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Speckle Noise Reduction Using Local Binary Pattern, Anisotropic Diffusion and Bilateral Filter

Mandeep Singh Sandhu[1], Rajandeep Kaur[2]

Bhai Maha Singh College of Engineering and Technology, Sri Muktsar Sahib, India

Abstract: ***Noise removal has received considerable attention from the research community. The reason for this interest is the removal of speckle noise from image can be done with minimum hardware added. However de-noising is susceptible to real life conditions like light etc. Hence, speckle noise removal is still a very challenging topic after decades of exploration. A number of typical algorithms have been derived by many researchers, and are categorized into template based, appearance-based, and model-based schemes. In the proposed work, investigated techniques are implemented which are not novel techniques; they are previously proposed and studied in the literature. In the first phase Local binary pattern is applied on the input image to generate LBP texton. The second method, anisotropic diffusion is applied on LBP texton to remove noise from our noisy image. In the last we apply bilateral filter to improve the resultant image.***

Keywords: Local Binary Pattern (LBP), Peak Signal to Noise Ratio (PSNR), Mean Square Value (MSE), Anisotropic Diffusion.

1. Introduction

Image is generally corrupted by different kind of noises like Gaussian noise, impulse noise, salt and pepper noise, white noise, uniform noise, Erlang noise, speckle noise. Different kinds of noises have their own properties. Some noises are additive in nature and some are multiplicative in nature. Additive noise is easily removed from the images but multiplicative noise is difficult to reduce from an image. Traditional techniques like mean filtering and median filtering are able to remove additive noise on the other hand, wiener filtering, lee filter, kaun filter, frost filter are being able to reduce the speckle noise in the images but at the cost of edge blurring. The purpose of this research work is to investigate the effectiveness of LBP and anisotropic diffusion for removal of speckle noise from an image and compare its effectiveness again some other promising speckle noise reduction techniques.

1.1 Local Binary Pattern

Local binary pattern (LBP) is a simple yet very efficient texture operator which labels the pixels of an image by thresh holding the neighbourhood of each pixel and considers the result as a binary number. Due to its discriminative power and computational simplicity, LBP texture operator has become a popular approach in various applications. It can be seen as a unifying approach to the traditionally divergent statistical and structural models of texture analysis. Perhaps the most important property of the LBP operator in real-world applications is its robustness to monotonic gray-scale changes caused, for example, by illumination variations. Another important property is its computational simplicity, which makes it possible to analyze images in challenging real-time settings.

1.2 Face description using LBP

In the LBP approach for texture classification, the occurrences of the LBP codes in an image are collected into a histogram. The classification is then performed by computing simple histogram similarities. However, considering a similar approach for facial image representation results in a loss of spatial information and therefore one should codify the texture information while retaining also their locations. One way to achieve this goal is to use the LBP texture descriptors to build several local descriptions of the face and combine them into a global description. Such local descriptions have been gaining interest lately which is understandable given the limitations of the holistic representations. These local feature based methods are more robust against variations in pose or illumination than holistic methods. The basic methodology for LBP based face description proposed by Ahonen et al. (2006) is as follows: The facial image is divided into local regions and LBP texture descriptors are extracted from each region independently. The descriptors are then concatenated to form a global description of the face, as shown in Fig.

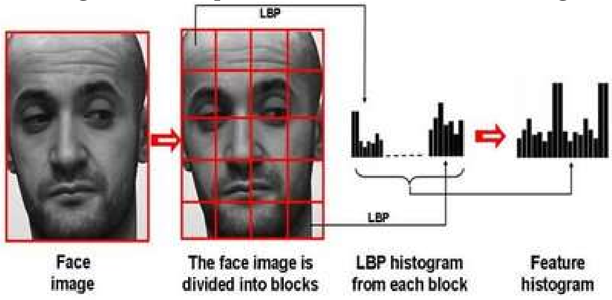
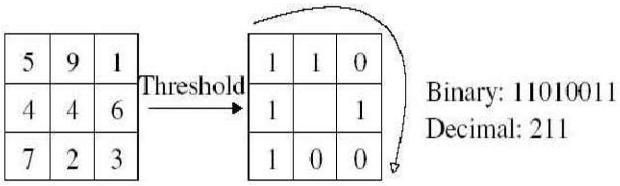


Figure 1: Face description with local binary patterns

This histogram effectively has a description of the face on three different levels of locality: the LBP labels for the histogram contain information about the patterns on a pixel-level, the labels are summed over a small region to produce information on a regional level and the regional histograms are concatenated to build a global description of the face.



