INITIALIZATION OF AN ACTIVE CONTOUR ALGORITHM FOR MRI USING BAYESIAN WAVELET SHRINKAGE AND MULTISCALE PRODUCTS

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This paper proposes a novel technique for initialization of a snake algorithm, which merges the merits of Bayesian wavelet shrinkage and wavelet interscale dependencies. The performance of the proposed algorithm is exemplified for the case of cardiac magnetic resonance images.

INTRODUCTION

Magnetic resonance imaging (MRI) is generally regarded as one of the most powerful diagnostic techniques. Nevertheless, the incorporated noise during image acquisition or transmission degrades human interpretation or computer-aided analysis of the image. Thus, it appears sensible to reduce noise before performing image analysis. However, this pre-processing step should be performed with care in a way that enhances the diagnostically relevant image content.

MRI magnitude images are generally modeled by a Rician distribution and the corresponding Rician noise is locally signal-dependent [1]. However, several authors have shown that in the wavelet domain the noise tends to an approximate Gaussian distribution. Also, in a number of recent publications [2, 3], we have shown that symmetric alpha-stable (SαS) distributions, a family of heavy-tailed densities, are sufficiently flexible and rich to appropriately model wavelet coefficients of images in various applications. This claim stands true for MRI as well. Consequently, in the undecimated wavelet domain, we apply a previously developed Bayesian estimator [2] that exploits these statistics to mitigate noise within each subband of interest. The use of an optimal Bayesian shrinkage technique guarantees that the edge information is not lost in the denoising process.

The next step of our algorithm consists in further emphasizing this information. To achieve this, we make use of wavelet product scales. The motivation for doing so is that high amplitude coefficients (corresponding to edges) and low amplitude coefficients (corresponding to homogenous areas) tend to appear at the same spatial positions in different scales respectively [4]. In our implementation, we use a redundant wavelet transform [5] to avoid aliasing artifacts and to keep the same number of wavelet coefficients along scales. We form two product functions in the x and y directions that incorporate two adjacent scales. The corresponding modulus image is further processed by appropriate thresholding in order to form a binary edge map.

Finally, the positions of the detected edges are used in the pixel domain in order to designate the initial contour of the boundary of interest toward which the snake algorithm should converge.

The details of the complete algorithm are outlined in the following.

METHODS

Our approach for snake initialization incorporates three main processing stages. First, the image is decomposed into several scales through a multiresolution analysis employing the 2-D wavelet transform. The second and third steps differentiate our technique from existing ones. After decomposing the original image, the signal and noise components are modeled as SαS and Gaussian processes, respectively. In other words, the observed signal is a mixture of SαS signal and Gaussian noise. The parameters of such a distribution can be estimated by means of a least-squares fitting in the characteristic function domain. Specifically, since the probability density function (pdf) of the measured coefficients (d) is the convolution between the pdfs of the signal (s) and noise components (n), the associated characteristic function of the measurements is given by the product of the characteristic functions of the signal and noise

$$\Phi_d(\omega) = \Phi_s(\omega) \bullet \Phi_n(\omega), \qquad (2.1)$$

where $\Phi_s(\omega) = \exp(-\gamma_s |\omega|^{\alpha_s})$.

We estimate the parameters α_s $(0 < \alpha_s \leq 2)$, $\gamma_s\left(\gamma_s > 0\right)$, and $\sigma = 2 \cdot \gamma_n$ by fitting the empirical characteristic function of the measured coefficients with function $\Phi_d(\omega)$. Being now equipped with distribution parameter estimates, we are able to compute numerically the Bayesian estimate of the signal component $\hat{s}$, which is given by

$$\hat{s} = \frac{\int P_n(n)\, P_s(s)\, s\, ds}{\int P_n(n)\, P_s(s)\, ds}. \qquad (2.2)$$

As shown in [2], this processor effectively reduces noise and most importantly, it preserves step edges that are needed for snake initialization.

For the purpose of further emphasizing edge information, the next step of our algorithm consists in forming products of denoised wavelet subbands. Specifically, in two dimensions, two product functions should be defined in x and y directions

$$P_j^{s,1}(x,y) = s_j^1(x,y) \cdot s_{j+1}^1(x,y) \qquad (2.3)$$
$$P_j^{s,2}(x,y) = s_j^2(x,y) \cdot s_{j+1}^2(x,y),$$

where the index j refers to the decomposition scale. The corresponding modulus image is then defined as

$$M_j s(x,y) = \sqrt{P_j^{s,1}(x,y) + P_j^{s,2}(x,y)} \qquad (2.4)$$

Finally, the edge map is obtained by appropriately thresholding the above modulus image [4].

RESULTS

Several sets of experiments were conducted in order to assess the effectiveness of the proposed method. First, we tested the performance of the denoising scheme alone, by decomposing an input MR image into four levels of decompositions, applying the Bayesian processor, and inverting the transform. The results are compared with the ones provided by many other recently proposed techniques including soft thresholding [6] and Wiener filtering. The improvement is quantified in terms of mean squared errors. Specifically, we employed the peak signal to noise ratio (PSNR) defined as

$$PSNR = 20\log_{10}\left(256 / \sqrt{\frac{1}{N^2}\sum_i \left(\hat{X}_i - X_i\right)^2}\right), \qquad (3.1)$$

where X and $\hat{X}$ denote the noise-free and the denoised images, respectively and N^2 is the total number of pixels. The results of applying our method to an MRI image are summarized in Table 1 for three different levels of noise, while for visual assessment an image is shown in Figure 1 (b).

Secondly, we compute the product of wavelet subbands at scales two and three. The resulting edge map is shown in Figure 1 (c).

