Noise Reduction and Signal Enhancement in IVR Images by ICA Shrinkage Filters and Multiscale Filters

Kiyotaka Matsuo[1], Xianhua Han[1], Koichi Shibata[2], Yukio Mishina[2], Yoshihiro Mukuta[2] and Yen-Wei Chen[1]
[1]Graduate School of Science and Engineering, Ritsumeikan University,
1-1-1 Nojihigashi, Kusatsu, Shiga 525-8577, Japan
[2] R&D Department, Medical System Division, Shimadzu Corporation,
1, Nishinokyo-Kuwabara-cho, Nakagyo-ku, Kyoto 604-8511, Japan
E-mail: [1]rs036031@se.ritsumei.ac.jp

Abstract: Interventional Radiology (IVR) is an important technique to visualize and diagnosis the vascular disease. In real medical application, a weak x-ray radiation source is used for imaging in order to reduce the radiation dose, resulting in a low contrast noisy image. It is important to develop a method to smooth out the noise while enhance the vascular structure. In this paper, we propose to combine an ICA Shrinkage filter with a multiscale filter for enhancement of IVR images. The ICA shrinkage filter is used for noise reduction and the multiscale filter is used for enhancement of vascular structure. Experimental results show that the quality of the image can be dramatically improved without any blurring in edge by the proposed method. Simultaneous noise reduction and vessel enhancement have been achieved.

1. Introduction

Interventional Radiology (IVR) is an important technique to visualize and diagnosis the vascular disease. In real medical application, a weak x-ray radiation source is used for imaging in order to reduce the radiation dose, resulting in a low contrast noisy image. It is important to develop a method to smooth out the noise while enhance the vascular structure. Several filters, such as Wiener filter [1] and Wavelet transform based filter [2] have been proposed for noise reduction. Though these filters are powerful method for noise reduction, but some blurring will be introduced and it is also not possible to enhance the vascular structure. In our previous works, we proposed a new shrinkage filter based on independent component analysis (ICA) for Poisson noise reduction in medical images [3-5]. The ICA Shrinkage filter can significantly reduce the noise without any blurring. In this paper, we propose a new method by combining the ICA Shrinkage filter with a multiscale filter [6] for enhancement of IVA images. The flowchart of our proposed method is shown in Fig.1. The ICA shrinkage filter is first used for noise reduction and then the multiscale filter is used for enhancement of vascular structure. Finally, the two results are combined to form an enhanced IVR image.

In our proposed ICA shrinkage filter method, we first learn basis functions for linear transform from the sample images using ICA and then the noise image is transformed to ICA domain by using the ICA basis functions. In ICA domain, the signal components and noise components can be selected and a shrinkage filter is performed on noise components [3-5]. Compared with conventional DCT or wavelet transform, the ICA based transform has the advantage that the transform can be adapted to the real images and the noise components can be easily detected by ICA transform. So we can significantly reduce the noise without any distortion of signals. In multiscale filter, the multiscale second order local structure of image (Hessian) is examined for vessel enhancements. A vesselness measure is obtained on the basis of all eigenvalues of the Hessian. By combining the ICA shrinkage filter with the multiscale filter, simultaneous noise reduction and vessel enhancement have been achieved and the quality of IVR images have been significantly enhanced and improved.

The paper is organized as follows: we describe details about ICA shrinkage filters in 2nd section and the multiscale filer in section 3. Experimental results are shown in section 4. The concluding remarks will be given in the final section.

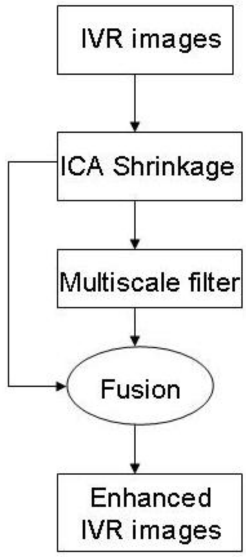

Fig. 1 The flowchart of our proposed method.

2. ICA Shrinakge Filter

2. 1 Image model

An image $\mathbf{x}$ can be represented by a linear combination of basis functions as Eq.(1), where $\mathbf{a}^i$ is the basis function and y^i is the coefficient, which can be used as image features or image coding. Unlike Fourier transform or wavelet-based method, in our proposed independent component analysis (ICA) based method [3-5], the basis functions are learned from similar images by ICA. The advantage of the ICA based method is that we can obtain a set of adaptive basis functions based on data or images alone.

$$\mathbf{x} = \sum_{i=0}^{N-1} y_i \mathbf{a}_i = y_0\mathbf{a}_0 + y_1\mathbf{a}_1 + y_2\mathbf{a}_2 + \cdots + y_{N-1}\mathbf{a}_{N-1} \quad (1)$$

