PSO Aided Adaptive Multiscale Products Thresholding for Magnetic Resonance Images

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Abstract

Edge-preserving denoising is an important task in medical image processing. In this paper a wavelet-based multiscale products thresholding scheme for noise suppression of magnetic resonance images optimized by PSO algorithm has been proposed. To exploit the wavelet inter scale dependencies, adjacent wavelet subbands are multiplied to enhance edge structures while weakening noise. In the multiscale products, edges can be effectively distinguished from noise and an adaptive threshold is calculated and imposed on the products, instead on the wavelet coefficients, to identify an important feature which is optimized by PSO algorithm. Experiments show that the proposed scheme is better optimized and suppresses noise and preserves edges than other wavelet-thresholding denoising methods.

Keywords: denoising, magnetic resonance image, multiscale products, thresholding, wavelet transform.

1. Introduction

Magnetic Resonance Imaging (MRI) is a powerful diagnostic technique. Time averaging of image sequences aimed to improve the signal-to-noise ratio (SNR) would result in additional acquisition time and reduce the temporal resolution. The denoising should be performed to improve the Image quality for more accurate diagnosis. Denoising can be applied to the real and imaginary channels rather than to the magnitude images. This technique has proved to be effective [6]-[8].In view of this, the additive Gaussian white noise model is adopted in this paper. In this paper, multiscale thresholding scheme to incorporate the merits of interscale dependencies is presented for medical image denoising. Two adjacent wavelet subbands are multiplied to amplify the significant features and dilute noise. In contrast to other schemes, thresholding is applied to the multiscale products instead of the wavelet coefficients and it can distinguish edge structures from noise more effectively. The variance of noise needs to be estimated to implement the denoising scheme. A noise level estimator optimized by PSO algorithm is also proposed in this paper.

The rest of the paper is organized as follows: section II details on wavelet multiscale products, section III briefs on adaptive multiscale product thresholding, section IV deals with PSO optimization, section V with experimental results and sec VI with results.

2. Wavelet Multiscale Products

2.1 Dyadic Wavelet Transform as a Multiscale Edge Detector

A wavelet transform represents a signal as a linear combination of elementary atoms that appear at different resolutions. It is computed by convoluting the input signal with dilated wavelet filters recursively. More details about the theory of wavelets and their applications in signal processing can be found in Daubechies [1], Meyer [2], Mallat [3], [4], and Vetterli[5]. The continuous wavelet transform of any measurable and square-integrable function $f(x), f \in L^2(R)$, at scale s and position x is defined as

$$W_s f(x) = f * \psi_s(x) \tag{1}$$

Where the symbol * denotes the convolution operation.

Then, $W_s f(x)$ can be written as

$$W_s f(x) = f * (s\frac{d\theta_s}{dx})(x) = s\frac{d}{dx}(f * \theta_s)(x) \tag{2}$$

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It can be seen that the wavelet transform $W_s f(x)$ is the first derivative of $f(x)$smoothed by $\theta_s(x)$ In particular, when $\theta(x)$ is a Gaussian function, the local extrema determination in $W_s f(x)$ is equivalent to the well-known Canny edge detection [9].The DWT of $f(x)$ at dyadic scale2^j and position x is

$$W_j f(x) = f * \psi_j(x) \quad (3)$$

The function $f(x)$ can be recovered from its DWT by

$$f(x) = \sum_{j=-\infty}^{\infty} Wjf * xj(x) \quad (4)$$

The wavelet used in this paper is the MZ wavelet constructed by Mallat and Zhong [4]. The wavelet is a quadratic spline that approximates the first derivative of Gaussian. Thus, the DWT behaves like a canny edge detector. Details about the derivation of the MZ wavelet can be found in [4].

2.2 Multiscale Products

Multiplying the DWT at adjacent scales would amplify edge structures and dilute noise. This favorite property has been exploited by Xu *et al.* [10] and Sadler [11] in noise reduction and step detection. In this paper, the multiscale products of $W_j f$ is defined as

$$p_j f(x) = \prod_{i=-k1}^{k2} w_{j+i} f(x) \quad (5)$$

Where $k1$ and $k2$ are non negative integers and an isolate edge will increase by two. So it is sufficient to implement the multiplication at two adjacent scales. Then the DWT scale product is

$$p_j f(x) = W_j f(x).W_{j+1} f(x) \quad (6)$$

3. Adaptive Multiscale Products Thresholding

3.1 The Thresholding Scheme

In this paper, a de-noising scheme, the *adaptive multiscale products thresholding*, to merge the merits of the thresholding technique and wavelet interscale dependencies is proposed. The algorithm is summarized as follows.

1) Compute the DWT of input image f up to J scales.

