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Gaussian mixture model-based gradient field reconstruction for infrared image detail enhancement and denoising

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ABSTRACT

Infrared images are characterized by low signal-to-noise ratio and low contrast. Therefore, the edge details are easily immerged in the background and noise, making it much difficult to achieve infrared image edge detail enhancement and denoising. This article proposes a novel method of Gaussian mixture model-based gradient field reconstruction, which enhances image edge details while suppressing noise. First, by analyzing the gradient histogram of noisy infrared image, Gaussian mixture model is adopted to simulate the distribution of the gradient histogram, and divides the image information into three parts corresponding to faint details, noise and the edges of clear targets, respectively. Then, the piecewise function is constructed based on the characteristics of the image to increase gradients of faint details and suppress gradients of noise. Finally, anisotropic diffusion constraint is added while visualizing enhanced image from the transformed gradient field to further suppress noise. The experimental results show that the method possesses unique advantage of effectively enhancing infrared image edge details and suppressing noise as well, compared with the existing methods. In addition, it can be used to effectively enhance other types of images such as the visible and medical images.

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1. Introduction

Image enhancement technology plays an important role in the whole image processing [1,2] and has been applied to many areas, such as remote sensing image, medical image [3,4], stereo image and retinex image [5–7]. Generally, infrared images have small signal to noise ratio (SNR) and low contrast, therefore the edge detail is easily immerged in the background and noise, making it difficult for target detection and tracking [8,9]. In order to provide high-quality infrared image information for applications, it is necessary to enhance edge details and denoising. For noisy infrared images, edge details can be enhanced by traditional methods, but noise increases simultaneously. This is because the weak details are submerged in the noise. For example, the classic histogram equalization [10,11] algorithms produce an unsatisfactory result when they enhance noisy infrared images. Therefore, it is a challenge and necessary for infrared image detail enhancement and denoising.

Many improvements have been proposed such as platform histogram equalization [12,13] and double platform histogram equalization [8,14]. They enhance the image details and suppress noise by setting one or two platform thresholds. But it is difficult to properly choose the threshold values. Another method is based on histogram specification [15]. Wang et al. find the guiding function by maximizing the entropy, under the constraints that the mean brightness. Other typical methods for infrared image enhancement and denoising are based on wavelet transform [16–18]. Zhou et al. use a stationary multi-wavelet transform method to remove noise [16]. Wang et al. extract signal from noise according to phases and modulus maxima of dyadic wavelet transform coefficients of the infrared image, and the wavelet coefficients belonging to noise are eliminated at each scale [17]. Ni et al. combine wavelet modulus and local singularity into a joint conditional model to build an elementary edge map, then the edge map with geometric consistency is updated to reduce noise in infrared images while enhancing edges [18]. For most infrared images, the above wavelet-based methods can suppress noise and enhance edge details. However, the complexity of the wavelet-based methods limits their application in engineering.

Gradients of the image play an important role, where the gradients are big and image edge details are clear. Wang et al. uses the image gradient to adaptively determine the scale and orientation of anisotropic Gaussian filter, and this suppresses noise while preserving the edge details [19]. Zuo et al. enhance image texture and denoising by enforcing the gradient histogram of the denoised image to be close to a reference gradient histogram of the original image [20]. In [21], Zhao et al. enhance the edge details of the

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infrared image by constructing a Gaussian function to expand the gradient histogram. For noise-free images, it can achieve good results. However, for noise images, it enhances image details while increasing noise. In this paper, Gaussian mixture model-based gradient field reconstruction for infrared image detail enhancement and denoising is proposed. Gaussian mixture model is used to simulate the distribution of the gradient histogram, dividing the gradients into three ranges corresponding to faint details, noise and the edges of clear targets and background, respectively. Then, the piecewise function is constructed to increase gradients of faint details and suppress gradients of noise, which will be introduced in part A of Section 2. In order to further suppress noise, anisotropic diffusion constraint is added while reconstructing enhanced image from the converted gradient field, which will be introduced in part B of Section 2. The effectiveness of the proposed method will be discussed in Section 3, followed by a brief conclusion.

2. Proposed method

For a pixel $i(x_1,x_2) \subset \Omega$ in the infrared image $\mathbf{I}$, where $(x_1,x_2) \subset \Omega = [0,L-1] \times [0,W-1]$, if the gradient is $\nabla i(x,y)$, then gradient magnitude value $|\nabla i(x,y)|$ and gradient direction θ are defined as:

$$\nabla i(x,y) = \left[\frac{\partial i(x,y)}{\partial x}, \frac{\partial i(x,y)}{\partial y}\right] \tag{1}$$

$$|\nabla i(x,y)| = \sqrt{\left|\frac{\partial i(x,y)}{\partial x}\right|^2 + \left|\frac{\partial i(x,y)}{\partial y}\right|^2} \tag{2}$$

$$\theta = \arctan\left[\left|\frac{\partial i(x,y)}{\partial y}\right| \Big/ \left|\frac{\partial i(x,y)}{\partial x}\right|\right] \tag{3}$$

where ∇ represents the gradient operator. In order to obtain the gradient histogram of the infrared image, we calculate the histogram of the image using the gradient values instead of the gray level values. For example, the gradient magnitude map and gradient histogram of the infrared image are shown in Fig. 1.

