Ultrasound Speckle Reduction and Edge Enhancing in Laplacian Pyramid

Baek-Sop Kim, Jeong-Sik Kim and He-Jeong Song

***Abstract*— A new method which reduce speckle noise and enhance contrast is proposed for medical ultrasound imaging. We modified the conventional nonlinear coherent diffusion (NCD) and proposed the edge enhancing nonlinear coherent diffusion (EENCD) for this purpose. The EENCD suppresses the speckle noise in a homogenous region, and it performs both directional filtering on the contour direction and edge enhancement on the tangential direction in a structural region. The EENCD is embodied in the Laplacian pyramid. An image is decomposed into a Laplacian pyramid, and then, the EENCD filtering is done during reconstructing the Gaussian layer images, to produce the filtered image. The proposed method was compared with the conventional CED and NCD methods on the real ultrasound images. It has been shown that the proposed method can enhance the edges and the contrast is enhanced more than the conventional methods.**

I. Introduction

ULTRASOUND imaging system is widely used because it is safe, non-invasive, relatively low cost and real-time imaging device. The image quality, however, is poor compared to other medical imaging modalities due to speckle noise as well as system noise. Speckle noise is inherent to ultrasound systems, which is formed by coherent interferences of backscattered echo from the scatters. Speckle noise produces a granular pattern, decrease contrast and obscure image details.

A number of techniques have been proposed to reduce the speckle noise. The spatial compounding technique combines a ultrasound images of the same target from different scan directions [1]. This can reduce the speckle noise, but the spatial resolution is degraded, and it requires a high speed computation, which is usually done by hardware during image acquisition.

The postacquisition image enhancement techniques are widely used nowadays since it does not require no or little additional hardware. Lee [2] proposed an adaptive filter that changes the amount of smoothing according to local variance. This method was proposed to reduce the speckle noise in SAR images, and smoothing is increased in homogeneous regions and reduced in the edge regions. Kim, *et al.* [3] modified Lee's filter for the ultrasound images, where the coherence measure is used to get the amount of smoothing. Loupas, *et al.* [4] proposed the adaptive weighted median filter, in which the pixels are duplicated as much as the weight and then the median among them are selected. The weight is a function of the distance from the center of the window, local mean, and local variance.

The anisotropic diffusion methods are quite useful for the enhancement of ultrasound images in that the method makes the directional diffusion possible and directional coherence enhancement is important feature in medical ultrasound images. Weikert [5] proposed the coherence enhancing diffusion (CED). CED calculates the structure tensor to get the strength and direction of diffusion, and diffusion is performed along the contour direction of edges. Abd-Elmoniem [6] proposed the nonlinear coherent diffusion (NCD) model which modified CED so that image is diffused in the homogeneous region as well as coherence enhancing. Both CED and NCD reduce the speckle noise while preserving edges, but they do not enhance edge boundaries which are important features to distinguish the structures of the organs.

In this paper, we propose the edge enhancing nonlinear coherent diffusion (EENCD) model, which is a modification of NCD to enhance the edge boundaries. The EENCD is implemented in the Laplacian pyramid domain. The Laplacian pyramid decomposes an image into a set of Laplacian layers, which can be reconstructed into the image without an error [7]. Zhang *et al.* [8] used the Laplacian pyramid for enhancement of the ultrasound images by processing each Laplacian layer by the isotropic nonlinear diffusion to reduce the speckle noise. We use the EENCD to process each layer, and it will be shown that the proposed method can enhance contrast as well as reduce the speckle noise.

In Section II, the conventional nonlinear anisotropic diffusion models are presented. Section III describes the proposed edge enhancing nonlinear coherent diffusion model and its implementation in the Laplacian pyramid. Section IV compares the performance of the proposed system with some other speckle reduction methods using the real ultrasound images.