2) Calculate the multiscale products $P_j^d f$ and preset the thresholds $t_p^d(j)$. Then threshold the wavelet coefficients by

$$\hat{W}_j^d f(x,y) = \{W_j^d f(x,y) \; P_j^d f(x,y) \geq t_p^d(j)$$

$$P_j^d f(x,y) < t_p^d(j)$$

$$j = 1, ..., J; d = x, y. \quad (7)$$

3) Recover the image from the thresholded wavelet coefficients $\hat{W}_j^x f(x,y)$ and $\hat{W}_j^y f(x,y)$.

3.2 Determination of the Threshold

Here the multiscale products threshold is set as

$$t_p^*(j) = 5kj\left(1 + \frac{\mu_\varepsilon^*(j)}{\mu_g^*(j)}\right) \quad (8)$$

3.3 Noise Level Estimation

The standard deviation of an additive Gaussian white noise σ should be estimated to implement the denoising scheme. The Median Absolute Value (MAV) of the wavelet coefficients at the finest scale is firstcalculated and the standard deviation of noise is then estimated a noise level estimation method is also used here. Orthogonal Wavelet Transform (OWT) is computed. OWT is a unitary trans-form, at each wavelet scale the noise standard deviation is equal to σ . Thus, the variance of W is

$$\sigma_f^2 = E\left[W^2\right] = \sigma_g^2 + \sigma^2 \quad (9)$$

Finally, the noise level can be estimated as

$$\hat{\sigma} = \frac{\sigma f}{\sqrt{1 + r^2}} \quad (10)$$

4. PSO Optimization

PSO has a fitness evaluation function to compute each position's fitness value [12]. Local bests are iteratively stored to workspace variable I. I stores the best position found by each particle's neighbourhood over the course of the search. The second particle's personal best outperformed those of the rest of the swarm; consequently, the first and third particles take the second particle's personal best to be their local best .Since the third particle had the second-best of all personal bests, its position became the local best of the neighboring fourth particle. The fifth particle took its own personal best as its local best since it produced the third-best of all personal bests. The location of this value is called the personal best solution Pi. The algorithm involves casting a population of particles over the search space and remembering the best solution encountered. For each iteration, all particles adjust its velocity vector based on its momentum, and the effect of both its best solution and the local best solution of its neighbors. N particles whose velocities and positions are updated accordingly are initialized, and the positions' fitness values are calculated. It reduces the computational time, while the accuracy of the solution is not affected. The process iterates until the maximum iteration number is reached or the minimum error condition is satisfied. The procedure of generalized algorithm of PSO model is given

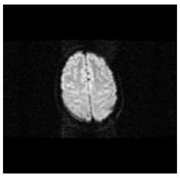
$$V_{id}(t) = \omega V_{id}(t-1) + c1rand()\big(P_{id}(t-1) - X_i(t-1)\big) + c2rand()\big(P_{id}(t-1) - X_i(t-1)\big) \tag{11}$$

$$Xid = Xid(t-1) + Vid(t-1) \tag{12}$$

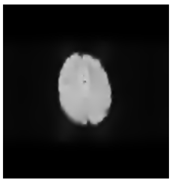
5. Experimental Results

The proposed method was tested on Magnetic resonance images of Head and Brain and it was optimized by PSO algorithm. The following figures show the Experimental Result of MRI Brain Image

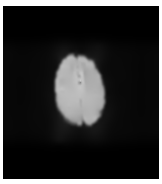
Figure (1) Proposed (With PSO)



1(a) Original Image

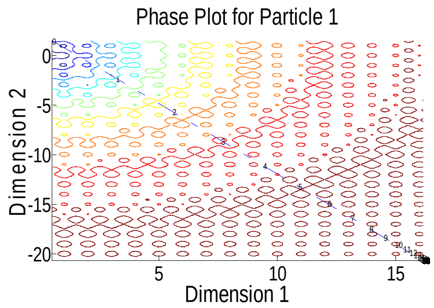


1 (b) Thresholding Image

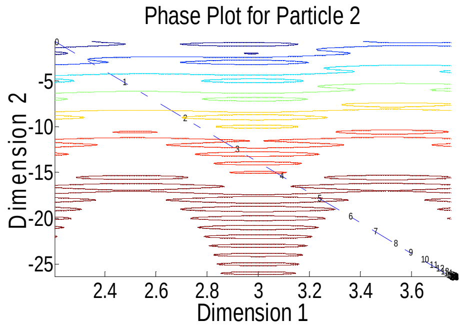


1 (c) SNR after thresholding

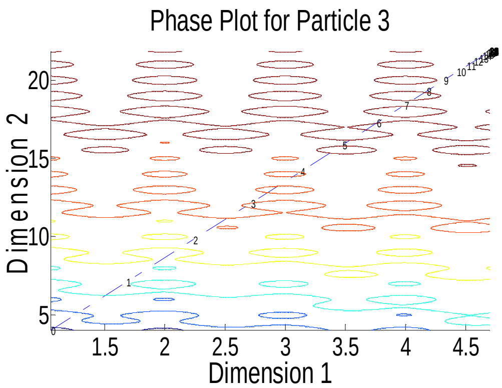
Figure 2 Shows the Phase Plot of four Particles.



