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A METHOD FOR IMAGE DE-NOISING BASED ON ANISOTROPIC DIFFUSION

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Abstract
The image may be corrupted by random variations in intensity, variations in illumination, or poor contrast that must be dealt with in the early stages of vision processing. In the existing method a weighted guided image filter is introduced by incorporating an edge-aware weighting into a guided image filter to address the problem. This paper provides the derivation of noise reducing anisotropic diffusion, a diffusion method tailored to imaging applications. Anisotropic diffusion can be used to remove noise from digital images without blurring edges. With a constant diffusion coefficient, the anisotropic diffusion equations reduce to the heat equation which is equivalent to Gaussian blurring. The experimental results show that the proposed method is better compare to the state of art of criteria.

Introduction
Most diffusion models in image processing smooth the images by modifying them via a partial differential equation or PDE. In the isotropic linear filtering, the model is given by the heat equation $\partial I/\partial t = 4I$, where I is the filtered image,

4 is the Laplacian operator, and the original (greyscale) image $I0$ is used as the initial condition. It is known that to solve the heat equation is equivalent to convolve the initial image with a Gaussian kernel $G\sigma$, for some σ. As a result of this smoothing the edges of the images become blurred (see Figure 1). An attempt to filter the images while trying to preserve their edges is given in the work of Perona and Malik [5]. They introduce the idea of anisotropic diffusion, that is, to smooth the image in the orthogonal direction to the gradient, $DI \perp$, and prevent, as much as possible, the diffusion across the direction of the edges (i.e. the direction of the gradient, DI). The previous approaches have focused on the filtering of grey-scale images. In the recent years, a number of authors have addressed the problem of color image diffusion and enhancement by using PDE‟s models for multi-valued images. The simplest way to handle these images is to smooth each color component (or „channel‟) independently of the others. This is equivalent to consider each channel as an independent grey-scale image, with its own edges, which is filtered using some PDE. The filtered color image is then obtained by combining together the filtered channels. The notion of „channel‟ depends on the method used to represent color information. For instance, it can be „red‟, „green‟, and „blue‟ when using the RGB color system, or „hue‟, saturation‟ and „illumination‟ when using HIS.

In the case of natural, non-synthetic, images, the modified images turn out to be visually identical to the original ones, which seem to support the proposed hypothesis. Based on this hypothesis, we give a new model for color anisotropic diffusion. This model can be interpreted as a diffusion of the color components in the orthogonal direction to the gradient of the luminance. That is, when each color component is filtered, the goal is not to preserve its own edges, but the „edges‟ (i.e. the topographic map) of the luminance component.

The rest of this paper is organized as follows. Section II first reviews existing method. Our proposed method is described in Section III. Then experimental results are reported in Section IV to demonstrate the superior performance of our framework. Finally, conclusions are presented in Section V.

Existing Method

In the existing method, an edge-aware weighting is introduced and incorporated into the GIF [14] to form a weighted GIF (WGIF). In human visual perception, edges provide an effective and expressive stimulation that is vital for neural interpretation of a scene. Larger weights are thus assigned to pixels at edges than pixels in flat areas. There are many methods to compute the edge-ware weighting. Local variance in 3 × 3 window of a pixel in a guidance image is applied to compute the edge-aware weighting. The weighting can be easily computed via the box filter in [14] for all pixels in the guidance image. The local variance of a pixel is normalized by the local variances of all pixels in the guidance image. The normalized weighting is then adopted to design the WGIF. Due to the proposed weighting, the WGIF can preserve sharp edges like the global filters [1],[2],[4], [8]. As a result, halo artifacts can be reduced/avoided by using the WGIF. Similar to the GIF in [14], the WGIF also avoids gradient reversal. In addition, the complexity of the WGIF is O(N) for an image with N pixels which is the same as that of the GIF in [14]. These features allow many applications of the WGIF in the fields of computational photography and image processing. The WGIF is applied for single image detail enhancement, single image haze removal, and fusion of differently exposed images. Experimental results of the three applications show that the resultant algorithms produce images with excellent visual quality as those of global optimization based algorithms, and at the same time the running times of the proposed algorithms are comparable to the GIF based algorithms.

