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Medical Image Denoising Using Bilateral Filter and the K-SVD Algorithm

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Abstract. Medical images are inevitably affected by noise in the acquisition process. This paper describes an image denoising method based on bilateral filter and the K-SVD algorithm. Firstly, the method uses bilateral filter to divide the image into edge layer and residual layer. Then the K-SVD algorithm is used to process the residual layer of the image to avoid damaging the edges of the image. Finally, the image denoising result is obtained by adding residual layer and edge layer. The experimental results for image with different intensity noise show that the proposed method can acquire higher peak signal-to-noise ratio (PSNR) than the K-SVD algorithm. In the denoising experiments of computed tomography (CT) and magnetic resonance (MR) images, the proposed method can obtain clearer soft tissue and bone structure than the K-SVD algorithm.

1. Introduction
Medical images are now widely used in disease diagnosis and disease treatment. The quality of medical images directly affects the diagnosis of diseases, image segmentation, image registration etc. In the process of image acquisition, it is inevitable to be interfered by various noise sources. Therefore, image denoising is a significant step in medical image preprocessing. The existing image denoising algorithms are divided into spatial domain algorithms and transform domain algorithms. The bilateral filtering algorithm [1] effectively protects the edges of the image while smoothing the image by introducing the weight of the image pixel similarity. By dividing the image into patches and utilizing the self-similarity of the image, the non-local mean filtering algorithm [2] protects the texture of the image while denoising. Another patch-based algorithm BM3D [3] achieves remarkable results by combining spatial domain algorithm with transform domain algorithm. With the rapid development of sparse representation theory, image denoising algorithm based on dictionary learning has shown excellent results, and is a hot research topic in the field of image denoising.

Since medical images contain rich edge details, this paper proposes a method based on K-SVD algorithm [4] to avoid loss of edge information while image denoising. Firstly, the edge layer and residual layer of the original image are obtained by using bilateral filter. Then K-SVD is used to denoise the residual layer. Finally, the image denoising results are obtained by adding residual layer and edge layer.

2. Background
In this section, we briefly introduce the bilateral filter and the K-SVD image denoising algorithm.

2.1Bilateral filter

Bilateral filter is a non-linear filter based on local image information [1]. Since the bilateral filter comprehensively considers the pixel value information and spatial position information of the image, the bilateral filter can well protect the edge of the image while denoising. Bilateral filter use weighted averaging of neighborhood to replace each noise pixel. This can be represented as,

$$f(x) = \frac{1}{w_h} \sum_{y \in \Omega} w_s(x, y) w_r(x, y) I(y) \tag{1}$$

where $f(x)$ is the output pixel value of the filter, $I(y)$ is any other pixel in the original image as the input of the filter, Ω is the neighborhood of pixel x, w_h is the normalization coefficient expressed as $w_h = \sum_{y \in \Omega} w_s(x, y) w_r(x, y)$, w_s is the spatial kernel, w_r is the range kernel. w_s is expressed as $w_s = exp(-\frac{|x-y|^2}{\sigma_s^2})$, and σ_s is smoothing parameter. w_r is expressed as $w_r = exp(-\frac{|I(x)-I(y)|^2}{\sigma_r^2})$, and σ_r is smoothing parameter.

2.2The K-SVD image denoising algorithm

The K-SVD algorithm first breaks the image into overlapping patches, and then denoises these patches by iteratively performing sparse decomposition and sparse dictionary learning [4]. Finally, these denoised patches are restored to the size of the original image by weighted averaging. Sparse decomposition can be expressed as,

$$\min_{\alpha} \|\alpha\|_0 \qquad s.t. \|D\alpha - x\|_2^2 < \epsilon^2 \tag{2}$$