II. Nonlinear Anisotropic Diffusion

The nonlinear anisotropic diffusion model takes the form

$$\frac{\partial I(x,y,t)}{\partial t} = div[D\,\Delta I] \qquad (1)$$

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where D is a diffusion tensor representing the amount of diffusion in gradient and contour directions, and I is an input image. The diffusion tensor is determined from the structure tensor which can be represented by the local contour and gradient direction and their relative contrast. The structure tensor takes the form

$$J_\rho(I) = \begin{pmatrix} K_\rho * I_x^2 & K_\rho * (I_x I_y) \\ K_\rho * (I_x I_y) & K_\rho * I_y^2 \end{pmatrix} = \begin{pmatrix} j_{11} & j_{12} \\ j_{12} & j_{22} \end{pmatrix} \tag{2}$$

where the symbol '*' stands for convolution and K_ρ is the Gaussian convolution kernel with the variance ρ. Using eigenvalue decomposition, the structure tensor can be rewritten as

$$J_\rho(I) = \begin{pmatrix} w_1 & w_2 \end{pmatrix} \begin{pmatrix} \mu_1 & 0 \\ 0 & \mu_2 \end{pmatrix} \begin{pmatrix} w_1^T \\ w_2^T \end{pmatrix}. \tag{3}$$

Here, the eigenvectors w_1, w_2 and the eigenvalues μ_1, μ_2 correspond to the gradient and contour directions and the contrast along these directions, respectively. Note that $\mu_1 \geq \mu_2$ is assumed. The eigenvalues of the structure tensor provide useful information on the coherence of the structure. The coherence measure is defined by [5]

$$C = (\mu_1 - \mu_2)^2. \tag{4}$$

It becomes large for edges where contrast along the tangential direction is much larger than that along the contour direction, and it tends to zero for the pixels in homogenous regions. The diffusion matrix D in (1) takes the form

$$D(I) = \begin{pmatrix} w_1 & w_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} w_1^T \\ w_2^T \end{pmatrix}. \tag{5}$$

Note that w_1 and w_2 are the eigenvectors of the structure tensor as in (3). λ_1 and λ_2 determine the amount of diffusion along each eigenvector, and these are different with the models.

A. Coherence Enhancing Diffusion (CED) Model

Weikert [5] proposed the Coherence Enhancing Diffusion (CED) model, in which the diffusion coefficients are set as follows.

$$\lambda_1 = \alpha$$
$$\lambda_2 = \begin{cases} \alpha & \text{if } C = 0 \\ \alpha + (1-\alpha)\exp\left(-\dfrac{K}{C}\right) & \text{otherwise}, \end{cases} \tag{6}$$

where, C is the coherence measure as in (4), and K is the user defined threshold. α is set to as a small constant as 0.01.

B. Nonlinear Coherent Diffusion (NCD) Model

The CED model enhances the coherence on the edge boundaries by diffusing the image along the contour direction, but it does not reduce noise in a homogeneous regions. Abd-Elmoniem [6] modified the CED model so that it can reduce noise in a homogeneous regions and proposed the Nonlinear Coherence Diffusion (NCD) model, in which

$$\lambda_1 = \begin{cases} \alpha\left(1 - \dfrac{C}{K}\right) & \text{if } C \leq K \\ 0 & \text{otherwise} \end{cases} \tag{7}$$
$$\lambda_2 = \alpha.$$

In this case, α is usually set to 1.

III. PROPOSED METHOD

While the NCD model can reduce noise and enhance the coherence without blurring edges, it does not enhance edge boundaries which are important features to distinguish the structures of the organs. In this paper, we propose the edge enhancing nonlinear coherent diffusion (EENCD) model, which is a modification of the NCD model to enhance the edge boundaries. The EENCD is implemented in the Laplacian pyramid domain for multiresolution representation

A. Edge Enhancing Nonlinear Coherent Diffusion (EENCD) Model

The proposed Edge Enhancing Nonlinear Coherent Diffusion (EENCD) model takes the form

$$\lambda_1 = \begin{cases} \alpha\left(1 - \dfrac{C}{K}\right) & \text{if } C \leq K \\ \beta\left(1 - \exp(-(C-K)\right) & \text{if } C > K \end{cases} \tag{8}$$
$$\lambda_2 = \alpha.$$

Here, α determines the amount of diffusion and is usually set to as high as 1, and β is a negative number whose absolute value determines the amount of edge enhancement. We set β to [-0.2, -0.1] in the experiments. In (8), λ_1 and λ_2 denote the diffusion coefficients along the tangential and contour direction, respectively. In the homogeneous region where C is small, diffusion becomes isotropic since $\lambda_1 \approx \lambda_2 = \alpha$.

When image anisotropy becomes large, which corresponds to structured tissue, image texture is rich of information about the imaged tissue and, therefore, diffusion should be selective in both direction and strength [6]. A fully specula region corresponding to $C>K$ is associated with diffusion only in the contour direction. In this case, the edge is enhanced rather than diffused in the tangential direction because the diffusion coefficient has a negative value.

