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Speckle Noise Reduction Using Local Binary Pattern

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Abstract

A novel local binary pattern (LBP) based adaptive diffusion for speckle noise reduction is presented. The LBP operator unifies traditionally divergent statistical and structural models of region analysis. We use LBP textons to classify an image around a pixel into noisy, homogenous, corner and edge regions. According to different types of regions, a variable weight is assigned in to the diffusion equation, so that our algorithm can adaptively encourage strong diffusion in homogenous/ noisy regions and less on the edge/ corner regions. The diffusion preserves edges, local details while diffusing more on homogenous region. The experiments results are evaluated both in terms of objective metric and the visual quality.

Keywords: Local Binary Pattern; Non-linear Diffusion; Context-Based Denoising

1. Introduction

Despite the progress in digital imaging, many image modalities produce images with noise affecting both the visual quality and hindering quantitative image analysis. So, the research in the area of image denoising is highly active. Among a great variety of image restoration and denoising methods the non-linear diffusion represents a simple yet efficient approach. Some of nonlinear anisotropic diffusion techniques are Perona–Malik (PM) filter [1], Weickert filter [2, 3], Vogel-Omans's [4], Rudin-Osher-Fatemi's [5]total variation diffusion, Gilboa's [6] forward and backward diffusion and Ma's [7] second eigen diffusion. These techniques rely on the diffusion flux to iteratively eliminate small variations due to noise, and to preserve large variations at edges. Nonlinear diffusion techniques use the gradient operator to discriminate the signal from the noise, and subsequently fail if the noise level is significant. Image denoising problems are better solved if a powerful signal/noise separating tool is incorporated before the diffusion process. A few recent developments in diffusion-based image denoising are discussed here. Mrazek et al. [8] have analyzed correspondences between explicit one-dimensional schemes for nonlinear diffusion and discrete translation-invariant Haar wavelet shrinkage. Weickert et al. [8, 9] described relation between (semi-)discrete diffusion filtering and Haar wavelet shrinkage, including an analytic

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four-pixel scheme, but focused on the 1-D or the isotropic 2-D case with a scalar-valued diffusivity. This allowed to enhancing edges compared to Perona-Malik diffusion [1]. Shih and Liao [10] addressed a single step nonlinear diffusion that can be considered equivalent to a single shrinkage iteration of coefficients of Mallat's Zhong dyadic wavelet transform (MZ-DWT) [11]. Nonlinear diffusion begins with a gradient operator, which may be badly influenced by the noise present in the image. MZ-DWT has its own subband filtering framework and a set of wavelet filters, derived from the derivative of a smoothing function. In [12] authors presented a nonlinear multiscale wavelet diffusion method for the ultrasound speckle suppression and edge enhancement. The edges are detected using normalized wavelet modulus and speckle is suppressed by an iterative multiscale diffusion of wavelet coefficients. The diffusion threshold is estimated from the normalized modulus in the homogenous speckle regions, in order to adapt to the noise variation with iteration.

In [13], Bruni et al. proposed another wavelet and partial differential equation (PDE) model for image denoising. The model establishes a precise link between corresponding modulus maxima in the wavelet domain and then allows predicting wavelet coefficients at each scale from the first one from waves obeying a precise partial differential equation. Bao and Krim [14] addressed the problem of texture losses in diffusion process in scale spaces by incorporating ideas from wavelet analysis. They showed that using wavelet frames of higher order than Haar's account for longer term correlation structure, while preserving the local focus on equally important features and illustrated the advantages of removing noise while preserving features. In [15], Chen developed three denoising schemes by combining PDE with wavelets. In the first proposed model, the diffusion is a function of the Rudin-Osher-Fatemi's total variation model and used amount of advection to diffuse differently in various directions. Nikpour and Hassanpour [16] perform diffusion of approximation coefficients of wavelet transform while applying shrinkage to detail coefficients. Chao and Tsai [17] proposed a diffusion model which incorporates both local gradient and gray-level variance to preserve edges and fine details while effectively removing noise. The major drawback of this method is it cannot be applied to the images containing high level of noise. Such noisy pixels in the image generally involve very large magnitudes of gray level variance and gradient than those of edges and fine details and the model.