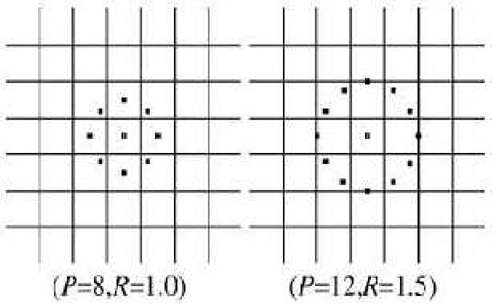


Figure 2: Left: the basic LBP operator; Right: Two examples of the extended LBP: A circular (8, 1) neighbourhood, and a circular (12,1.5) neighbourhood.

It should be noted that when using the histogram based methods the regions do not need to be rectangular. Neither do they need to be of the same size or shape, nor do they not necessarily have to cover the whole image. It is also possible to have partial overlapping regions.

2. Anisotropic Diffusion

In this section, we summarize the idea of the anisotropic diffusion scheme. For each pixel (i,j) of the image we use a 3x3 neighborhood window. For each neighbor with respect to (i,j) corresponds to one direction {N= North, S= South, W = West, E= East}. If we denote I as the input image and x is the 3x3 neighborhood window, then the gradient Δ_p x(i, j)= x(i+ m, j+n)- x(i, j) with (m,n)ε {-1,0,1} where (m,n) corresponds to one of the four directions and (i,j) is called the center of the gradient. We derive the LBP texton for the same 3x3 window. This textons can be used to determine whether the center pixel is spot/flat/edge/line/corner pixel. According to different types of pixel contexts the discrete diffusion is performed based on Eq. With the diffusivity function c1, relative adjustments to weights of the diffusion are made such strong diffusion on spot/ flat pixels i.e. Δt = 0.04 is encouraged whereas edge/line/corner pixels are diffused slower/lesser i.e.Δt = 0.01.The following steps are performed until the PSNR decreases in the subsequent iteration.

3. Bilateral filter

A Bilateral filter is nonlinear, edge preserving and noise reducing smoothing filter for images. The intensity values at each pixel in an image are replaced by a weighted average of intensity values from nearby pixels. This weight can be based on a Gaussian distribution .Crucially the weight does not only on Euclidean distance of pixels but also on the radiometric difference(e.g. range of differences, such as color intensity, depth distance etc). This preserves sharp edges by systematically looping through each pixel and adjusting weights to the adjacent pixels accordingly.

$$I^{filtered}(x) = \sum_{x_i \epsilon \Omega} I(x_i f_r(\|I(x_i) - I(x)\|) g_s(\|x_i - x\|)$$

The bilateral filter is defined as:
Where:

- $I^{filtered}$Is the filtered image;
- IIs the original image t be filtered;
- $x$are the coordinates of the current pixel to be filtered;
- $\Omega$is the window centered in$x$
- $f_r$is the range kernel for smoothing difference in intensities;
- $g_s$is the spatialkernel for smoothing difference in coordinates;

Algorithm LBPD

1. Input the image data I.
2. Place the window W at (i,j), store the image I values inside W in x
3. Derive the LBP texton as shown in Fig. 1. If LBP texton is spot or flat then Δt=0.4 else Δt=0.01
4. Calculate the local gradient using equation
   $\Delta_N x_{i,j} = x_{i-1,j} - x_{i,j}$; $\Delta_S x_{i,j} = x_{i-1,j} - x_{i,j}$;
   $\Delta_E x_{i,j} = x_{i-1,j} - x_{i,j}$; $\Delta_W x_{i,j} = x_{i-1,j} - x_{i,j}$
5. Use the discrete diffusion equation to diffuse
   $$I_{i,j}^{n+1} = I_{i,j+}^{n}(\Delta t)\big[C_N(\Delta_N x_{i,j}^N).\Delta_N x_{i,j}^N + C_S(\Delta_S x_{i,j}^S).\Delta_S x_{i,j}^S + C_E(\Delta_E x_{i,j}^E).\Delta_E x_{i,j}^E + C_W(\Delta_W x_{i,j}^W).\Delta_W x_{i,j}^W\big]$$
6. Let output image I (i, j) =$I_{i,j}^{n+1}$
7. Repeat 3 to 5 until the PSNR decrease in the subsequent iteration
8. Use the output image of diffusion as input for bilateral filter and compare the PSNR of resultant image.

PSNR – PSNR stands for the peak signal to noise ratio. It is an engineering term used to calculate the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. Because many signals have a very wide dynamic range, PSNR is usually expressed in terms of the logarithmic decibel scale. It is most commonly used as a measure of quality of reconstruction in image compression etc. It is calculated as the following:

$$\textbf{PSNR}=\textbf{10log}_{10}\frac{255\times 255}{MSE} \quad \textbf{............. (1)}$$

$$\textbf{MSE} = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[X(i,j)-Y(i,j)\right]^2 \quad \textbf{....... (2)}$$

Where X and Y are the original and noisy or de-noised image respectively. M and N represent the width and height of image.