where x is a noisy image patch and $x \in \mathbb{R}^n$, D is overcomplete dictionary and $D \in \mathbb{R}^{n \times m}$, α is sparse representation vector and $\alpha \in \mathbb{R}^m$, ϵ indicates error, $\|\alpha\|_0$ is ℓ_0 pseudo-norm,which counts the number of non-zero components of α. Sparse decomposition is a known NP-hard problem. Therefore, OMP [5] is used here to approximate the solution of this problem. Sparse dictionary learning aims at finding a better dictionary D. The K-SVD algorithm uses a strategy that updates a column in the dictionary D each time. This can be represented as:

$$\|Y - DX\|_F^2 = \left\| Y - \sum_{j=1}^{k} b_j a^j \right\|_F^2 = \left\| \left(Y - \sum_{j \neq i} b_j a^j \right) - b_i a^i \right\|_F^2 = \left\| E_i - b_i a^i \right\|_F^2 \tag{3}$$

Next use SVD to decompose E_i into $U\Delta V^T$. b_i is updated to the first column of U,and a^i is updated to the first column of $V \times \Delta(1,1)$.

3. The Proposed Method

K-SVD can denoise while protecting the texture information of the image, but K-SVD will damage the edge information of the image while denoising. Spatial domain denoising algorithms such as bilateral filter can protect the edges of the image but damage the low-contrast texture [6]. Therefore, we use bilateral filter to preprocess the image and decompose the image into an edge layer and a residual layer. The edge layer contains the edge information of the image, and the residual layer contains the noise of the image and the texture details of the image. As shown in figure 1, K-SVD is used to process the residual layer, thus avoiding K-SVD from damaging the edges of the image while denoising. Finally, the denoising results of the residual layer and the edge layer are superimposed to obtain the output of the algorithm.

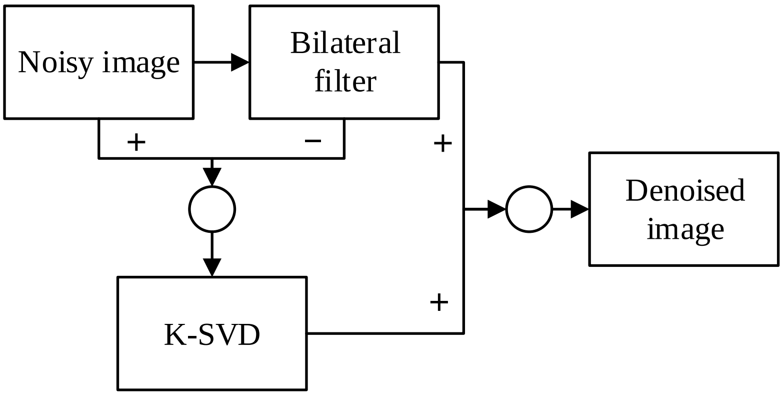


Figure 1. A Block diagram of the proposed method.

As shown in figure 2, the bilateral filter can effectively separate the texture and edges of the image. The noisy image is obtained by adding white Gaussian noises with standard deviation$\sigma=30$ to the original image. As described in the section 2, the filtering results of bilateral filter depend on the filtering parameters σ_s and σ_r.As proposed in [7], we have selected empirical values for the bilateral filter parameters.

(a) (b) (c)

Figure 2. (a) Noisy image ($\sigma = 30$). (b) Result image of bilateral filter. (c) Residual image.

4. Experimental Result

We evaluated the proposed method through widely used test image barbara. It is usually assumed that the image is contaminated by additive white Gaussian noise (AWGN). All experiments in this paper follow this assumption. We add three different intensities of noise to the image. The low intensity noise standard deviation $\sigma = 10$, the medium intensity noise standard deviation $\sigma = 20$, and the high intensity noise standard deviation $\sigma = 30$. As shown in table 1, algorithms are evaluated by calculating PSNR after image denoising. As shown in (2), the result of sparse decomposition is determined by the error ϵ. As proposed in [8], the value of ϵ is linear with σ. ϵ is define as $\epsilon = \sqrt{n}C\sigma$ where n is the size of image patch. As shown in table 1, the method proposed in this paper obtains a higher PSNR denoising image under different intensity noises at $C = 0.5$.

