorithm is applied based on Curvelet Transformation. This NLM algorithm is modified to include energy of the reconstructed images to improve PSNR. The modified algorithm is compared with traditional NLM based on Curvelet transformation and results shows that PSNR has considerably improved for all noise levels. The noise is imparted using Gaussian distribution.**

Keywords— NLM; Curvelet transformation; Gaussian distribution; PSNR.

I. INTRODUCTION

Image processing applications are mainly found in two principle areas; one is the improvement of pictorial information for human interpretation and the other is processing the image data for autonomous machine perception [1, 2]. Nowadays, successful applications of image processing methods can be found in numerous fields such as astronomy, biology, defense, medication, nuclear science, and satellite imaging etc [3]. In all these fields scientists are mainly faced with problem of recovering original images from incomplete and noisy images. Noise may be caused by wide range of sources, like atmospheric turbulence, variation in the detector sensitivity [4], environmental variations, the discrete nature of radiation, transmission and quantization errors etc. An image is inevitably corrupted by noise in its acquisition, coding and transmission. For instance, during image acquisition the performance of imaging sensors is affected by a variety of factors, like environmental conditions such as light levels and sensor temperature, which causes noise. Images are also corrupted at transmission, due to interference in the channel used for communication and transmission. The major objective of image denoising is to remove the noise effectively while preserving as much as possible significant signal information and features [5]. Many different ways like spatial filtering methods and Fast Fourier Transform (FFT) [6] based methods are there to reduce or remove noise in an image. But these methods remove noises and cannot preserve edges in an image.

II. LITERATURE REVIEW

Reducing the disadvantageous influence of noise has always been one of the typical problems of the image analysis and processing area. Often, during the same time as reducing the noise in a signal, as well as it is important to preserve the image details like edges. Edges are critical significance to the visually appearance of images [7, 8]. So, it is advantageous to preserve important image features, such as smoothness, edges, variations and sharp structures, at the denoising process. This section describes a review of some significant work in the field of image denoising.

Ideally image denoising is all about filtering noise from the degraded noisy image even as keeping other significant details unchanged. Definitely, filtering is the main fundamental operation of image processing and computer vision, and it is used broadly in different applications, including noise removal, edge detection, image smoothing and sharpening etc. In the widest sense of the term "filtering", the value of the filtered image at a specified location is a function of the values of the input (noisy) image in a small neighborhood of the same location [2].

The simple type of filtering is a precise Linear Translation Invariant (LTI) filtering and that can be implemented by using a local neighborhood. As an example, box filtering also well known as averaging or mean filtering [1, 9], is implemented with a local averaging process where the value of each pixel is replaced by the average of all its neighbor pixels. Even though box filter gives the fastest filtering output result, but its smoothing impact is often not enough.

Additional LTI filters that do not occupy the computation of the mean of a neighborhood also are typically used for smoothing. Mostly common of those are the Gaussian smoothing filter [1, 6] and Weiner filter. The weights for Gaussian smoothing filter are preferred according to the shape of a Gaussian (normal) distribution function [10, 11]. Gaussian filter has been proved to existing a good alternative for removing noise drained from a normal distribution and also the perfect multi-scale space representation [15] of an image can be obtained simply by Gaussian smoothing with increasing variance [12]. Wiener filters are a class of optimum linear filters which involve linear evaluation of a preferred signal sequence from any more associated sequence.

Although Linear Translation Invariant (LTI) filtering is the simplest form of filtering and is used broadly in early vision process, it also has some drawbacks. LTI filtering is the fastest approaches for smoothing the noise but some important structures and details are also often obtain blurred along with noise. To attenuate these undesirable effects of linear filtering several of edge-preserving filtering techniques have been proposed throughout the last few years.

III. METHODOLOGY

The proposed approach is based on non local means using curvelet transformation.

STEP 1: Curvelet transform

The Curvelet transformation is a multi-scale space transform which provides a novel mathematical multi-resolution and object representation with various details and features that are better to existing representations like wavelets and steerable pyramids [5, 14]. An extension of the wavelet concepts, they are popular in similar fields, in image processing and scientific computing. The idea of curvelet transformation is decomposed the signal in various sub-bands at different scales that are with different positions and orientations in the frequency domain and differentiate the signal obeying the scale rule. The curvelet transform has been broadly used for denoising because of curvelet transform reconstructions demonstrate superior perceptual class than wavelet transform based reconstructions, presenting visually fine images and in particular superior quality recovery of corners, edges and of soft linear and curve features [16].

STEP 2: Non local means (NLM)

A non local means filter replaces each pixel in the noisy image with the weighted average of all other pixels in the image.

In non local means [13], for denoised image each pixel is calculated as:
$$NL(V)(i) = \sum_{j \in V} w(i, j)V(j)$$

In this approach NLM is calculated as:
$$NLM(i) = 1/C(i) * \sum_{j \in \Omega} w(i, j)L_0(j)$$

$$w(i, j) = \exp(- \|L_0(N(i)) - (L_0(N(j))\|^2_{2,a} / h^2)$$

Terminology

V = noisy image.
L_0 = noisy image.
$L_0(j)$ = intensity of jth pixel in noisy image L_0.
Ω = search window.
$C(i) = \sum_{j \in \Omega} w(i, j)$ is a normalization constant.
$W(i,j)$ = represents the similarity between pixels i and j.
$\|.\|_{2,a}$ = Gaussian weighted Euclidean distance function.
a = standard deviation of the Gaussian kernel.
h = decay parameter related to the noise standard deviation σ.
E_{total} = Total energy of all the reconstructed images.
σ^2 = Noise variance.
E = energy of ith image.
$Sum(d_i)$ = Sum of all the values of d.