Finally, we illustrate the use of our algorithm as an initialization procedure in an active contour algorithm. By using the detected edges connected in a closed loop as initial contour, a snake is able to converge to an equilibrium position after only a small number of iterations. Figure 1 (d) shows the result after the initialization procedure and a few iterations of the snake algorithm proposed by Xu and Prince in [7].

Table 1: PSNR values (dB) obtained by pre-processing a cardiac MR image using three denoising methods

Noisy	**Wiener**	**Soft thresholding**	**Bayesian**
27.99	30.41	32.58	32.89
22.00	28.13	29.34	30.27
18.52	26.62	27.10	27.84

CONCLUSIONS

We have proposed a novel approach for active contour algorithms initialization, which is based on multiscale Bayesian processing for noise reduction followed by scale multiplication for edge detection and further feature enhancement. The technique was tested in order to assess the effectiveness of each individual building block. The Bayesian denoising component clearly outperforms other effective noise reduction techniques proposed in the recent literature. On the other hand, edge detection by scale multiplication was found to be more effective than the classical Canny edge detector. Preliminary trials showed that together these two modules could be useful initialization steps for an active contour algorithm.

REFERENCES

[1] P. Bao, L. Zhang, "*Noise reduction for magnetic resonance images via adaptive multiscale products thresholding*", IEEE Trans. Med. Imag., Vol. 22, No. 9, pp. 1089-1099, Sept. 2003.

[2] A. Achim, A. Bezerianos, P. Tsakalides, "*Novel Bayesian multiscale method for speckle removal in medical ultrasound images*", IEEE Trans. Med. Imag., Vol. 20, No. 8, pp. 772-783, Aug. 2001.

[3] A. Achim, P. Tsakalides, A. Bezerianos, "*SAR image denoising via Bayesian wavelet shrinkage based on heavy-tailed modeling*," IEEE Trans. Geosc. and Remote Sensing, vol. 41, pp. 1773-1784, Aug. 2003.

[4] L. Zhang, P. Bao: "*Edge detection by scale multiplication in wavelet domain,*" Pattern Recognition Letters, vol. 23, pp. 1771-1784, 2002.

[5] S. Mallat, S. Zong: "*Characterization of signals from multiscale edges,*" IEEE Trans. Pattern Anal. Machine Intell., vol. 14, pp. 710-732, 1992.

[6] D. L. Donoho, "*Denoising by soft-thresholding,*" IEEE Trans. Inform. Theory, vol. 41, pp. 413-627, May 1995.

[7] C. Xu, J.L. Prince: "*Snakes, shapes, and gradient vector flow,*" IEEE Trans. Image Proc., vol. 7, pp. 359-369, 1998.

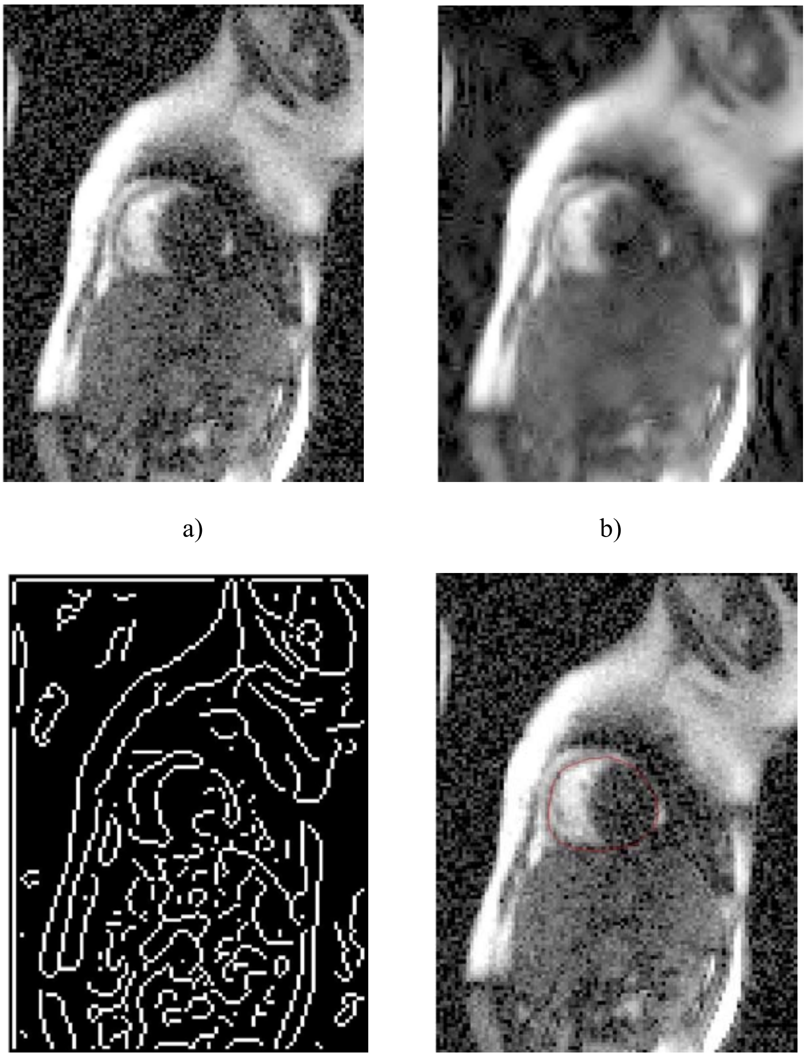

Figure 1: Illustration of the different steps of the algorithm: Noisy image (a) Image denoised using the SαS Bayesian processor (b); edge map after scale multiplication and thresholding (c); initialization of a snake algorithm using detected edges connected in a closed loop.