

文章编号 : 1003-501X(2008)06-0015-05

Dim Target Enhancement Algorithm for Low-contrast Image based on Anisotropic Diffusion

WANG Yan-hua^{1,2}, LIU Wei-ning¹

(1. Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Sciences,
Changchun 130033, China; 2. Graduate School of Chinese Academy of Sciences, Beijing 100039, China)

Abstract: In a sensed image of long distance, the gray levels of target and background are hardly distinguishable, which results in a low-contrast image. Dim-target detection is always a difficult problem. The aim of this paper is to propose an anisotropic diffusion filtering algorithm based on partial differential equation to enhance the dim targets. The algorithm establishes a new filter model by improving the traditional P-M model based on the anisotropic diffusion theory. The proposed method adaptively performs the smoothing process in the faultless areas to make the background uniform, and performs the sharpening process in the variational areas to enhance dim targets. Simultaneously, we can select the smoothing and sharpening degree by adjusting the parameter K and w to satisfy different environments. Experimental results show the efficiency of the proposed diffusion scheme in dim-target enhancement with low-contrast.

Key words: partial differential equation; anisotropic diffusion; low-contrast image; image enhancement; adaptive filter

CLC number: TP391.41

Document code: A

基于各向异性扩散的弱小目标增强算法

王艳华^{1, 2}, 刘伟宁¹

(1. 中国科学院长春光学精密机械与物理研究所, 长春 130033 ;
2. 中国科学院研究生院, 北京 100039)

摘要: 针对弱小目标对比度较低、边缘模糊、难以准确探测的问题, 本文提出一种基于 PDE 的改进的各向异性扩散滤波算法增强弱小目标。该方法根据各向异性扩散原理, 通过改进传统的 P-M 方程建立新的滤波模型, 采用自适应滤波的方法在非目标区进行背景平滑, 在局部变化的区域进行锐化处理增强弱小目标, 从而达到背景平滑的同时增强边缘的效果。同时可以通过调节参数 k 和 w 选择平滑和锐化的程度, 以适应不同的环境变化。实验结果表明, 该方法能够有效的增强低对比度图像中的弱小目标。

关键词: PDE; 各向异性扩散; 低对比度图像; 图像增强; 自适应滤波器

中图分类号: TP391

文献标志码: A

1 Introduction

In low-contrast images, a local dim-target has a smooth change of brightness from its neighboring region, therefore provides no clear edges to apply the gradient-based methods for target detection. The non-uniform intensity of the background area and the low-contrast intensity of the target region all deter the use of the simple threshold method. It is extremely difficult to reliably identify small target in low-contrast images without false detection of noise. Much research has been done on dim-target detection in low-contrast images. Some adopted a spatial-temporal detection method derived from a model of temporally stationary and spatially non-stationary

收稿日期: 2007-05-20; 收到修改稿日期: 2008-01-10

作者简介: 王艳华(1982-), 女(汉族), 河南许昌人, 博士研究生, 主要从事基于 DSP 弱小目标捕获、跟踪算法研究。

E-mail: wangyanhua919@163.com

clutter statistics^[1-2]. However, these methods require a number of sequence images that the background must be quiescence, simultaneously the spatial model and temporal model are not always modeled exactly. The others developed all kinds of filters^[3-4] to enhance and detect small dim-target. Such as, high-pass filter, background-suppressed filter, local statistic filter, morphologic filter, adaptive lattice algorithm etc, all these methods contain the contradictory process that target-enhancement and noise-smooth.

We are eager to discover a useful way to overcome this major disadvantage. To solve this problem, the challenge is to design methods that can selectively smooth an image without losing significant features. In this paper, we propose an anisotropic diffusion scheme based on partial differential equation (PDE) to tackle the problem. It was first proposed by Perona and Mailik^[5] for scale-space description of images and edge detection, much research has been devoted to its theoretical and practical understanding. Catta et al^[6] proposed performing selective smoothing using Gaussian smoothing. Y. Chen et al^[7] improved the method by introducing the energy descent equation. The diffusion method was also introduced to image enhancement^[8-10]. Here we study the dim-target enhancement in low-contrast by the anisotropic diffusion method.