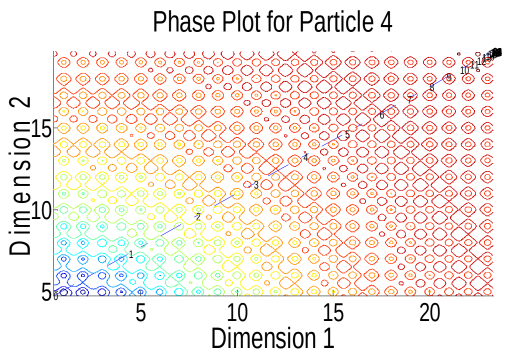
2(a)



2(b)

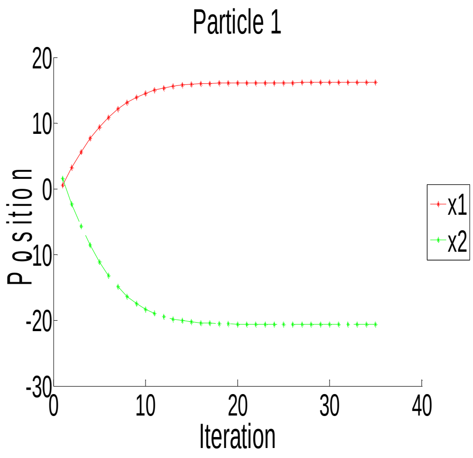


2(c)

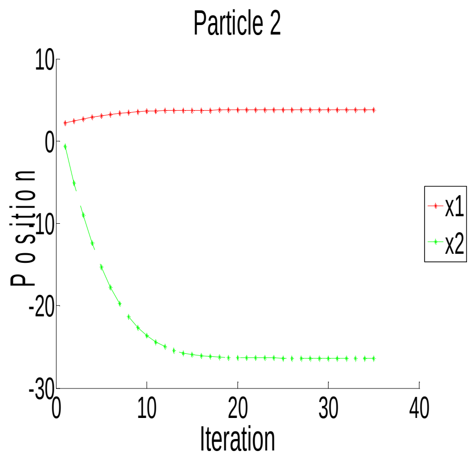


2(d)

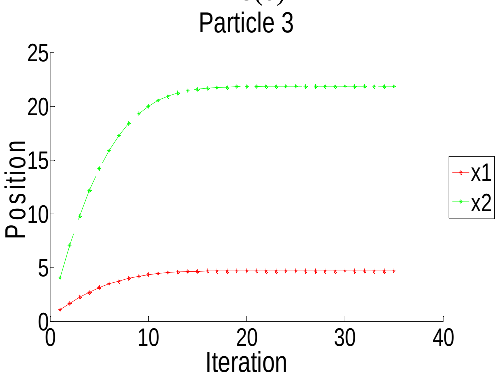
Figure 3 shows the Position of four Particles.



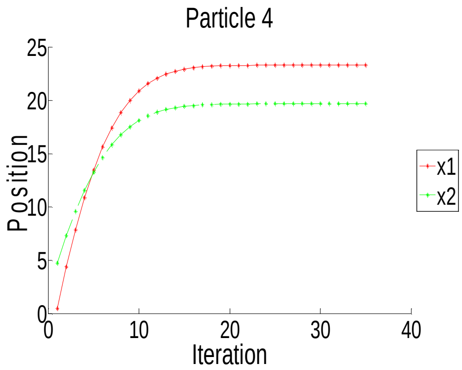
3(a)



3(b)



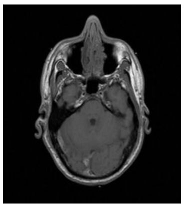
3(c)



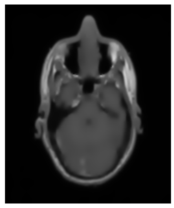
3(d)

The following figure (4) shows the Experiments on MRI Head Image

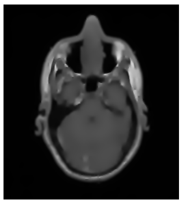
Figure (4) Proposed (with PSO)