Yu et al. [18] proposed a SUSAN controlled diffusion, the SUSAN edge detector finds image features by using local information from a pseudo global perspective. Noise insensitivity and structure preservation properties of SUSAN guides the diffusion process in an effective manner. Wang [19] et al. proposed a local variance controlled scheme in context of image enhancement and noise reduction. In this scheme, spatial gradient and contextual discontinuity of a pixel are jointly employed to control the evolution. Wang [20] et al. proposed a tunable FAB diffusion. In this algorithm it is possible to modulate all aspects of the diffusion behavior. Although the algorithm turns out to be effective for miscellaneous images, there are still several open problems. In [21], we proposed the context-based diffusion; the multi-scale stationary wavelet analysis of the local neighborhood provides the edge information partially free of noise and thus makes possible the tunable diffusion. As a result, and due to the shift invariance of stationary wavelet transform the PSNR has been improved compared to Shih's diffusion [22].

We refer to the integration of nonlinear diffusion and LBP textons [23]. This approach has more favorable denoising properties than nonlinear diffusion in the intensity domain and exhibits improved edge-enhancement. The analysis of the work on adapting diffusion to local structure and consideration of a type of the context for diffusion shows improvements and thus inspires for researching further in this direction. In this paper, we use LBP textons for deriving the context information and control diffusion. The method is called LBP Based Diffusion (LBPD) method. The rest of the paper is organized as follows: Section 2 provides a theoretical background and introduces the method. Section 3 introduces results of the experiment; thereafter we conclude.

2. Background

2.1 Non-Linear Diffusion

The first nonlinear diffusion technique was described by Perona and Mallik [1]. Their method encourages intra-region smoothing while inhibiting inter-region smoothing. The diffusion process by Perona and Malik is mathematically described as

$$\frac{\partial}{\partial t} I(x,y,t) = \nabla \bullet (c(x,y,t)\nabla I) \tag{1}$$

where I(x,y,t) is the image, t is the iteration steps and c(x,y,t) is the so called diffusion function and is monotonically decreasing function of the image gradient magnitude. Perona and Mallik suggested two diffusivity functions

$$c_1(x,y,t) = \exp\left(-\left(\frac{|\nabla I(x,y,t)|}{k}\right)^2\right) \tag{2}$$

and

$$c_2(x,y,t) = \frac{1}{1+\left(\frac{|\nabla I(x,y,t)|}{k}\right)^2} \tag{3}$$

where k is referred to as a diffusion constant. Depending on the choice of the diffusivity function, equation (1) covers a variety of filters. The discrete diffusion structure is

$$I_{i,j}^{n+1} = I_{i,j}^{n} + (\nabla t)\bullet\begin{bmatrix} c_N\left(\nabla_N I_{i,j}^n\right)\bullet\nabla_N I_{i,j}^n + c_S\left(\nabla_S I_{i,j}^n\right)\bullet\nabla_S I_{i,j}^n + \\ c_E\left(\nabla_E I_{i,j}^n\right)\bullet\nabla_E I_{i,j}^n + c_W\left(\nabla_W I_{i,j}^n\right)\bullet\nabla_W I_{i,j}^n \end{bmatrix} \tag{4}$$

The letter N, S, E and W (north, south, east and west) describe the direction of the local gradient, and the local gradient is calculated using nearest-neighbor differences

$$\nabla_N I_{i,j} = I_{i-1,j} - I_{i,j} \;;\; \nabla_S I_{i,j} = I_{i+1,j} - I_{i,j} \quad \nabla_E I_{i,j} = I_{i,j+1} - I_{i,j} \;;\; \nabla_W I_{i,j} = I_{i,j-1} - I_{i,j} \tag{5}$$

2.2 Local Binary pattern

Ojala et al. [23] first introduced the LBP operator for texture classification. Success in terms of speed, accuracy and performance is reported in many active research areas such as texture classification [24-27], object detection [28-30], face recognition [31-35] and image retrieval[36, 37]. The LBP operator combines characteristics of statistical and structural texture analysis: it describes the texture with primitives called as textons.

Fig.1. shows how a texton and LBP code are derived; the LBP takes the 3x3 neighborhood of a central pixel and generates a binary 1 if the neighbor of that pixel has a larger value than the otherwise, it produces a binary 0. An LBP code for a neighborhood is produced by multiplying the threshold values with weights given to the corresponding pixels, and summing up the result. Thus each LBP can be regarded as a micro-texton [23].