B. Laplacian Pyramid

The Laplacian pyramid decomposes an image into a set of Laplacian layers, which can be reconstructed into the image without an error [7]. In the decomposition stage, an image is successively convolved with a Gaussian kernel to produce the layers of a Gaussian pyramid. A layer of the Laplacian pyramid is computed as the difference between two layers of the Gaussian pyramid. Since each Laplacian layer is the difference between two layers of the Gaussian pyramid, the Laplacian pyramid becomes a set of band-pass filtered images.

Two operators, REDUCE and EXPAND are commonly used in implementation of the Laplacian pyramid. The REDUCE operator performs a two-dimensional lowpass filtering followed by sub-sampling by a factor of two in both directions. A layer in the Gaussian pyramid is calculated from the lower layer using the REDUCE operator, that is,

$$G_n = REDUCE(G_{n-1}), \text{ or} \tag{9}$$

$$G_n(x,y) = \sum_{m=-2}^{2}\sum_{n=-2}^{2} w(m,n)G_{n-1}(2x+m, 2y+n). \quad (10)$$

Here, $w(\cdot,\cdot)$ are the coefficients for the Gaussian lowpass filter. The lowest layer of the Gaussian pyramid is the input image, that is, $G_0 = I$. The EXPAND operator enlarges an image by up-sampling by a factor of two followed by a two-dimensional lowpass filtering. That is,

$$G_n^e = EXPAND(G_n) \quad (11)$$

means that

$$G_n^e(x,y) = 4\sum_{m=-2}^{2}\sum_{n=-2}^{2} w(m,n)G_n\left(\frac{x-m}{2}, \frac{y-n}{2}\right). \quad (12)$$

The multiplication factor 4 is included in (12) to maintain the average intensity being reduced by up-sampling. The Laplacian pyramid is obtained from the Gaussian pyramid using the EXPAND operator, as follows

$$L_n = G_n - EXPAND(G_{n+1}). \quad (13)$$

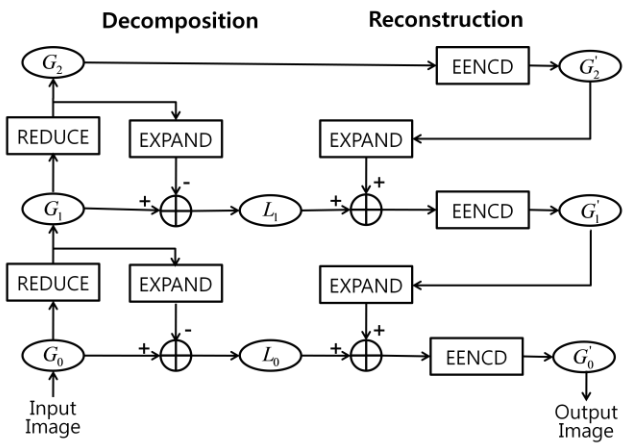

Fig. 1. Block diagram of the proposed method.

C. *The Proposed Method*

The proposed method can be divided into two parts as shown in Fig. 1. The left part denotes the decomposition stage. An image is decomposed into the Gaussian and Laplacian pyramids using the REDUCE and EXPAND operators described above. The Gaussian pyramid is not necessarily stored except the image at the highest layer (G_2 in Fig. 1). The right part of Fig. 1 denotes the reconstruction stage. In the reconstruction stage, the Gaussian pyramid is reconstructed from the Laplacian pyramid. Each layer of the Laplacian pyramid represents a bandpass image and it is usually processed before reconstruction [7], [8]. In the proposed system, processing is done on each layer of the reconstructed Gaussian pyramid as shown in Fig. 1. Since the Gaussian images have contrast information while the Laplacian images do not, contrast can be enhanced by this way.

IV. EXPERIMENTAL RESULTS

To evaluate the performance of the proposed method, real ultrasound images captured from the Medison Accuvix™ scanner were used. In each study, the performance of the proposed method was compared with those of CED and NCD.