Proposed Algorithm:
{
1. First take the curvelet transformation of the noisy image to decompose it into n-scale curvelet coefficients.
2. Store curvelet coefficients of each scale separately.
3. Reconstruct the n-images from each of the stored n-scale curvelet coefficients.
4. Calculate E_{total}.
5. Calculate σ^2.
6. Apply NLM.
7. Rearrange de-noised blocks to form de-noised image.
}

Algorithm NLM
{
1. Define NLM filter Kernel size and its search space size.
2. Generate filter kernel K.
3. Calculate E.
4. Divide image onto blocks of kernel size.
5. For each block extracted search the closest block in the search space using distance formula:

$$d_i = E/E_{total} * K * (W^i_{blk} - W^i_{search})^2$$
6. Repeat 2 to 5, for each reconstructed image and calculate Sum(d).
7. Calculate weight w_i as:

$$w_i = \exp(- Sum(d) / \sigma^2)$$
8. Search space block which gives maximum value of w and $Sum(w_i) > 0$. Construct denoised image as:
$$W_{denoised} = 1/Sum(w_i) * \sum^n_{i=1} w_i * W^i_{search}$$
}

STEP 3: Energy of image

Energy is simply defined based on a normalized histogram, a graphical representation of the image. Energy exhibits how the grey levels are distributed. When the number of grey levels is low then energy is high. Energy and Entropy are directly related terms and in the same way entropy and randomness are also strongly related. Thus in Image Processing, energy might be similar to randomness. For instance, a picture of a plain wall has low energy, while the picture of a city taken from a helicopter might have high energy. Image "energy" should be inversely proportional to Shannon entropy of an image. However as already said that image energy is loosely coupled term, it is better use "compressibility" term instead of energy. That is high image "energy" should correspond as high image compressibility.

IV. EXPERIMENTAL SETUP & RESULTS

In this work, we have taken Barbara, Lena, Cameraman, Satellite Image, Couple, MRI and Cell images are taken. The noise is imparted to these images using Gaussian distribution with noise scale 20, 30 and 50 respectively. All the experiments are performed on the tool MATLAB R2012b [17].
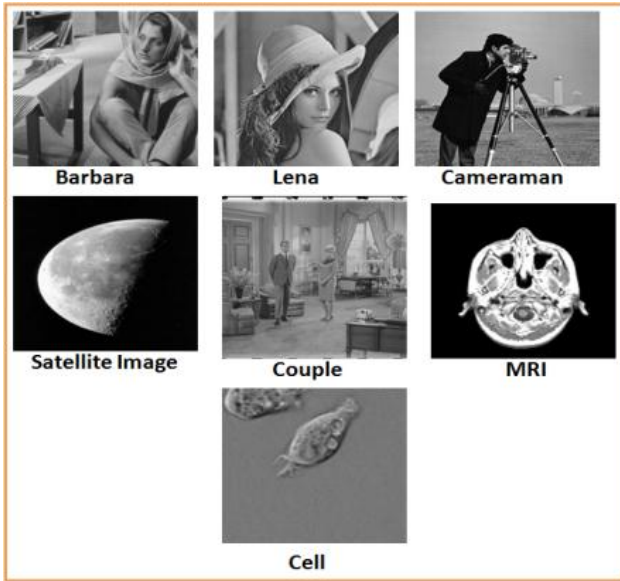
Fig. 1. Test images of Barbara, Lena, Cameraman, Satellite Image, Couple, MRI and Cell.

Table. 1. Experiment Results for different test images corrupted by different noise level.

Test Images	Noise Level (σ)	Previous Method PSNR	Proposed Method PSNR
Barbara	20	22.9091	25.4264
	30	19.336	21.9531
	50	14.9551	17.4923
Lena	20	22.5172	25.0094
	30	18.9706	21.5298
	50	14.5081	17.1093
Camera man	20	23.9465	26.4713
	30	20.4432	23.0196
	50	16.0135	18.6184
Satellite Image	20	24.0861	26.5248
	30	20.4842	22.9301
	50	16.1078	18.5793
Couple	20	23.9965	26.5711
	30	20.4977	22.9955
	50	16.0198	18.5344
MRI	20	14.784	17.3332
	30	11.2003	13.6863
	50	6.8874	9.4127
Cell	20	21.3247	23.8089
	30	17.7735	20.3405
	50	13.3577	15.761

V.   CONCLUSION

In this paper non local means algorithm is being modified. First curvelet transformation is applied to form reconstructed images. Then similarity between pixels of the noisy image and these reconstructed images is calculated based on the energy of both the blocks of images. And it is found that the PSNR is considerably improved for all noise levels.

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