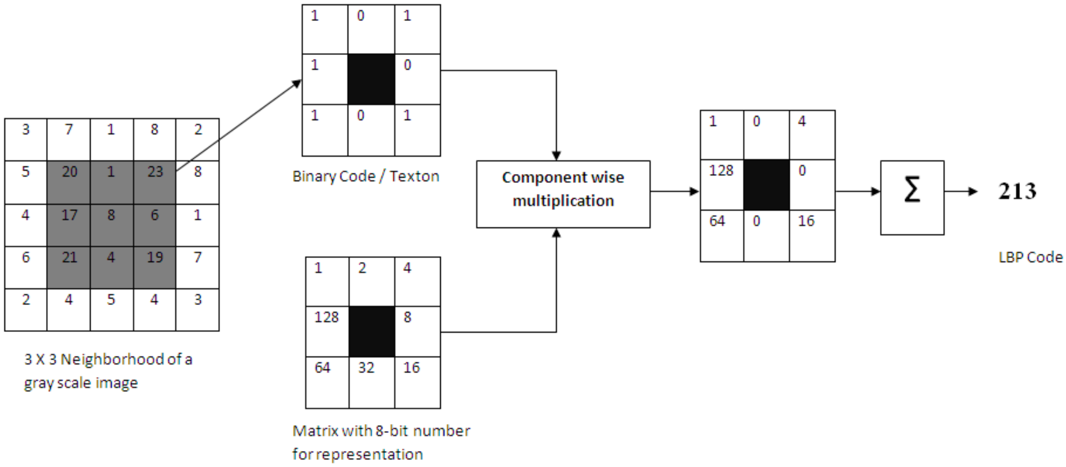

Fig.1. Example of obtaining LBP for 3x3 neighborhood

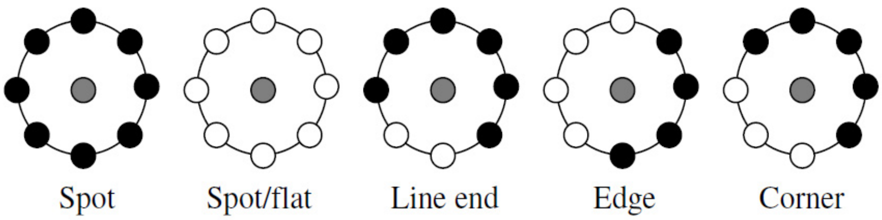

Fig.2. Different texture primitives detected by the LBP [23]

Local textons include spots, flat areas, edges, line ends and corners. Fig.2. shows the different texture primitives detected by the LBP. In the figure, gray circle indicates center pixel, white circles indicate ones and zeros are indicated by black.

2.2 Local Binary Pattern based Diffusion (LBPD)

In this section, we summarize the idea of the local binary pattern based 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 $\nabla_p x(i,j) = x(i+m, j+n) - x(i,j)$ with (m, n)Є {-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 as shown in Fig.1. 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. 4 with the diffusivity function c_1, relative adjustments to weights of the diffusion are made such strong diffusion on spot/ flat pixels i.e. ∇t = 0.04 is encouraged whereas edge/line/corner pixels are diffused slower/lesser i.e. ∇t = 0.01.The following steps are performed until the PSNR decreases in the subsequent iteration.

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 ∇t = 0.04 else ∇t = 0.01
4. Calculate the local gradient using equation
   $\nabla_N x_{i,j} = x_{i-1,j} - x_{i,j}$; $\nabla_S x_{i,j} = x_{i+1,j} - x_{i,j}$ $\nabla_E x_{i,j} = x_{i,j+1} - x_{i,j}$; $\nabla_W x_{i,j} = x_{i,j-1} - x_{i,j}$
5. Use the discrete diffusion equation to diffuse
   $$I_{i,j}^{n+1} = I_{i,j}^{n} + (\nabla t) \bullet \begin{bmatrix} c_N\left(\nabla_N x_{i,j}^n\right) \bullet \nabla_N x_{i,j}^n + c_S\left(\nabla_S x_{i,j}^n\right) \bullet \nabla_S x_{i,j}^n + \\ c_E\left(\nabla_E x_{i,j}^n\right) \bullet \nabla_E x_{i,j}^n + c_W\left(\nabla_W x_{i,j}^n\right) \bullet \nabla_W x_{i,j}^n \end{bmatrix}$$
   let output $I(i,j) = I_{i,j}^{n+1}$
6. Repeat 3 to 5 until the PSNR decreases in the subsequent iteration

3. Experiment

In order to verify the performance of LBPD we have tested on a number of benchmark images corrupted by an speckle multiplicative noise producing image J from image I as J = I + n*I, where n is uniformly distributed random noise with μ=0 and variance σ^2= 0.02, 0.04, 0.06, 0.08.

