Adaptive Anisotropic Diffusion For Improved Image Filtering And Enhancement

Lee Seng Soon
School of Computer Sciences
Universiti Sains Malaysia
sengsoon@cs.usm.my

Dhanesh Ramachandram, Mandava Rajeswari
School of Computer Sciences
Universiti Sains Malaysia
mandava@cs.usm.my

ABSTRACT

Anisotropic diffusion is a selective and non linear filtering technique which improves the image qualitatively and quantitatively by removing the noise while preserving and even enhancing details. The anisotropic diffusion employs the diffusion coefficients, k that continuously depends upon the gradient magnitude to determine the amount of smoothing that should be applied to each pixel of the image. However, the existing works are only capable of preserving a narrow range of edges. The final outcome often results in blurred or staircased edges. Thus, in this paper, an automatic assignment of the diffusion coefficient using multiple scales to augment the performance of anisotropic diffusion is introduced. The magnitude of the diffusion coefficient at each pixel is determined by taking in to consideration the local property of the image through the scales. The expected outcome of the proposed diffusion process is that the strong as well as weak edges are well preserved, while noise is effectively removed. The performance of proposed diffusion process is compared qualitatively against anisotropic diffusion and coherence enhancing diffusion on a phantom image.

KEYWORDS

Noise filtering, anisotropic diffusion, multiple scales.

1. Introduction

Image segmentation is a longstanding problem in computer vision. The goal of segmentation is to find regions that represent an object or meaningful parts of an object. It relies on semantic interpretation of geometric image features, such as edges, ridges and corners. However, the semantic interpretation of images may be affected by noise or other type of artifacts introduced by unwanted variation of image intensity during image acquisition, thus causing inaccuracies in the image segmentation process. Therefore, the image data needs to be filtered to remove noise prior to segmentation. Various filtering approaches have been introduced, such as statistical driven filtering, wavelet-based denoising, diffusion process and the like to overcome the accuracy and reliability problem of segmentation.

The anisotropic diffusion is popular and has been improved and utilized in a variety of images. Among the notable improvements include scalar and adaptive type of diffusion approaches. In the scalar diffusion approach, a single value of the diffusion coefficient is applied to all pixels in the image, while in adaptive type of diffusion approach, the diffusion coefficient at each pixel varied in accordance to strength of edges at that pixel. The diffusion coefficient may be based upon statistical metric, either by means of single scale or multiple scales information. The anisotropic diffusion in [1] is a scalar diffusion approach in which the scalar diffusion coefficient is determined either manually or automatically . The automatic selection of diffusion coefficient is based upon the principle of noise estimator by canny in [2]. The diffusion approach proposed by Whitaker and Pizer in [3] is an adaptive approach which is based on multiscale information. The gradient magnitude at a chosen pixel is assigned to be the value of k at the pixel. Similarly, Yoo [4] presented another adaptive approach based upon multiscale information. IN his work, Yoo [4] determines the based scale that represents an edge at a pixel. The best scale is sought by comparing the variance throught a range of scales. The scale with the minimum variance is selected as the best scale. The gradient magnitude at that selected scale is computed and assigned as the value of k at corresponding pixel. Weickert [5] proposed an adaptive approach that utilizeds a coherence measure which reflectes the contrast of edges at a asingle scale, to assign the value of k. In [6], an adaptive approach is introduced based upon single scale information. Yeh value of k is addinged by choosing the maximum value of gradient magnitude among four iamge gradient. These image gradient s are computed by means of curvature in [7] and statistical based directional estimation procedure in [6].

In this paper, an adaptive diffusion equation based upon multiple scale information is introduced. The value of k is estimated based upon the maximum difference of variance of gradient magnitude between the one scale and the neighboring scale. The value of k is estimated in such a way that retains prominent strong and weak edges from being smoothed and only eliminates the noise. To achieve, this, a novel method to automatically assign an appropriate value to diffusion coefficient, k by means of statistical metric via multiple scale information is proposed. The objective is to smooth the noisy image adaptively so that shape are well preserved and do not reflect the so called *rounded effect*.

The paper is organized as follows: Section 2 introduces general theory of anisotropic diffusion. In section 3, the idea of novel adaptive anisotropic diffusion and a serried of algorithm for implementation are introduced. Section 4 presents the experimental results and qualitative comparisons with other diffusion approaches. The final section devoted to the conclusion.

2. Diffusion Theory

The original formulation of the anisotropic diffusion approach is proposed by Perona and Malik in [1]. The diffusion process can be briefly stated as in Equation 1.

Where I_0 is the original image, c is the diffusivity function, ∇I is the gradient intensity, t is the number of iteration and $\partial_t I$ is the amount of diffusion. The formulation of diffusivity function is expressed as in Equation 2.

Where the parameter k is known as the diffusion coefficient or flow constant. The k controls the bi-functions of the anisotropic diffusion process, which are the smoothing and preserving. The intensity at subsequent iteration, I_{t+1} is obtained through a discretization scheme, as described in Equation 3. In this scheme, the I_{t+1} is accumulated by It at the current iteration and $\partial_t I$ from four neighbouring pixels.

The subscript n, e, s and w indicate the neighbouring pixels at the top, right, bottom and left location with respect to the current pixel. The lambda, λ is a constant value. The diffusivity function, $c(|\nabla I|)$ in Equation 1 determines the amount of smoothing that applied to each pixel of the image. It is a monotonically decreasing function which is inverse proportionate to the strength of gradient magnitude. The following section describes the novel approach to augment the capability of existing anisotropic diffusion method.