2 Perona and Malik Anisotropic Diffusion Model

Perona and Malik proposed a nonlinear diffusion method for avoiding the blurring and localization problems of linear diffusion filtering. They applied an inhomogeneous process that reduces the diffusivity at those locations, which have a larger gradient. The P-M continuous anisotropic diffusion is given by

$$\frac{\partial I_t(x, y)}{\partial t} = \text{div}[g(|\nabla I_t|)\nabla I_t] \quad (1); \quad I_0(x, y) = I(x, y) \quad (2)$$

Where $I_t(x, y)$ refers to the image at time t , div is the divergence operator, $\nabla I_t(x, y)$ is the gradient of the image, and $g(|\nabla I_t|)$ is the diffusion coefficient. If $g(|\nabla I_t|)$ is a constant, equation (1) is reduced to the isotropic diffusion equation. It is then equivalent to convolving with a Gaussian function. The idea of anisotropic diffusion is to adaptively choose $g(|\nabla I_t|)$ so intra-regions become smooth while edges of inter-regions are preserved. The diffusion coefficient $g(|\nabla I_t|)$ is generally selected to be a nonnegative function of gradient magnitude so that small variations in intensity such as noise or shading can be well smoothed, and edges with large intensity transition are retained. The $g(|\nabla I_t|)$ is a smooth, non-increasing function with $g(0)=0$, and $g(s)$ when $s \rightarrow \infty$. The usual choice for g is of the form

$$g(s) = \frac{1}{1 + (s/k)^2} \quad (3)$$

3 The Proposed Anisotropic Diffusion Model

In the low-contrast images, the traditional anisotropic diffusion model cannot sufficiently enhance hardly-visible target by simply smoothing low-gradient regions and passively preserving high-gradient edges. In order to enhance the dim-target effectively in low-contrast images that the gray levels of target and the background are hardly distinguishable, we incorporate the sharpening process in the classical diffusion model. The proposed diffusion model not only provides different degrees of smoothing for intra-regions but also provides different degrees of sharpening for edges in inter regions^[10]. The new diffusion model proposed is given by

$$\frac{\partial I_t(x, y)}{\partial t} = \text{div}[g(|\nabla I_t|)\nabla I_t] - \text{div}[v(|\nabla I_t|)\nabla I_t] \quad (4)$$

The proposed diffusion model unifies both the smoothing and sharpening processes in one single equation. The diffusion and sharpening strengths are adaptively adjusted by the diffusion coefficient function $g(|\nabla I|)$ and sharpening coefficient function $v(|\nabla I|)$. The first term on the right hand side of eq.(4) is the same classical

diffusion process as the P-M model in eq. (1). The second term is interpreted as the sharpening operation. In the proposed diffusion model the sharpening coefficient function $v(|\nabla I|)$ has to be a non-negative monotonically increasing function with $v(0)=0$, and $\lim_{|\nabla I| \rightarrow \infty} v(|\nabla I|) \rightarrow 1$. This function $v(|\nabla I|)$ should result in high coefficient values at edges that have relatively high gradient magnitudes so that they can be distinctly enhanced. It must generate low coefficient values for pixels within image regions that have low gradient magnitudes to inhibit the sharpening process. Therefore, we define the sharpening coefficient as

$$v(|\nabla I|) = w[1 - g(|\nabla I|)] \quad (5)$$

Where w is the weight of sharpening coefficient function with 0~1. This weighting factor determines the degree of sharpening with respect to the diffusion coefficient. So the eq. (4) reformulated as

$$\frac{\partial I_t(x, y)}{\partial t} = \text{div}[(g(|\nabla I_t|) - v(|\nabla I_t|))\nabla I_t] \quad (6)$$

Then we define

$$c_t(|\nabla I_t|) = g(|\nabla I_t|) - v(|\nabla I_t|) \quad (7)$$

as the new diffusion coefficient function in the proposed diffusion model. We can compare the new diffusion coefficient with the traditional diffusion coefficient through figure 1 to figure 2.