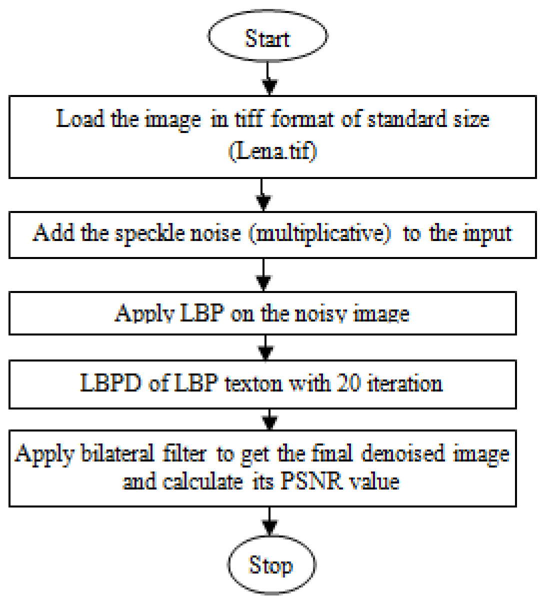


Figure 3: Flowchart for image de-noising algorithm

4. Results

Figure4: The first two rows: Leena image with speckle noise with noise density level D = 0.02, 0.04, 0.06, 0.08; secondtwo rows: corresponding results of Bilateral

Comparison of PSNR of different de-noising filters on leena (512 x 512) image corrupted by speckle noise

Table 1: The PSNRcomparison of different leena images with different noise density and the resultant denoised image which are shown in fig 4.

σ^2 / PSNR	0.02	0.04	0.06	0.08
AnisotropicDiffusion	34.33	30.61	29.55	29.02
MedianFilter	32.32	30.73	30.07	29.58
WeinerFilter	33.50	31.69	30.69	30.37
Bilateral filter	29.06	29.28	20.22	18.4

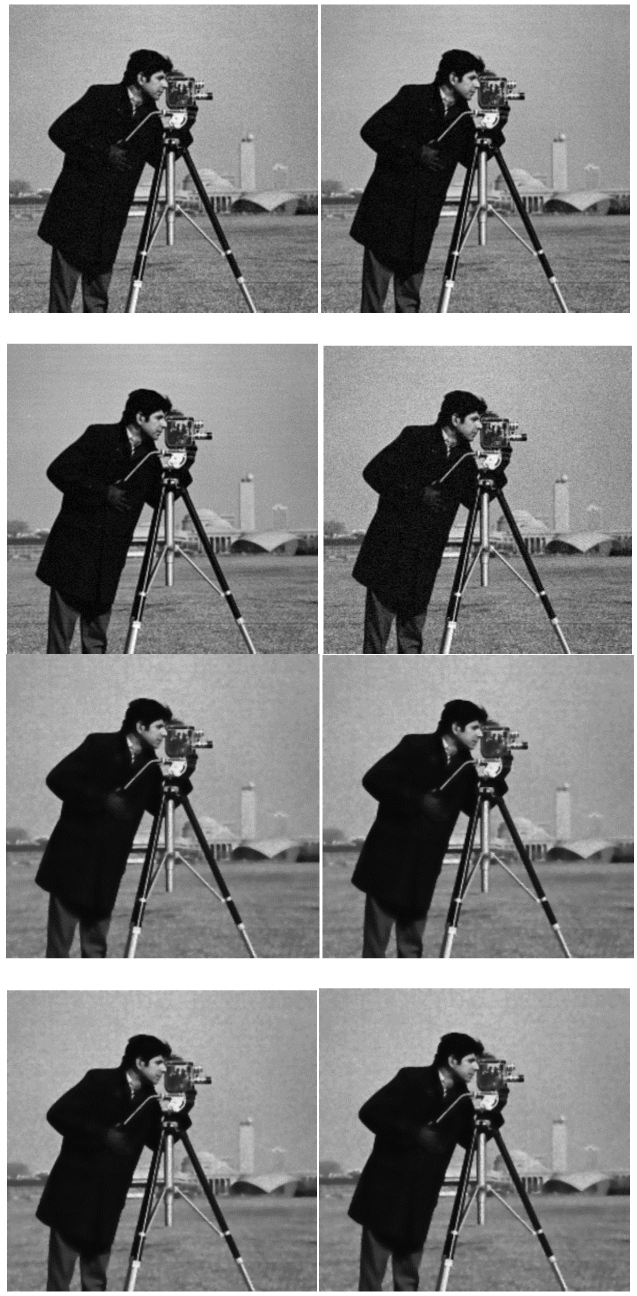


Figure 5: (a) the first two rows: Cameraman image with speckle noise with noise density level D = 0.02, 0.04, 0.06, 0.08; Second two rows: corresponding results of Bilateral and other filters.

