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A total variation model based on edge adaptive guiding function for remote sensing image de-noising

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ABSTRACT

The unexpected noise generated during the process of remote sensing images formation and transmission process is a main factor undermining the images' quality and usage. In recent years, thanks to its local self-adapting characteristics, formal normalization, and modeling flexibility, PDE has received wide attention for its image de-noising functions, thus pushing the realization of maintaining image details while successfully de-noising a new goal for remote sensing images filtering. Having firstly analyzed and discussed the TV model and M model, a modified variation-model (S model for short) based on edge adaptive guiding function is proposed in this paper. The model introduces edge adaptive guiding function based on the standard gradient into the non-linear diffusion term and re-constructed approaching term, which adaptively adjust the smooth intensity around edge and texture information-rich regions of remote sensing images. S-model does not only overcome staircase effect that is easily produced in the TV model, but also avoids losing details and texture information which is often seen in M model, it can efficiently eliminate noises, maintain a good image edge and keep texture details perfectly. The experimental results validate the effectiveness and stability of the proposed model.

Introduction

Image recognition and analysis are often difficult due to the noises generated during image acquisition and transmission both internally and externally. So, it is necessary to remove the noises before using the pictures (Bo and Wang, 2003). Image noise analysis, evaluation and filtering are always hot research areas in remote sensing image processing (Lianru et al., 2007; Song et al., 2009; Wang et al., 2010). The transformation or degradation to which an image is subjected during formation, transmission and recording processed is in general the result of two phenomena. The fist one is deterministic and is related to the mode of image acquisition. The second is a random phenomenon and corresponds to the inherent noise coming from the quantum nature of light emission (Ding and Bian, 2009). Denoising is the problem that only takes into account the random phenomenon and it consists of removing noise from an image. The most commonly studied noise model is additive white Gaussian noise, where the observed noisy image f is related to the underlying true image u by the degradation model $f = u + n$, and n is supposed to be at each point in space independently and identically distributed as a zero mean Gaussian random variable (Lianru et al., 2007; Song et al., 2009; Wang et al., 2010; Ding and Bian, 2009).

In recent years, total variation image processing based on partial differential equation (PDE) has become a new image processing tool after wavelet as it received more attentions due to its edge-preserving (Ding and Bian, 2009; Lin and Qin, 2011; Gilboa et al., 2002a; Chen, 2005). To introduce PDE into image noise reduction, target detection and other problems derives from the concept of multi-scale proposed by Jain and Farroihnia (1991). The classical TV model (Rudin et al., 1992) has a good edge retention when de-noising. However, the TV model may not comply entirely with image morphology principle, and the stationary solution always has an apparent staircase effect under a great noise situation. To avoid the staircase effect, Marquina and Osher (2000) proposes a modified method based on the TV model. The method inherits the merits of TV model. But when the image is blurry and rich of texture and details, the method can lose some important image information easily. Gilboa et al. (2002b) proposes FB algorithm based on the TV model, which can both effectively eliminate the noise and maintain the image edge well. Nevertheless, it makes the edge sharpen

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exceedingly and easily produces more staircases at the same time (Saradhadevi and Sundaram, 2011; Dai, 2011).

Many algorithms for TV-denoising have been developed, especially for the Gaussian noise model. To name a few, there are algorithms based on duality. Newton-based method (Alvarez and Morel, 1994), graphcuts (Goldstein and Osher, 2009), frame shrinkage (Galatsanos and Katsaggelous, 1992; Ciarlet, 1990), and operator splitting methods, particularly the split Bregman algorithm discussed in the paper by Getreuer (Aujol, 2009; Nikolova, 2000).

To effectively eliminate noises and keep image details, the paper primarily analyzed the TV model and proposed an edge-adaptive guiding function based on standard gradient. The proposed model can efficiently eliminate noises in remote sensing images and maintain image edge information and texture details greatly. The experiment results validate the effectiveness and stability of the proposed model.

A variation-model

The joint total variation cost functional is alternating minimized with respect to the estimation of the image and PDE within certain criterion (Feng and Wang, 2009). As practiced in the variational methodology, it is more convenient to solve the de-noising problem:

$$\min E(u) = \int_{\Omega} \varphi(\left|\nabla u\right|) d\Omega + \frac{\lambda}{2} \int_{\Omega} (u - u_0)^2 d\Omega \tag{1}$$

The Euler–Lagrange equation for the functional is:

$$div\left(\frac{\phi'(\left|\nabla u\right|)}{\left|\nabla u\right| \nabla u}\right) + \lambda(u_0 - u) = 0 \tag{2}$$

where ϕ is a strict non-decreasing convex function and satisfied with $\phi(0) = 0$ and $\lim_{x\to\infty} \phi(x) = \infty$.