It is worth noting that an adaptive GIF (AGIF) was proposed for image sharpening and de-noising by borrowing a shifting technique in [15]. It was shown in [18] that the complexity of the AGIF is O(N) for an image with N pixels.

On the other hand, both the ABF in [15] and the AGIF are training-based approaches while no training is required by the WGIF. Four different exposure fusion algorithms are compared, and they are 1) the exposure fusion algorithm 2) the fully detail-enhanced exposure fusion algorithm in [3],3) a fully detail-enhanced exposure fusion algorithm based on the GIF in [14], and 4) a fully detail-enhanced exposure fusion algorithm based on the WGIF. It is worth noting that the detail enhancement algorithm in [3] is a global optimization based approach. The values of λ and $\zeta 1$ are respectively selected as 1/4 and 16 for both the WGIF and the GIF in [14]. As indicated by the red arrows in Fig. 11, there are visible halo artifacts in the final images by the GIF in [14] while halo artifacts are reduced/avoided by the WGIF. The visual quality of the fused images by the WGIF is comparable to that of the fused images by the global optimization based approach in [3].Therefore, the WGIF can be applied to design a detail enhanced fusion algorithm with the fast speed of the GIF based algorithm and at the same time, it has excellent visual quality of the global optimization based algorithm in In addition, similar idea can be used to improve the anisotropic diffusion in Poisson image editing in [6], etc.

Proposed Method

In this paper, we have outlined a partial differential equation (PDE) approach to noise removal that we call noise reducing anisotropic diffusion. The PDE-based noise removal approach allows the generation of an image scale space (a set of filtered images that vary from fine to coarse) without bias due to filter window size and shape. AD not only preserves edges but also enhances edges by inhibiting diffusion across edges and allowing diffusion on either side of the edge. AD is adaptive and does not utilize hard thresholds to alter performance in homogeneous regions or in regions near edges and small features. The new diffusion technique is based on the same minimum mean square error (MMSE) approach to filtering as the Lee (Kuan) and Frost filters. In fact, we show that the AD can be related directly to the Lee and Frost window-based filters. So, AD is the edge sensitive extension of conventional adaptive filter, in the same manner that the original Perona and Malik anisotropic diffusion [15] is the edge sensitive extension of the average filter. In this sense, we extend the application of anisotropic diffusion to applications such as radar and medical ultrasound in which signal-dependent, spatially correlated multiplicative noise is present.

A. Anisotropic Filtering Algorithm

Anisotropic diffusion resembles the process that creates a scale space, where an image generates a parameterized family of successively more and more blurred images based on a diffusion process. Each of the resulting images in this family is given as a convolution between the image and 2Disotropic Gaussian filter, where the width of the filter increases with the parameter. This diffusion process is a linear and space invariant transformation of the original image. Anisotropic diffusion is a generalization of this diffusion process: it produces a family of parameterized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. According to the concept of divergence field, anisotropic diffusion equation can be described in the following equation:

$$I_t = div\left(c\left(t,x,y\right)\nabla I\right)$$

In Equation (5), div is divergence operator, □gradient operator, I is the function of (x,y), c(t,x,y) is spatial scale function, namely the diffusion coefficient, which is a nonnegative monotonic decreasing function, Ii is the derivative of I with respect to time t, t is the time of thermal diffusion. The selection of diffusion coefficient c(t,x,y) will directly influence the filtering effect and in general, diffusion coefficient c(t,x,y) is given a value of the norm of a vector, which has the following attributes:

- In interior area E(t,x,y)=0
- In the boundary area, E(t,x,y)= □. e(t,x,y) , e(t,x,y) is the unit vector of the gradient of point (x,y) in the boundary area. □is the strength difference at each side of the boundary.