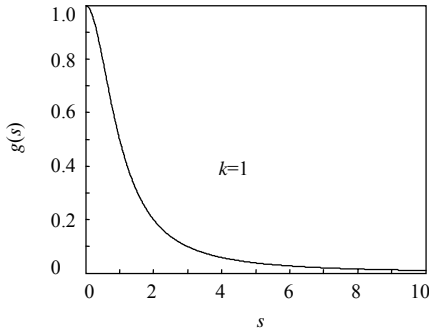


Fig.1 P-M diffusion coefficient

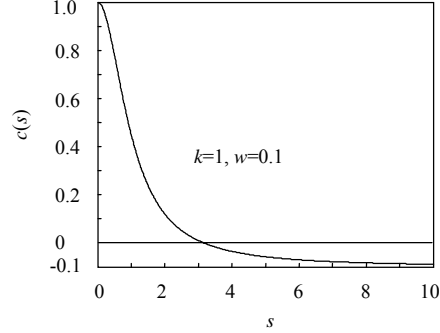


Fig.2 Proposed diffusion coefficient

From the chart, we can see that the diffusion process of the P-M model performs heavy smoothing for lower gradient areas and carries out light smoothing for higher gradient areas. Since the diffusion coefficient can only have a minimum value approximate to zero, the P-M model can only passively preserve the original gray-levels of edges. It cannot aggressively enhance the edges of a target to intensity the gray-level difference from the smoothed background. In contrast, the proposed diffusion model can actively perform the sharpening process when the diffusion coefficient becomes negative. For the dim-target detection in low-contrast images, the model can efficiently enhance target in the diffused image.

To the discrete digital image, the formula (6) is given as

$$I_{i,j}^{t+1} = I_{i,j}^t + \frac{1}{4}[c_t(N)N + c_t(S)S + c_t(E)E + c_t(W)W] \quad (8)$$

There:

$$N = I_{i-1,j}^t - I_{i,j}^t, \quad S = I_{i+1,j}^t - I_{i,j}^t, \quad E = I_{i,j+1}^t - I_{i,j}^t, \quad W = I_{i,j-1}^t - I_{i,j}^t$$

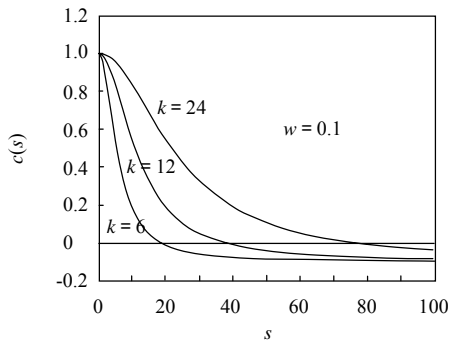


Fig.3 The influence of k

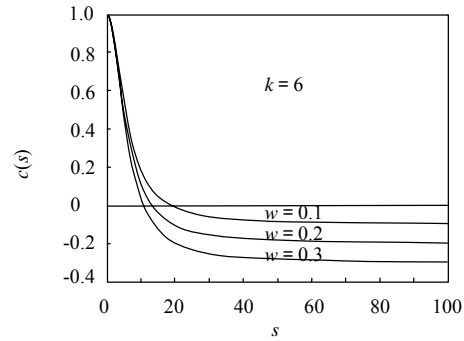


Fig.4 The influence of w

Where the improved diffusion coefficient is defined as

$$\begin{aligned} c_t(s) &= g(s) - w(1 - g(s)) \\ c_t(s) &= (1 + w) \times (1 / (1 + (s/k)^2)) - w \end{aligned} \quad (9)$$

From fig.3 and fig.4, we can the influence of the parameters k and the weight of sharpening coefficient w .

3 Experiment Results

In this section, we present experimental results for enhancing the dim-target in the low-contrast images with non-uniform gray scale. The algorithm was implemented on Pentium 4 personal computer using Visual C++ 6.0.

