Iterative Regularization Denoising Method Based on OSV Model for BioMedical Image Denoising

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Abstract Biomedical image denoising algorithm based on gradient dependent energy functional often compromised the biomedical image features like textures or certain details. This paper proposes an iterative regularization denoising method based on OSV model for biomedical image denoising. By using iterative regularization, the oscillating patterns of texture and detail are added back to fit and compute the original OSV model, and the iterative behavior avoids overfull smoothing while denoising the features of textures and details to a certain extent. In addition, the iterative procedure is proposed in this paper, and the proposed algorithm also be proved the convergence property. Experimental results show that the proposed method can achieve a batter result in preserving not only the features of textures for biomedical image denoising but also the details for biomedical image.

1. Introduction
Image denoising methods aim at recovering the original image from a noisy measurement. Such a research has significant theoretic values in the general fields of image processing¹. In the past decade, the representative research achievements obtained at edges and details preserving smoothing based on nonlinear image filter method, including minimizer of energy functional method, regularization method, anisotropic diffusion method and nonlinear digital filter method. Compared the other denoising methods, Image denoising algorithm based on gradient dependent energy functional preserved more edges of the biomedical image than other denoising algorithm, but it often compromised the biomedical image features like textures or certain details². At Present, the details of the texture and details of biomedical image denoising technique consists mainly of two types: one is to adjust parameters of the adaptive variational method ³, at different scales of space down noise, thereby maintaining the texture; another is to medicine image space by the BV space up to the G space ⁴ or other space in order to maintain the texture and detail, in the instance of the application of both methods achieve a certain effect, but all these method will lose the detail and texture in some extent⁵. This paper would propose an denoising method based on OSV model for biomedical image denoising, iterative regularization is added to modified the noises image, in order to achieve better results.

2. Method

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In this paper, the oscillate decomposition model of image Characteristic Waveforms with textures or details Based on Meyer is introduced. Meyer’s model divides the image into two parts: \( f = u + v \), where \( u \) is the part of structure feature information of decomposition image, and \( v \) is the part of textures details or noise information. The model expatiate the oscillate decomposition from the theoretical perspective, and establish the decomposition and denoising model based on minimizer of energy functional method. Through using of dual space(G space), the model improve and expand the application of BV space. The G space is defined as:

\[
G = \{ v \mid v = \partial_x g_1(x, y) + \partial_y g_2(x, y), g_1, g_2 \in L^2(\Omega) \}
\]

The norm of the space is:

\[
\| v \|_G = \inf_{g \in (g_1, g_2)} \{ \sqrt{\| g_1 \|_2^2 + \| g_2 \|_2^2} \mid v = \partial_x g_1 + \partial_y g_2 \}
\]

If image \( f \in L_2(\Omega), \Omega \subset \mathbb{R}^2 \), the Me ye’s model is

\[
E(u) = \int _\Omega | \nabla u | + \lambda \| v \|_G, f = u + v
\]

Where the oscillate degree of textures information \( v \) could be computed with \( \| v \|_G \). Because the value is difficult to be computed in G space, there is no general method to the minimize the Euler-Lagrange equation. Some approximation models for Me ye’s model are proposed, and the model with better effect is OSV model which is improved from V O model by Osher, Sole and Vese:

\[
\begin{align*}
E(u) &= \int _\Omega | \nabla u | + \lambda \int _\Omega | \nabla \Delta^{-1}(f - u) |^2, f = u + v \\
&= \| u \|_{L^1(\Omega)} + \lambda \| f - u \|_{L^2(\Omega)}, f = u + v
\end{align*}
\]

Through using OSV model and other different norm of the model can preserved overmuch smoothing the image texture details when denoising with the variational models of ROF in a certain extent, but it still has many improvement of space.

3. Numerical analyses

In order to preserve more features of textures and the details for biomedical image, we fixed the original OSV model, added an iterative regularization. The iterative behavior avoids overfull smoothing while denoising the features of textures and details to a certain extent.

