Local Binary Pattern Adaptive Diffusion for Image Denoising

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Abstract - A novel local binary pattern (LBP) based adaptive diffusion is presented for image denoising. 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 introduced into the diffusion equation, so that the algorithm can adaptively encourage strong diffusion in homogenous/noisy regions and less on the edge/corner ones. Quantitative analyses based on peak signal to noise ratio shows the high performance of the method.

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. Among a great variety of image denoising methods the non-linear diffusion represents a simple yet efficient approach.

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

$$\frac{\partial I(x,y,t)}{\partial t} = \nabla \cdot (c(x,y,t)\nabla I)$$  \hspace{1cm} (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 Malik suggested two diffusivity functions

$$c_1(x,y,t) = \exp\left(-\frac{\|\nabla I(x,y,t)\|^2}{k}\right)$$ \hspace{1cm} (2)

and

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

$$I_{i,j}^{n+1} = I_{i,j}^n + (\nabla I) \cdot \left[ c_1(\nabla N I_{i,j}^n) \nabla N I_{i,j}^n + c_2(\nabla S I_{i,j}^n) \nabla S I_{i,j}^n \right]$$ \hspace{1cm} (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

$$\nabla N I_{i,j} = I_{i-1,j} - I_{i,j}; \quad \nabla S I_{i,j} = I_{i+1,j} - I_{i,j}$$  \hspace{1cm} (5)

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 due to edges. Nonlinear diffusion techniques rely on the gradient operator to discriminate the signal from the noise, and sometimes fail in reliably separating them. Image denoising problems are better solved if a powerful signal/noise separating tool, such as for example feature analysis is incorporated during the diffusion.

We explore the integration of nonlinear diffusion and LBP textons [8]. This approach has more favorable denoising properties than basic gradient based nonlinear diffusion and exhibits improved edge-enhancement. A few recent developments based on feature/context based image diffusion are discussed below.

Chao and Tsai [9] 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 that it cannot be applied to the images with a high level of noise. Such noisy pixels in the image generally involve very large magnitudes
of gray level variance and gradients than those of edges and fine details.

Yu et al. [10] 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. Several parameters have to be tuned for a desirable diffusivity. Being a powerful tool for finding closed contours fairly good results can be attained however at the cost of elaborate image analysis.

Wang [11] 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. However, a solution to estimating the contextual discontinuity leads to an exhaustive search procedure, which causes algorithm complexity to be too costly. Furthermore, an optimal strategy for evaluating two gradient thresholds in the forward and backward (FAB) diffusion scheme is unknown and hence, it is often necessary to select the threshold by guesswork.

Wang [12] 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. First, the spatial gradient makes it difficult to distinguish significant discontinuities from noise due to overlocalization, making the diffusion coefficient unreliable. Next, several parameters have to be tuned for a desirable diffusivity. If any proper parameters fail to be achieved, it is easy to lead to unsatisfactory results. Finally edge orientations are not taken into account in the diffusion scheme, which is inefficient for edge preserving smoothing.

In [13], a new method is proposed which combines advantages of non-linear diffusion and multi-resolution analysis using stationary wavelet. The latter has been employed to evaluate the context and then use it for controlled diffusion. The proposed diffusivity function is a weighting function to the wavelet coefficients. In diffusing the detail coefficients, the local context is derived directly from the transforms energies at first two levels of two level stationary wavelet transform. Obtained results have shown the improvement to diffusion without using the context information. The method is computationally efficient due to the Haar wavelet, and fast convergence is attained due to exploiting the context information.

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. Here, 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 Local Binary Pattern

Ojala et al. [14] 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 [15-18], object detection [19-21], face recognition [22-26] and image retrieval [27, 28]. 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 central pixel; 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. Each LBP can be regarded as a micro-texton [8].

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

2.2 Local Binary Pattern Based Diffusion

In this section, we introduce the idea of the local binary pattern based diffusion scheme. For each pixel (i,j) of the image we use a 3x3 neighborhood window. Each neighbor with respect to (i,j) corresponds to one direction {N= North, S= South, W = West, E= East}. If we denote I as an input image and x is a 3x3 neighborhood window, then the gradient \( \nabla_{p} x(i, j) = x(i + m, j + n) - x(i, j) \) with (m, n) \( \in \{-1,0,1\} \), where (m,n) corresponds to one of four directions and (i,j) is called the center of the gradient. We derive the LBP texton for 3x3 windows as shown in Fig.1. Textons can be used to determine whether the central pixel is a spot, flat, edge, line or corner. According to different types of pixel contexts the discrete diffusion is performed based on Eq. 4 with the diffusivity function \( c_{i} \), relative adjustments to weights of the diffusion are made such as stronger diffusion of spot/flat pixels, is encouraged whereas edge/line/center pixels are diffused slower/lesser. This is implemented by using i.e. \( \nabla t = 0.04 \) and \( \nabla t = 0.01 \) in the former/latter cases, respectively. The algorithm performs as follows:
**LBPD Algorithm**