The evaluation is performed based on $PSNR = 10\log I_{\max}^2 / MSE$, where MSE is a mean square error. The parameters we used are $\nabla t1$ = 0.04, $\nabla t2$ = 0.01 and diffusivity function c1 with diffusivity constant k =10;

Table I shows the PSNR attained by LBPD with the speckle noise density levels of D = 0.02, 0.04, 0.06, 0.08. Fig. 4 and 5 allows for evaluating the visual quality of the resultant images produced by LBPD. We observe that the proposed method works better in smooth regions providing better visual quality. Specifically, they are diffused in a greater extent while preserving edges and local details.

4. Conclusion

We have described a novel feature-preserving adaptive non-linear diffusion algorithm based on local binary pattern texton. The proposed method is based on local structure and involves local binary texton for the denoising process. First, we classify the centre pixel as edge, spot, flat region, line end or corner using LBP texton. According to different types of pixel texton, relative adjustments to weights of the diffusion are made such strong diffusion on spot/flat pixels is encouraged whereas edge/line/corner pixels are diffused slower/lesser. We believe this method represents an important step forward for the use of neighborhood design that captures local context in images. Experimental results demonstrate its potential for the feasibility of structure context based controlled diffusion approach.

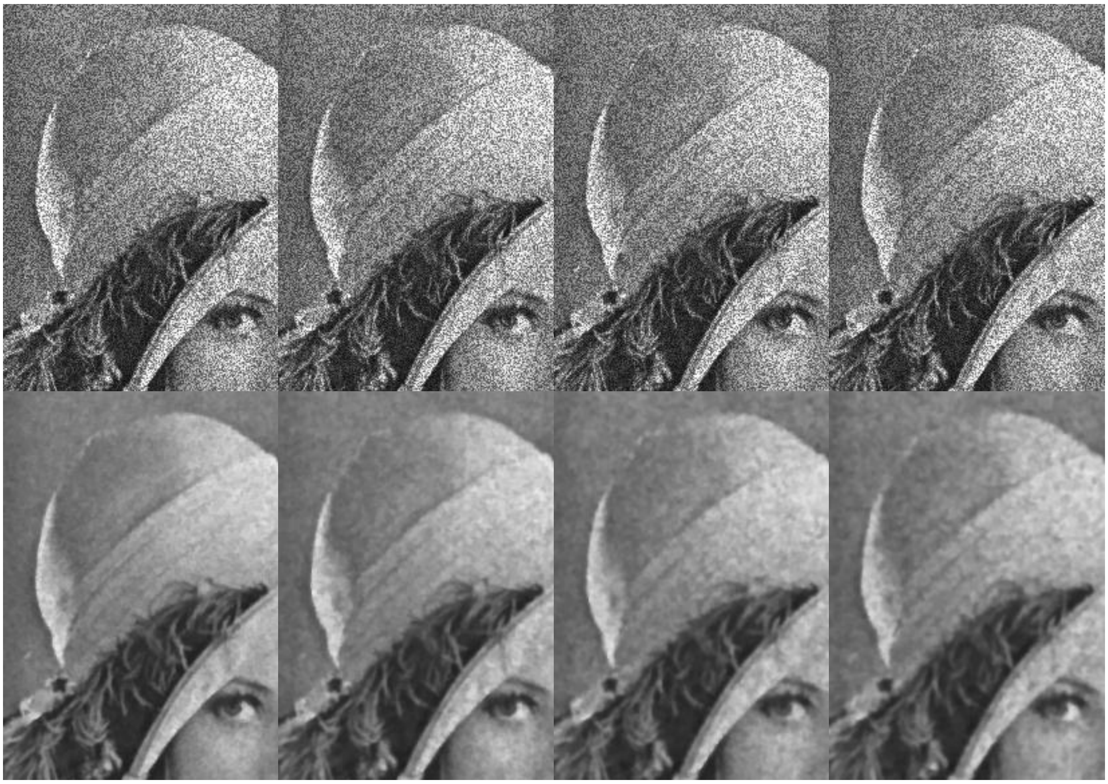

Fig.4 First row: a part of the "Lena" image with speckle noise with noise density level D = 0.02, 0.04, 0.06, 0.08; Second row: corresponding results of LBPD

Fig.5 First row: a part of the "Cameraman" image with speckle noise with noise density level D = 0.02, 0.04, 0.06, 0.08; Second row: corresponding results of LBPD

Table I: PSNR for denoising of Speckle noise (D = 0.02, 0.04, 0.06, 0.08)

Image/Noise Density	0.02	0.04	0.06	0.08
Cameraman	30.53	28.71	27.55	26.7
Lena	30.3	28.66	27.67	26.94
Peppers	30.83	29.31	28.39	27.58
House	32.15	30.15	28.91	28.03

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