As can be seen from Fig. 1(a), faint details of noisy infrared image are fuzzy, such as the windows of the ship. And the gradients of the faint details are small, as shown in Fig. 1(b). Fig. 1(c) is the gradient histogram of the noisy infrared image. It consists of three ranges: small gradient range corresponding to faint details, the transition range of the small gradients to large gradients mainly containing noise, and large gradient range corresponding to clear object edges. What we will do is using Gaussian mixture model to simulate the distribution of the gradient histogram, dividing the gradient histogram into the above three gradient ranges. Then, the piecewise function is constructed based on the characteristics of the correspondent gradient range to enhance the faint details while suppressing noise.

A. Gaussian mixture model-based gradient field enhancement

The gradient distribution $p^g(i^g)$, where $i^g = |\nabla i|$ is the gradient value of the pixel i, of the input image $\mathbf{I}$ can be modeled as a density function composed of a linear combination of functions [22]:

$$p^g(i^g) = \sum_{n=1}^{N} P^g(w_n) p^g(i^g|w_n) \tag{4}$$

where $P^g(w_n)$ is the prior probability of the Gaussian component w_n and $p^g(i^g|w_n)$ is the nth component density. The component density function is defined as:

$$p^g(i^g|w_n) = \frac{1}{\sqrt{2\pi\sigma_{w_n}^2}} \exp\left(-\frac{(i^g - \mu_{w_n})^2}{2\sigma_{w_n}^2}\right) \tag{5}$$

where μ_{w_n} and $\sigma_{w_n}^2$ are the mean and the variance of gradients of the nth component, respectively.

A Gaussian mixture model is completely determined by the parameters $\theta = \{P(w_n), \mu_{w_n}, \sigma_{w_n}^2\}_{n=1}^{N}$. In order to estimate θ, maximum-likelihood-estimation techniques are widely used, such as the expectation maximization (EM) algorithm [23]. Assuming the gradients $\nabla \mathbf{I} = \{i_1^g, i_2^g, \ldots, i_{L\times W}^g\}$ are independent, the likelihood of gradients $\nabla \mathbf{I}$ is computed as follows:

$$\zeta(\nabla \mathbf{I}; \theta) = \prod_{\forall k} p(i_k^g; \theta) \tag{6}$$

In order to easily analyze equation (6), the log-likelihood is used:

$$L(\nabla \mathbf{I}; \theta) = \log \zeta(\nabla \mathbf{I}; \theta) = \sum_{\forall k} p(i_k^g; \theta) \tag{7}$$

The goal of the estimation is to find $\hat{\theta}$ which maximizes the log-likelihood, which is expressed as:

$$\hat{\theta} = \arg\max_{\theta} L(\nabla \mathbf{I}; \theta) \tag{8}$$

The EM is a local optimization algorithm, and it is sensitive to initial value [23]. Here, we use its improved variant: the Figueiredo–Jain (FJ) algorithm [24], which overcomes the major shortcomings of the EM algorithm, for parameter estimation. It can automatically remove the data that is not supported in the process of estimation, which avoids the generation of the variation element. In addition, it sets an element for each sample, and allows an arbitrary initial value of the EM algorithm as the initial guess value of the element. The initial guess value can be distributed into the whole space by continuous sampling. The detailed description of the FJ algorithm can be found in Figueiredo and Jain's paper [24]. Fig. 2 illustrates the Gaussian mixture model distribution of the gradient histogram of Fig. 1(c).

As is shown in Fig. 2(a), the gradient histogram is modeled using three Gaussian components, i.e., $N = 3$. The close match between the gradient histogram (shown as blue line) and the

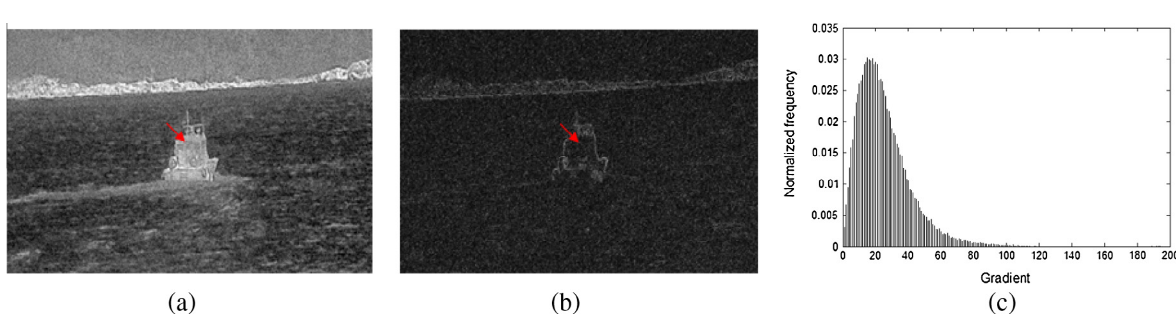

Fig. 1. An example about infrared image and its gradient histogram, (a) noisy infrared image; (b) gradient magnitude map; (c) gradient histogram, where the horizontal axis represents the gradient values and ordinate represents the normalized frequency of the gradient values.

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