3. Proposed Methodology

The core idea of the proposed adaptive anisotropic diffusion is to determine the value of k adaptively over the entire image according to the strength of edges via multiple scales information. Different values of k produce corresponding value of diffusivity function, which is also equivalent to the different degrees of smoothing. Thus, a range of degrees of smoothing is appropriately applied to each pixel to preserve both strong and weak edges. The proposed adaptive anisotropic diffusion undergoes the following processes:

- The value of k is determined in such a way that small value is applied to regions with strong edges, whereas appropriately large value of k is applied to any regions with noise or low fluctuation. This idea is derived form the work in [8]. The task of searching the regions with strong and weak edges is performed via multiple scales.
- Once the value of k at each location of the image is estimated statistically via multiple scale information, these variables are not kept constant, but are linearly decreased according to the number of iterations of the anisotropic diffusion process.

The processes involve in assigning appropriate values for the diffusion coefficient, k is expressed graphically in Figure 1.

3.1 Algorithm Description

Prior to diffusion procedure, a range of sigma is manually defined by setting the maximum and minimum value of sigma, $[\sigma_{min} - \sigma_{max}]$ and the number of iteration, n. Sigma determines the width of Gaussian filters. At each iteration, sigma is increased as $\sigma_i=\sigma_{i-1} + \nabla\sigma$. The regular interval, $\nabla\sigma$ is set in accordance with the chosen number of iteration, n. It is expressed in Equation 4.

With that, a range of sigma value is generated, initiating from the minimum, σ_{min} to maximum, σ_{max}. A range of values of sigma is generated in such a way that the noisy image is smoothed by Gaussian convolution with slowly increasing sigma value to generate a stack of increasing scaled images. Then, the gradient magnitude of each location of the smoothed image sis computed by the first order derivative. The procedure is also repeated with other scaled images, in order to generate a stack of gradient images. The gradient magnitude of smoothed images of varying scales are denoted as σ_I and are obtained as follows:

And are the gradient magnitude of x and y direction at i-th respectively. The gradient magnitude is obtained using the Equation 5.

By using Equation 4 and 5, a stack of images with gradient magnitude information is obtained.

The variance of gradient magnitude is computed within a window size of N over the entire image. This is performed on a scale. This procedure is then repeated for all scales. In this procedure, a N dimensional array is generated and stored for subsequent processing. Variance can be simply denoted as *var*. The ratio of difference of variance, ∇var_i at each location of image at a single scale is then computer by taking the difference variance at i-th scale and i+1-th scale. The difference of variance is normalized by the variance at i-th scale. The process is repeated for the same location of image for all scales. The formula for obtaining the ratio of variance's difference is mathematically described as follows.

Where var_i indicated the variance at i.

The concept of automatically assigning the value of diffusion coefficient, k at each location of the image is to search for the scale that best represents the edges at that particular location. In this procedure, the search for the best scale is based upon the difference of variances, ∇var between i-th scale and i+1 scale. The i-th scale is taken as the best scale to represent the edges at the particular location if the variance's difference i-th scale and i+1 scale is the maximum magnitude for all scales. Using the sigma that corresponds to the best scale, σ_i and the gradient magnitude, ∇I at that best scale, diffusion coefficient, k is computed as in Equation 7.

3. Experiments and Results

In order to gauge the performance of the proposed diffusion approach, four different diffusion approaches are compared against the proposed anisotropic diffusion. They are the anisotropic diffusion reported in [1] and the coherence enhancing diffusion reported in [5]. For simplicity, the anisotropic diffusion is denoted as *PM*, coherence enhancing diffusion is denoted as *coherence* and the proposed approach is simply denoted as *proposed*.
The performance of each diffusion approach is tested on a phantom image which contains objects of various sizes, shapes and edges' strength. The phantom image is corrupted with 8 different degrees of noise, starting from 6.35% to 50%. As the noise corruption increased, the visibility relative small objects are de-escalated. This is owing to the existence of intensity fluctuation in the vicinity of relative small objects that weaken the strength of edges. This decreased contrast of relatively small objects may challenge the task of noise removal and object enhancement. Thus, the ability to remove noise as well as enhance these relatively small objects is the key to excellent filtering tool.\par
In this experiment, the phantom images with various degree of noise corruption is smoothed by the diffusion approaches: *PM*, coherence and *proposed*. The two example of noise corrupted images and original used in this experiment are shown in Figure 2. For each diffusion approach, the best result are selected. For qualitative comparison, the resulting images with the 32.15% and 37.5% noise corruption are presented in Figure 3.

The performance of diffusion approaches are compared qualitatively by observing the relatively small object before and after diffusion process. As Overall, the *proposed* shows comparatively better diffused images than other diffusion approaches. This is owing to the ability of the *proposed* approach to remove noise effectively and enhance (preserve) the relative small objects well. Apart from that, the *proposed* also able to remove noise in the background region. This is clearly seen in Figure 3 in third row.

3. Conclusion

This paper has introduced an adaptive anisotropic diffusion method that adaptively varies the degree of smoothing at every location of the image. The degree of smoothing is varied by determining an appropriate value for the diffusion coefficient, k by means of statistical metric via multiple scale information. A small-valued diffusion coefficient, k is applied in the vicinity of strong edges, while a large but appropriately-valued diffusion coefficient, k is applied to homogeneous and low fluctuation regions. Based on the obtained results, it is evidently shown that the *proposed* outperforms than *PMI*, *PMII* and *coherence* in various noise corruption.

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Should be brief and should not include authors' biographies.

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