1. Input image data $I$.
2. Place the window $W$ at $(i,j)$, store image $I$ values inside $W$ in $x$
3. Derive the LBP texton as shown in Fig. 1.
4. Check if LBP texton is of type “spot” or “flat” then
   \[ \nabla t = 0.04 \] else \[ \nabla t = 0.01 \]
5. Calculate the local gradient as follows
   \[ \nabla_N x_{i,j} = x_{i-1,j} - x_{i,j} \]
   \[ \nabla_S x_{i,j} = x_{i+1,j} - x_{i,j} \]
   \[ \nabla_E x_{i,j} = x_{i,j+1} - x_{i,j} \]
   \[ \nabla_W x_{i,j} = x_{i,j-1} - x_{i,j} \]
6. Use the discrete diffusion equation to diffuse

\[
I_{n+1}^{i,j} = I_{n}^{i,j} + (\nabla t) \left[ \begin{array}{c}
    c_S (\nabla_S x_{n,i,j}^*) 
    \nabla_S x_{i,j} + c_S (\nabla_S x_{i,j}^*) 
    \nabla_S x_{i,j}^* 
    + \\
    c_E (\nabla_E x_{n,i,j}^*) 
    \nabla_E x_{i,j} + c_E (\nabla_E x_{i,j}^*) 
    \nabla_E x_{i,j}^* \\
    c_N (\nabla_N x_{n,i,j}^*) 
    \nabla_N x_{i,j} + c_N (\nabla_N x_{i,j}^*) 
    \nabla_N x_{i,j}^* \\
    c_W (\nabla_W x_{n,i,j}^*) 
    \nabla_W x_{i,j} + c_W (\nabla_W x_{i,j}^*) 
    \nabla_W x_{i,j}^* 
\end{array} \right]
\]

let output $I(i,j) = I_{n+1}^{i,j}$
7. Repeat steps 3 to 6 until the PSNR decreases in a subsequent iteration.

### 3 Experiment

In order to verify the performance of LBPD we have tested on a number of benchmark images corrupted by an
additive white Gaussian noise of zero mean $\mu=0$ and $\sigma = 5, 10, 15, 20$.

The evaluation is performed based on

$$PSNR = 10\log\frac{I_{max}^2}{\text{MSE}},$$

where MSE is a mean square error. The parameters we used are $\nabla t_1 = 0.04$, $\nabla t_2 = 0.01$ and diffusivity function $C_I$ with diffusivity constant $k = 10$.

Table I presents PSNR attained by LBPD for several benchmark images with the additive white Gaussian noise and Table II presents PSNR yielded by the LVCFAB method in [11], and results produced by LBPD for Cameraman, Lena, House and Peppers images for different levels of noise reported in the reference paper. The comparison shows that the PSNR values of the restored images achieved by our algorithm are higher. Fig. 3 and 4 allows for evaluating the visual quality.

### 4 Conclusion

In this paper a novel approach to the problem of edge preserving diffusion is proposed. In the proposed scheme, we first use LBP texton to detect a context such as edge, spot, flat region, line end or corner. According to different types of pixel contexts, 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. As a result a fairly good performance has been achieved showing the feasibility of structure based controlled diffusion approach.

### 5 Acknowledgement

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**Fig. 3** First row: a part of the “Lena” image with additive white Gaussian noise level $\sigma = 5, 10, 15, 20$; Second row: corresponding results of LBPD
Fig. 4 First row: a part of the “House” image with additive white Gaussian noise level $\sigma = 5, 10, 15, 20$; Second row: corresponding results of LBPD

**Table I:** PSNR for denoising of additive white Gaussian noise ($\sigma = 5, 10, 15, 20$).

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<tr>
<th>Image/Noise Level</th>
<th>5</th>
<th>10</th>
<th>15</th>
<th>20</th>
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<td>30.43</td>
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<td>40.61</td>
<td>36.95</td>
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<td>33.12</td>
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**Table II:** Comparison of LBPD and LVCFA [11].

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6 References