The images are 256 pixels \times 256 pixels size with 8-bit gray levels. From figure 5, we can see the enhancing results of dim-targets in low-contrast images. Figure 5 (a1) is the original image with low-contrast. Figure 5 (a2) is the contrast-stretched image, we can see the dim-targets in this image. Figure 5 (b1)~(b2) are the results of P-M diffusion method with $k=4$, iteration $n=30$ and $n=50$. Figure 5 (c1)~(c4) are the results of the proposed anisotropic diffusion method with the iteration $n=30$, the sharpening coefficient $w=0.1$ and with the $k=12, 24, 36, 48$ respectively. Figure 5 (d1)~(d4) are the results of the proposed anisotropic diffusion method with the iteration $n=30, k=48, w=0.1, 0.2, 0.3, 0.4$ respectively.

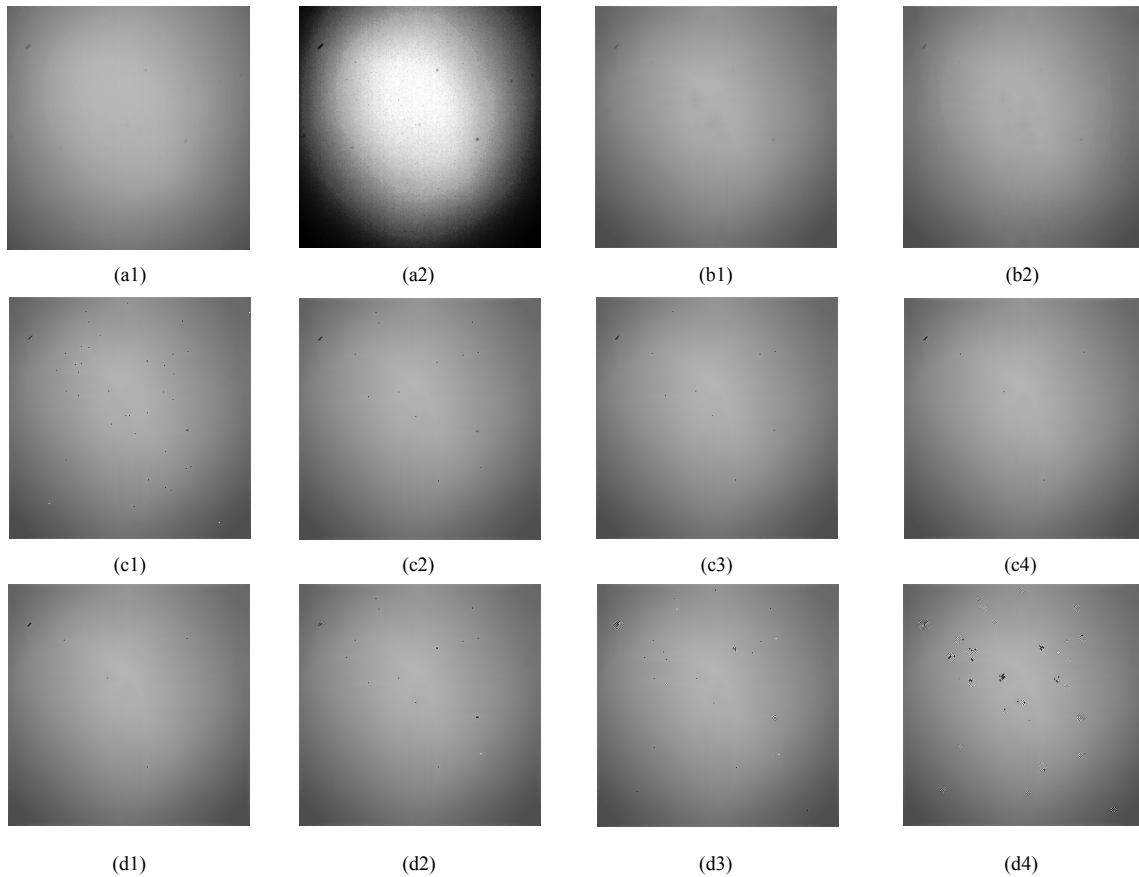


Fig.5 Enhancing results of dim-targets in low-contrast images

- (a1) the original image with low-contrast; (a2) contrast-stretched image;
 (b1)~(b2) P-M algorithm with different iteration;
 (c1)~(c4) the proposed anisotropic diffusion method with different k ;
 (d1)~(d4) the proposed anisotropic diffusion method with different w .