Table 1. PSNR (dB) results for various algorithms using barbara with different intensity noise. Bold indicates the best result.

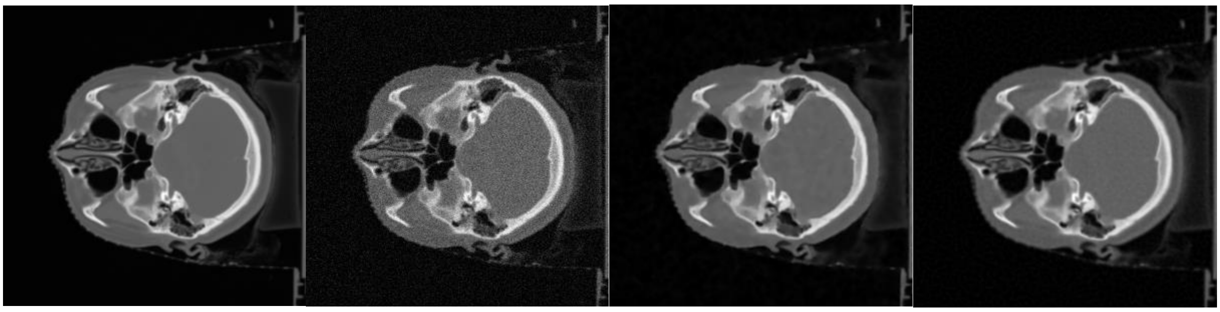
Noisy level(σ)	K-SVD	BM3D	The proposed method
10	34.43	34.98	**39.78**
20	30.80	31.78	**34.21**
30	28.53	29.81	**30.72**

Parameter C is used in the stopping condition of the OMP. As shown in table 2, with the decrease of the parameter C, the proposed method can obtain a higher PSNR, which is different from the the K-SVD algorithm. However, with the decrease of C, the proposed method needs to spend more time in the sparse decomposition stage. Therefore, in order to balance the denoising effect and the time consumed by the algorithm, C is set to 0.5.

Table 2. The effect of different parameters C on the PSNR result using barbara with noise($\sigma = 30$).

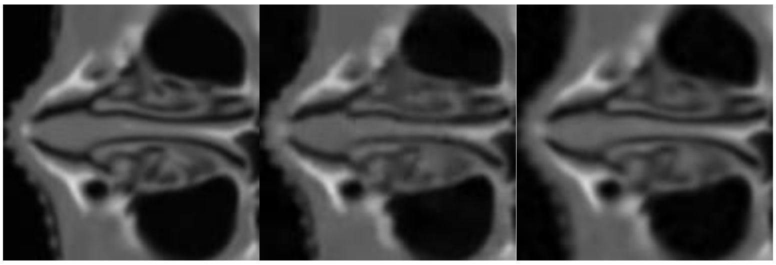
The value of C	0.6	0.5	0.4	0.3	0.2
PSNR(dB)	29.59	30.72	32.44	34.57	37.55

As shown in figure 3, head CT image with rich edge information are used to test the edge protection ability of algorithms. The results of the proposed method are visually closer to the original image versus K-SVD. As shown in the partial enlarged view of figure 4, the edges of the image processed by the K-SVD algorithm are too smooth. The results of the proposed method contain a clearer edge. Cone beam computed tomography (CBCT) is widely applied in image-guided radiation therapy (IGRT) because of its fast scanning speed, low radiation dose and easy integration with radiotherapy equipment [9]. As shown in figure 5, the proposed method obtains a result image with a clearer bone structure than K-SVD. And the result image of the proposed method has fewer artifacts than the original image. As shown in figure 6, soft tissue is preserved better by the proposed method than K-SVD. Because of the protection of the edges of the image, the proposed method can obtain clearer soft tissue and bone structure in the denoising of CT and MR images.