Comparison of PSNR of different denoising filters on cameraman (512 x 512) image corrupted by speckle noise

Table 2: The PSNR comparision of different cameraman images with different noise density and the resultant denoised image which are shown in fig 5.

σ^2 / PSNR	0.02	0.04	0.06	0.08
Anisotropic Diffusion	32.65	29.88	29.32	29.05
Median Filter	31.82	30.53	30.10	29.74
Weiner Filter	33.31	31.39	30.76	30.31
Bilateral filter	24.57	21.93	19.52	17.87

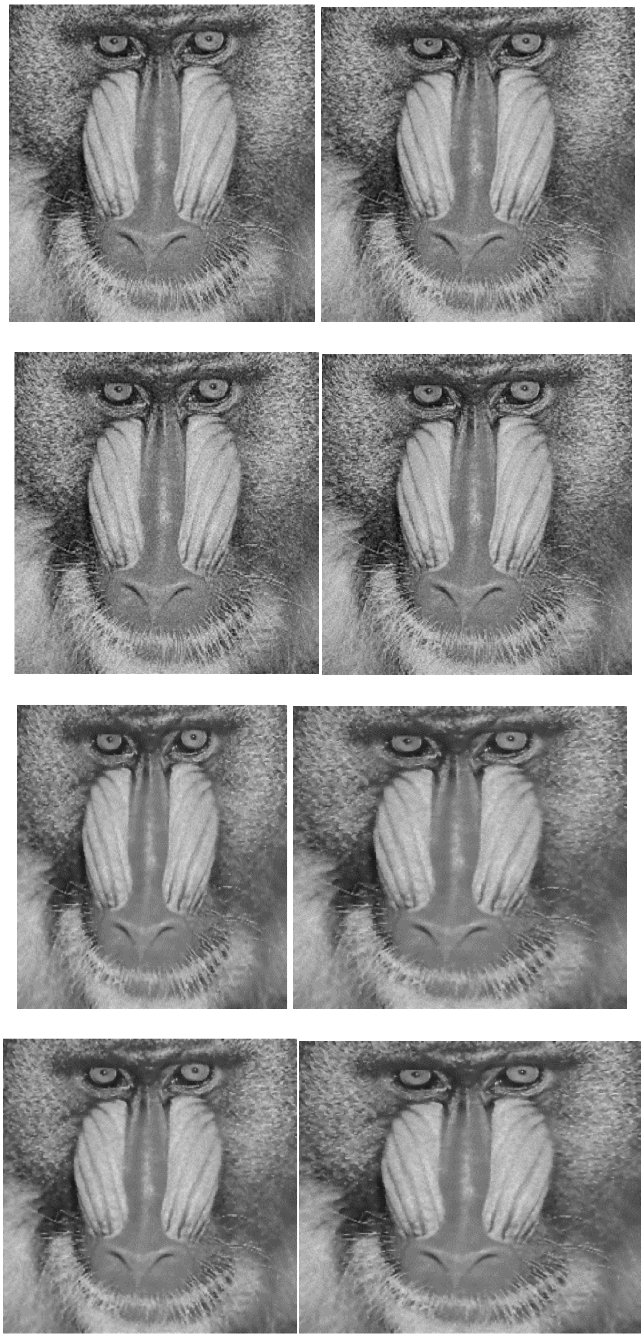


Figure6: (a) the first row: Mangril image with speckle noise with noise density level D = 0.02, 0.04, 0.06, 0.08; Second row: corresponding results of Bilateral and other filter.

Comparison of PSNR of different denoising filters on mandril (512 x 512) image corrupted by speckle noise

Table 3: PSNR comparison of different mandril images with different noise density and the resultant denoised image which are shown in fig 4

σ^2 / PSNR	0.02	0.04	0.06	0.08
Anisotropic Diffusion	31.13	29.51	28.83	28.50
Median Filter	30.58	29.61	29.17	28.93
Weiner Filter	32.11	30.87	30.28	29.94
Bilateral filter	19.66	19.04	17.95	16.98

5. Conclusion

In this thesis work we studied some of the traditional techniques for speckle noise reduction bilateral filtering and also LBPD based techniques studied and implemented. The main goal of the speckle noise reduction is to satisfy the important factors during image enhancement: edge preservation, speckle noise removal, better smoothing of an image. In this thesis work we try to explore the bilateral based method for speckle noise reduction and performance of LBPD based method is compared with existing traditional techniques in terms of PSNR (peak signal to noise ratio) and visual results. It has been observed that combination of LBPD based method and bilateral filtering does perform better than the existing techniques.

6. Future Scope

In future work we suggest a modification to the proposed combination of LBPD based method and bilateral filtering to remove some artifacts in an image. Also this method is further implemented with curvelet transform, undecimated wavelet transform for speckle noise reduction. Our future research will focus on finding the proper PSNR value for LBPD coefficients.

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