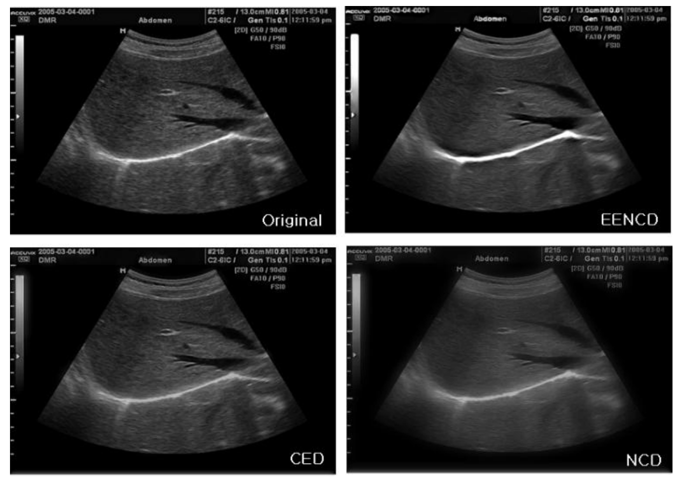

Fig. 2. Ultrasound liver image and its filtered results.

Fig. 2 shows the result on the liver image which shows clear edge boundaries around the structures. CED enhances the coherence of the structure region, but the noises in the homogeneous regions are not suppressed. NCD reduce noise in the homogeneous regions while preserving the edge boundaries of the structure regions. The proposed method (denoted by EENCE) enhances both the edge boundaries and contrast in the structure regions, e.g., diaphragm shown in white, and blood vessels shown in black. In the homogeneous regions where $C \le K$, the EENCE is the same as the NCD as shown in (7) and (8). They do not look the same because we set α to 0.5 instead of 1.0 used in [6], as the sonographers liked this amount of smoothing.

In order to measure how much the contrast is enhanced, the contrast to noise ratio (CNR) is calculated in two regions shown in Fig. 3. In each ROI in the figure, the pixels are divided into two groups using the optimal thresholding method. The CNR is the normalized mean difference of the intensity of each group, which is

$$CNR = \frac{|\mu_1 - \mu_2|}{\sqrt{\frac{1}{n_1+n_2}(n_1\sigma_1^2 + n_2\sigma_2^2)}}, \quad (14)$$

where, μ_i, σ_i^2 and n_i are the mean, the variance and the number of pixels, respectively, for the i-th group.

Fig. 3. ROIs for calculation of CNR.

Table 1 shows the result. The table shows that CNR of the EENCD is larger than the other methods.

Table 1. CNR on ROIs in Fig. 3.

	Original	CED	NCD	EENCD
ROI 1	2.67	2.78	2.43	**2.87**
ROI 2	2.90	2.91	3.12	**3.72**

The edge boundaries of the thyroid and fetal images shown in Fig. 4 and Fig. 5 are not as clear as that of the liver image. In these cases too, the proposed method showed higher edge enhancement capability and contrast enhancement than the conventional methods.

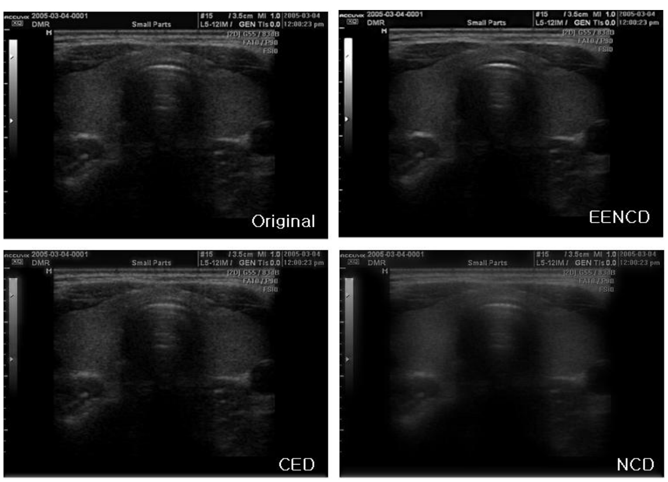

Fig. 4. Ultrasound thyroid image and its filtered results.

V. CONCLUSION

A new nonlinear anisotropic diffusion model is introduced and a system for ultrasound image enhancement has been proposed. It has been shown that the proposed system enhances edges and contrast of the structures while suppressing noise in the homogeneous regions.

The proposed system uses the Laplacian pyramid, and the new edge enhancing nonlinear coherent diffusion model enhances the image during reconstruction of the Gaussian layer images while the Laplacian layer images are not changed. The performance could be further improved if speckle reduction filter is added to the Laplacian layer images.

Fig. 5. Ultrasound fetal image and its filtered results.

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