We can determine c(t,x,y)

$$c\left(t,x,y\right) = g\left(\|E\|\right).$$

The classical g(x) can be described as

$$g\left(x\right) = \frac{1}{1+\left(x/k\right)^2}$$

$$g\left(x\right) = \exp\left(-\left(x/k\right)^2\right)$$

Here, k is the controlment coefficient of diffusion strength; x is the gradient of the diffusion point. According to the definition of diffusion coefficient, in different directions different coefficients are adopted. In addition, the monotonic decreasing function was taken in different directions as the diffusion coefficient. In background area or interior area of image, the gray level values are similar and gradient is very small, so the diffusion coefficient is large to implement smoothing. On the contrary, in the area of boundary, gray level value changes much and accordingly the gradient increases, diffusion coefficient is very small to preserve the boundary information. Here we consider the processing in eight directions. The advantages of anisotropic diffusion include intra-region smoothing and edge preservation. Anisotropic diffusion performs well for images corrupted by additive noise. Several enhancements and edge detection methods have been described in the literature for images with additive noise. In cases where images contain noise, anisotropic diffusion will actually enhance the noise, instead of eliminating the corruption. The work of this paper uses the strengths of the PDE approach to produce edge-sensitive noise reduction.

B. Applications

Nonlinear diffusion filters have been applied for post-processing fluctuating data for visualizing quality-relevant features in computer aided quality control and for enhancing textures such as fingerprints. They have proved to be useful for improving sub-sampling and line detection for blind image restoration, for scale-space based segmentation algorithms for segmentation of textures and remotely sensed data and for target tracking in infrared images. Most applications, however, are concerned with the filtering of medical images

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Results

Results of this paper is as shown in bellow Figs.1 to 5.

Fig.1.Source image.

Fig.2. Image its Weighting.

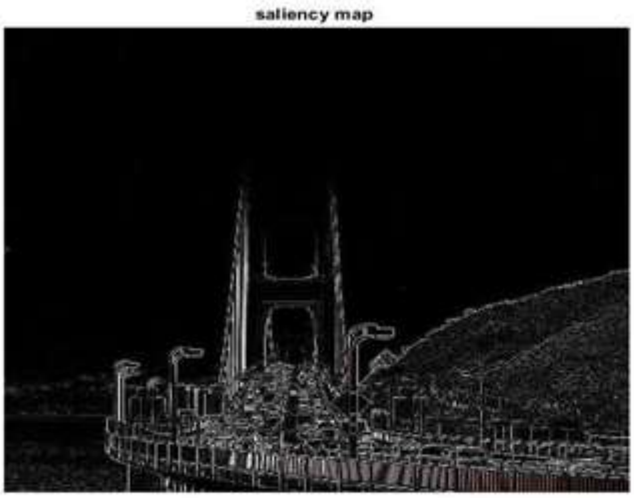

Fig.4. Saliency Map.

Fig.5. Filtered Image Using Anisotropic Diffusion Filter.

TABLE I: Comparison Table

	Existing method	Proposed method
PSNR	49.3848	54.4412
MSE	0.0075	0.2339

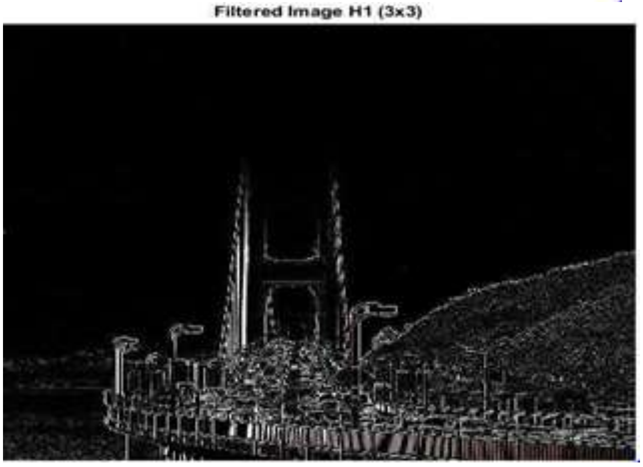

Fig.3. Filtered Image.

Conclusion

In this paper we studied carefully all steps of the Anisotropic Diffusion algorithm and came up with the best choice among the various options at each step. By applying the Anisotropic Diffusion algorithm the image filtering is done accurately than the WGIF.The Experimental Results shown that the Proposed Anisotropic Diffusion algorithm is the best algorithm for image filtering. The metrics PSNR and MSE calculated here also shows that the proposed filter is best than the state –art-of criteria.

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