Qsher proposed the TV model in Rudin et al. (1992), let $\varphi(\left|\nabla u\right|) = \left|\nabla u\right|$ in Eq. (1), and the cost function can be minimized in the following form:

$$\min E(u) = \int_{\Omega} \left|\nabla u\right| dxdy + \frac{\lambda}{2} \int_{\Omega} (u - u_0)^2 dxdy \tag{3}$$

In Eq. (3), $\int_{\Omega} \left|\nabla u\right| dxdy$ is the regularization term with respect to image smoothing, de-noising and edge- keeping, $\int_{\Omega} (u - u_0)^2 dxdy$ is the fidelity term with respect to reflecting the difference of the restored image u and the observed image u_0, $\lambda (\lambda > 0)$ plays the role of balance the regularization term and fidelity term.

The evolution equation according to the Euler–Lagrange is:

$$\begin{cases} \dfrac{\partial u(x, y, t)}{\partial t} = div\left(\dfrac{\nabla u}{\left|\nabla u\right|}\right) + \lambda(u_0 - u) \\ u(x, y, t)|_{t=0} = u_0(x, y) \end{cases} \tag{4}$$

for all $(x, y) \in \Omega$ and $t > 0$.

The TV model is good at keeping image edge (Osher, 2003), but it does not conform to image processing morphology principle exactly. For example, when u is replaced by $h(u)$ satisfied with $h'(u) > 0$, $h(0) = 0$ and $h(255) = 255$, Eq. (4) will change even if $\lambda = 0$. That is to say, Eq. (4) changes with image level set as well as image gray value u. It leads to the obvious staircase effect in fact.

To solve the above problem, Marquina and Osher improved the TV model (Marquina and Osher, 2000). Gradient magnitude $\left|\nabla u\right|$ is multiplied on the right side of Eq. (4). And then we got a improved model as follows (M model for short):

$$\begin{cases} \dfrac{\partial u(x, y, t)}{\partial t} = \left|\nabla u\right| div\left(\dfrac{\nabla u}{\left|\nabla u\right|}\right) + \left|\nabla u\right| \lambda(u_0 - u) \\ u(x, y, t)|_{t=0} = u_0(x, y) \end{cases} \tag{5}$$

It is considered that we combine the non-diffusion term $\left|\nabla u\right| div\left(\frac{\nabla u}{\left|\nabla u\right|}\right) = \kappa \left|\nabla u\right|$ and Hamilton–Jacobi term $\left|\nabla u\right| (u_0 - u)$ in M model. The former is the pure anisotropic diffusion mentioned in Alvarez and Morel (1994), and it will not cause image singularity, control the image diffusing only in the orthogonal direction of image gray-grad. So the image smooths both inside and onsides fully. Since eliminating the noises of image by the diffusion term is similar to processing the image with mid-filter, the diffusion term has a good effect on reducing the salt-pepper noises of remote sensing images. Compared with the TV model, the M model in Osher (2003) can satisfy morphology principle and restrain the staircase effect to some degree by loosening the Courant Friedrichs Lewy (CFL) condition and the gray transformation of u and u_0 in Eq. (5). However, experiments show that the M model may lose some important details and texture information due to its over diffusion for the remote sensing images.

The variation model based on edge adaptive guiding function

Standard gradient

Be different from traditional gradient, standard gradient filer Gaussian noise on the image so it reduces the edge noise to a certain extent. And it also induction the information of image covariance that keeps the image detail well. The simple image gradient is to compute a directional change in the intensity of the image. Each pixel of a gradient image measures the change in intensity of the same point in the original image and in a given direction. We may use a gradient function which is called the normal gradient modulus function. That smoothing on both sides of an edge is much stronger than smoothing across it, which will keep the edge of the image information better.

Supposing that the size of the noise image is $M \times N$, then the result of Gaussian filter $f(x, y)$ is as follows:

$$f(x, y) = \frac{1}{2\pi MN} \sum_{i=1}^{M} \sum_{j=1}^{N} K(x - i) K(y - j) u(i, j) \tag{6}$$

where $K(x) = 1/\sqrt{2\pi}\sigma \exp(-x^2/2\sigma^2)$, σ is variance and $u(i, j)$ is the gray value at point (i, j).

The partial derivative of $f(x, y)$ in the direction of x and y is:

$$\begin{cases} f_x = \dfrac{1}{2\pi MN} \displaystyle\sum_{j=1}^{N} K(y - j) \left\{ \sum_{i=1}^{M} K'(x - i) u(i, j) \right\} \\ f_y = \dfrac{1}{2\pi MN} \displaystyle\sum_{i=1}^{M} K(x - i) \left\{ \sum_{j=1}^{N} K'(y - j) u(i, j) \right\} \end{cases} \tag{7}$$

And the variance between the original image and the processed image by Gaussian filter is:

$$D^2 = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (u(i, j) - f(i, j))^2 \tag{8}$$