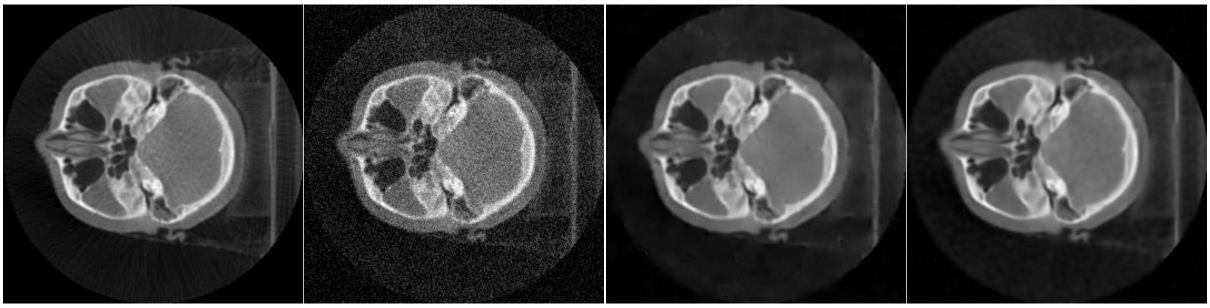
(a) (b) (c) (d)

Figure 3. (a) Original head CT image. (b) Head CT image with noise ($\sigma = 20$). (c) Result image of the K-SVD algorithm. (d) Result image of the proposed method.



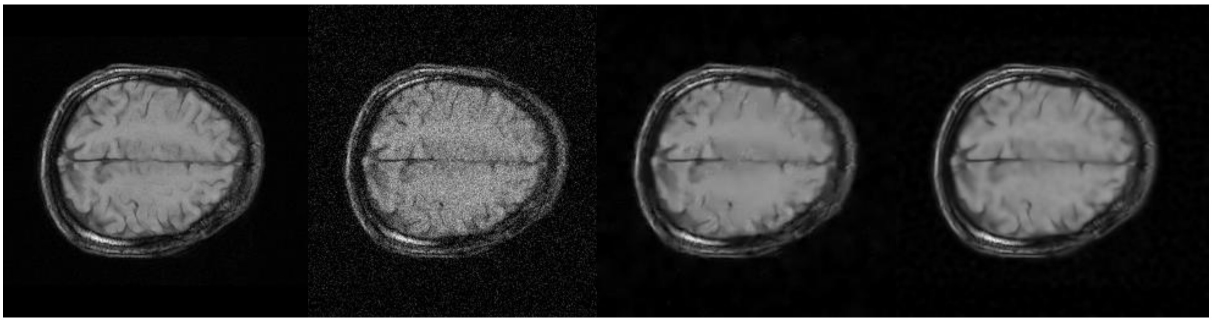
(a) (b) (c)

Figure 4. (a) Partially enlarged view of the original. CT image (b) Partially enlarged view of the result image of the K-SVD algorithm. (c) Partially enlarged view of result image of the proposed method.



(a) (b) (c) (d)

Figure 5. (a) Original head CBCT image. (b) Head CBCT image with noise ($\sigma = 20$). (c) Result image of the K-SVD algorithm. (d) Result image of the proposed method.



(a) (b) (c) (d)

Figure 6. (a) Original brain MR image. (b) Brain MR image with noise ($\sigma = 20$). (c) Result image of the K-SVD algorithm. (d) Result image of the proposed method.

5. Conclusion

Sparse representation theory has been widely used in image denoising, image compression and super-resolution reconstruction. The denoising algorithm based on sparse representation theory can restore texture details better than the traditional algorithm for medical images. The improved method proposed in this paper separates the edge and texture of the image, and denoises the texture part of the image using K-SVD. Considering the protection of image edge, the method proposed in this paper can obtain clearer result images of soft tissue and bone structure. This method has practicality in the preprocessing of medical images. Next, we will study how to reduce the time complexity of the algorithm.

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