Step 1: We fix the original OSV model as:

\[
u_i = \text{arg min}\{ | \nabla u | + \lambda \int _\Omega | \nabla \Delta^{-1}(f - u) |^2 \}
\]

And define

\[
n_i = \frac{\nabla u_i}{| \nabla u_i |}
\]

Step 2: Through further revision, the fixed OSV model can express as:

\[
u_i = \text{arg min}\{ | \nabla u | - \Delta^{-1} n_i \nabla u) + \lambda \int _\Omega | \nabla \Delta^{-1}(f - u) |^2 \}
\]

Apparently, \(-\int n_i \nabla u = \int u \nabla \cdot n_i = \int u \nabla (\frac{\nabla u_i}{| \nabla u_i |})\)

At the same time, \( f = u_i + v_i \), so \( \nabla \cdot \frac{\nabla u_i}{| \nabla u_i |} = \frac{\nabla u_i}{| \nabla u_i |} = -2\lambda (f - u_i) = -2\lambda v_i\)

And \(-\int n_i \nabla u = -2\int \lambda u v_i\), we substitut it into the result of step 2, then continue to calculate the equation:
\[ u_2 = \arg \min \left\{ \int (|\nabla u|) + \lambda \int |\nabla \Delta^{-1} (f - u)^2 - 2uv_1| \right\} \]

\[ = \arg \min \left\{ \int (|\nabla u|) + \lambda \int |\nabla \Delta^{-1} (f + v_1 - u)|^2 - \lambda \int (v_1^2 + 2v_1f) \right\} \]

(7)

Where the last item \( \lambda \int (v_1^2 + 2v_1f) \) isn’t restricted by \( u \). Therefore, we only need to calculate in front of two items:

\[ u_2 = \arg \min \left\{ \int (|\nabla u|) + \lambda \int |\nabla \Delta^{-1} (f - u + v_1)|^2 \right\} \]

(8)

The iterative regularization model:

In our method, the noised item \( v_1 \) computed from the previous calculations is added to the result \( f \) of original image, then the original equation is constantly updated and modified to get more accurate results.

The proposed algorithm as follows:

- initialize \( u_0 = 0, v_0 = 0 \);
- let \( k = 0,1,2, \ldots \) using OSV model to calculate the results \( u_{k+1} \):

\[ u_{k+1} = \arg \min \left\{ \int (|\nabla u|) + \lambda \int |\nabla \Delta^{-1} (f - u_k + v)| \right\} \]

(9)

- Update \( v_{k+1} \):

\[ v_{k+1} = f + v_k - u_{k+1} \]

(10)

In the iterative process of solving, we need to consider the variational problem of step 2. The corresponding Euler-Lagrange equation as follow:

\[ 2\lambda \Delta^{-1} (f + v - u) = \text{div} \left( \frac{\nabla u}{|\nabla u|} \right) \]

(11)

The iterative regularization model is:

\[ u_i = -\frac{1}{2\lambda} \Delta \left[ \text{div} \left( \frac{\nabla u}{|\nabla u|} \right) \right] - (u - v - f) \]

(12)

4. Results

In order to validate the result of image enhancement and denoising worked with the scheme in this paper, we choose heart image which add standard deviations std =15 of the white Gaussian noise, compare the effects with different models.

Figure 1 shows the results of image denoising with original OSV model, our models with parameters: iterations=3, and our models with parameters: iterations=6. Contrasting Fig. 1(d) to Fig. 1(c), we can notice that the original OSV model could only preserve the great vessels of the heart in Fig. 1(c), while the details of the capillary vessels are smoothed in excess. the details in Fig. 1(d,e) are preserved great better than the same parts in Fig. 1(c), the capillary vessels are reserved in more distal. And PSNR in Fig. 1(d,e) are 18.8391 and 19.4425, are also bigger than PSNR in Fig. 1(c) 18.0885.

Experimental results show that this iterative regularization method obtain good results in both subjective and objective, the proposed method can achieve a batter result in preserving not only the features of textures for biomedical image denoising but also the details for biomedical image.
5. Conclusions
Some processes based on the original OSV model filters are presented, moreover, the principles, and the problem of them are analyzed. A new iterative regularization denoising Method Based on OSV Model is presented for image smoothing in this work. The noised item computed from the previous calculations is added to fix the result of original image. Then, the new Iterative Regularization is constantly updated and modified to get more accurate results. The new denoising method based on OSV Model can not only well restrain noise but also keep much more textures details of a biomedical image. Experimental results also show that the effectiveness for biomedical images denoising with our method is better than the original method’s.

Fig. 1(a-e). Filtering a heart image.
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