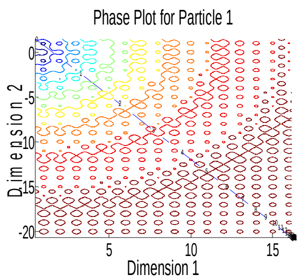
4 (a) Original Image



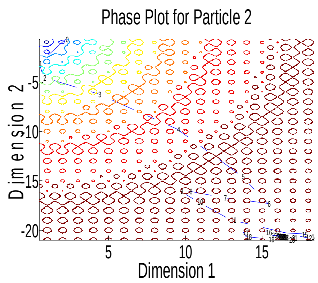
4 (b) Thresholding Image



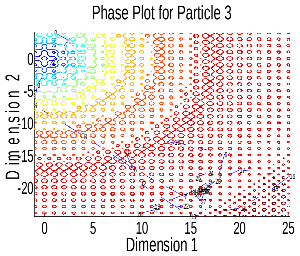
4(c) SNR after Thresholding



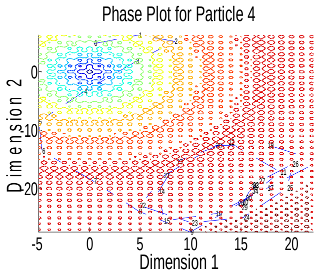
5 (a)



5 (b)

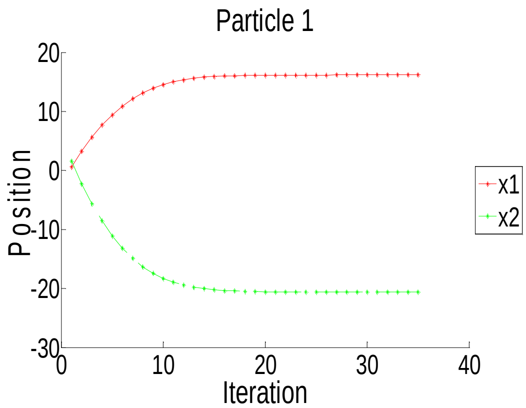


5 (c)

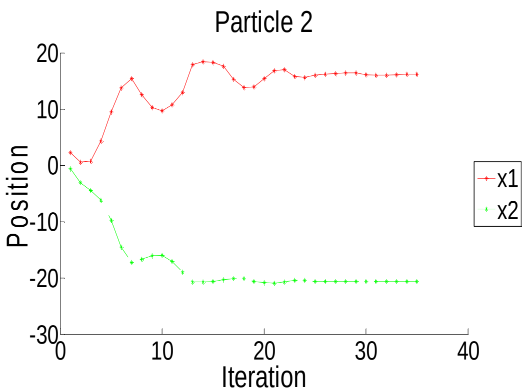


5 (d)

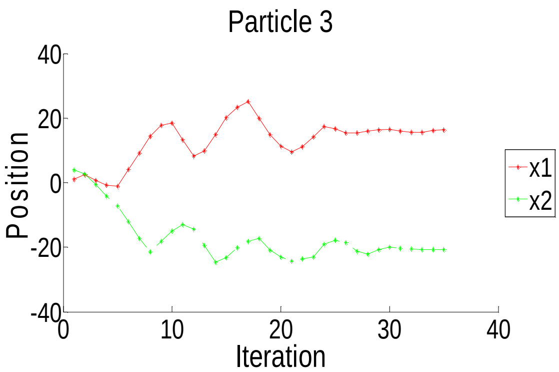
Figure 6 shows the Position of four Particles.



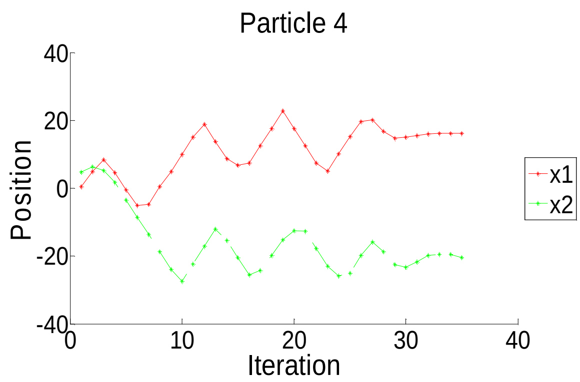
6(a)



6(b)



6(c)



6(d)

Table 1: Noise Level Estimation And Elapsed Time Calculation

Sample data Calculation	**Existing (Brain)**	**Proposed (Brain)**	**Existing (Head)**	**Proposed (Head)**
Snr_O	6.3662	6.3662e+000	5.5209	5.5209e+000
Snr_ft	17.4195	1.7940e+001	14.4989	1.4874e+001
Snr_f	18.2282	1.8925e+001	15.4193	1.5850e+001
Elapsed Time	1.315325 (sec)	0.457504 (sec)	1.999646 (sec)	1.393313 (sec)

6. Conclusions

This paper proposes an MRI image denoising scheme using an adaptive wavelet thresholding technique and the particle is optimized by PSO algorithm. In this it multiplies the adjacent wavelet subbands to amplify the significant features and then applies the thresholding to the multiscale products to differentiate the edge structures from noise. Then adaptive threshold was formulated to remove most of the noise. The PSO method reduces the time and the algorithm has very low computation time.

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