From figure 5 (b1)~(b2), the traditional P-M diffusion model can effectively perform the smoothing process to the background in the image. However, it can only passively stop the smoothing process to preserve original

gray values of dim-targets. For given parameters, the proposed diffusion model can automatically and adaptively perform the smoothing or sharpening process in an image according to the local gradient magnitudes. From figure 5 (c1)~(c4), we can see that if the k is lower, more dim-targets are enhanced, there will be too many noise points existing; inversely the targets only with higher magnitude are enhanced. Simultaneously, from figure 5 (d1)~(d4), the parameter w is also influence the dim-targets enhancement. Increasing w will enhance the degree of sharpening.

Above all, the selection of parameter k and w is crucial in the enhancement process. The parameter k determines the threshold of smoothing and sharpening. From figure 3 and figure 5 (c1)~(c4), we know, if the parameter k is small, the sharpening process will start at the lower gradient of image. Inversely, if the parameter k is large, the sharpening process will start at the higher gradient of image with more smoothing at lower gradient point. From figure 4 and figure 5 (d1)~(d4), the sharpening degree is determined by the parameter w . If the w is too large, there will be large oscillations. So the setting of k and w is based on the intensity characteristics and image content.

4 Conclusion

In this study, we have proposed an improved version of anisotropic diffusion for enhancing the dim-targets in the low-contrast image. It can efficiently perform smoothing and sharpening process according to the local gradient magnitudes, and enhance the dim-targets. However, the selection of parameters is needed to study further.

References:

- [1] POHLIG S C. Spatial-Temporal detection of electro-Optic moving targets [J]. **IEEE Trans. on Aerospace and Electronic System**, 1995, **31**(2) : 608-616.
- [2] Tzannes A P, Brooks D H. Detecting small moving objects using temporal hypothesis testing [J]. **IEEE Trans. on Aerospace and Electronic System**, 2002, **38**(2) : 570-585.
- [3] HUANG Kai-qi, WU Zhen-yang, WANG Qiao. Image enhancement based on the statistics of visual representation[J]. **Image and Vision Computing**, 2005, **23** : 51-57.
- [4] Pearse A Ffrench, James R Zeidler, Walter H Ku. Enhanced detectability of small objectives in correlated clutter using an improved 2-D adaptive lattice algorithm [J]. **IEEE Trans.on Image Processing**, 1997, **6** : 383-397.
- [5] Persona P, Malik J. Scale-space and edge detection using anisotropic diffusion [J]. **IEEE Transaction on Pattern Analysis and Machine Intelligence**, 1990, **12** : 629-639.
- [6] Catte F, coll T, Lions P L, et al. Image selective smoothing and edge detection by nonlinear diffusion [J]. **SIAM J Number Anal**, 1992, **29** : 182-193.
- [7] Chen Y, Barcelos C A Z. Smoothing and Edge Detection by Time-Varying Coupled Nonlinear Diffusion Equations [J]. **Computer Vision and Image Understanding**, 2001, **82** : 85-100.
- [8] Guy Gilboa, Nir Sochen, Yehoshua Y Zeevi. Forward-and-Backward Diffusion Processes for Adaptive Image Enhancement and Denoising [J]. **IEEE Transaction on image processing**, 2002, **11**(7) : 689-704.
- [9] FU Shu-jun, RUAN Qiu-qi, WANG Wen-qia. Feature Preserving Image Resolution Enhancement Using Adaptive Bidirectional Flow [J]. **Chinese Journal of Electronics**, 2006, **15**(1) : 103-107.
- [10] Chao S M, Tsai D M. Anisotropic diffusion-based defect detection for low-contrast glass substrates [J]. **Image and Vision Computing**, 2008, **26**(2) : 187-200.
- [11] Andres Fco Sole, Antonio Lopez, Guillermo Sapiro. Crease Enhancement Diffusion [J]. **Computer Vision and Image Understanding**, 2001, **84** : 241-248.