2. 2 Basis functions learned by ICA

The Eq. (1) can be rewritten as

$$\mathbf{x} = \mathbf{A}\mathbf{y} \quad (2)$$

Since we must obtain the **A** from sample images **x** alone, the solution of Eq.(2) can be viewed as a blind source separation problem, which can be solved by ICA. The goal of ICA is to find a matrix **W** that results in the estimates of coefficient **y** being statistically as independent as possible over a set of data (**x**) as shown in Eq. (3)

$$\mathbf{y} = \mathbf{W}\mathbf{x} \quad (3)$$

The estimates or independent components **y** may possibly be permuted and rescaled. The rows of **W** respond to the columns of **A** (basis function $\mathbf{a}^i$)**.** Bell & Sejnowski proposed a neural learning algorithm for ICA [7]. The approach is to maximize the joint entropy by stochastic gradient ascent. The updating formula for **W** is:

$$\Delta\mathbf{W} = (\mathbf{I} + g(\mathbf{y})\mathbf{y}^{\mathrm{T}})\mathbf{W} \quad (4)$$

where **y=Wx**, and $g(\mathbf{y}) = 1 - 2/(1+e^{-\mathbf{y}})$ is calculated for each component of **y**. Before the learning procedure, **x** is sphered by subtracting the mean $\mathbf{m}_x$ and multiplying by a whitening filter:

$$\mathbf{x} = \mathbf{W}_0(\mathbf{x} - \mathbf{m}_x) \quad (5)$$

where $\mathbf{W}_0 = [(\mathbf{x}-\mathbf{m}_x)(\mathbf{x}-\mathbf{m}_x)^{\mathrm{T}}]^{-1/2}$. Therefore, the complete transform is calculated as the product of the whitening matrix and the learned matrix:

$$\mathbf{W}_I = \mathbf{W}\mathbf{W}_0 \quad (6)$$

In our experiments, the training data set consists of 10000 samples, which are randomly selected form natural images. The size of each image sample is 8x8. By the ICA algorithms (Eq. (4)-(6)), we can obtain 64 basis functions, which are shown in Fig. 2(a) [8]. In order to make a comparison, we also show basis functions of PCA (principle component analysis) and DCT (discrete cosine transform) in Fig.2 (b) and 2(c), respectively.

As shown in Fig. 1, most of basis functions of ICA are localized and oriented and show some properties of wavelet Gabor filters, while the basis functions of PCA, which is also learned from sample images by PCA, are similar to those of DCT. Since the basis functions of ICA are similar to localized and oriented receptive fields, we can use ICA bases functions to extract the efficient features of images [8], [9]. Another advantage of ICA is that the ICA basis functions are not fixed, but they are extracted from training images. We can adapt them by selecting training images according to different applications.

2. 3 ICA based shrinkage algorithm

Shrinkage is an increasingly popular method in wavelet domain for curve and surface estimation. The wavelet shrinkage procedure for statistical application was developed by Donoho[10]. This shrinkage method relies on the basic idea that the energy of a signal (with some smoothness) will often be concentrated in a few coefficients in wavelet domain while the energy of noise is spread among all coefficients in wavelet domain. Therefore, the shrinkage function in wavelet domain will tend to keep a few larger coefficients representing the signal while noise coefficients will tend to reduce to zero.

As we know that in image decomposition by ICA, most independent components have super-Gaussian distribution and then are very sparse. The energy of an image will be concentrated in a few coefficients of ICA components. While if noise was projected to ICA basis functions, the energy will uniformly spread in ICA domain. Hence we can remove noise with shrinkage method in ICA domain just like wavelet shrinkage procedure.

Assume that we observe an *n*-dimensional vector contaminated by noise. We denote by **x** the observed noisy vector, by **P** the original non-Gaussian vector and by **v** the noise signal. Then we have

$$\mathbf{x} = \mathbf{P} + \mathbf{v} \quad (7)$$

The goal of signal denoising is to find **P'**=*g'*(**x**) such that **P'** is close to **P** in some well-defined sense. The following gives the ICA based shrinkage procedure:

Step 1 Estimate an orthogonal ICA transformation matrix **W** using a set of noise-free representative data **z**.

Step 2 For observed data **x** (corrupted by noise), use the ICA transformation matrix **W** to transform into ICA-domain components:

$$\mathbf{y} = \mathbf{W}\mathbf{x} \quad (8)$$

where **y** can be considered to be sparse variables, but also is corrupted by noise.

Step 3 Use the shrinkage method in ICA domain to estimate noise-free components **y'** for the noisy variables **y**:

$$\mathbf{y'}_i = g_i(\mathbf{y}_i) \quad (9)$$

Step 4 Invert the denoised variables **y'** and get an estimation of original data **P**:

$$\mathbf{P'} = \mathbf{W}^T \mathbf{y'} \quad (10)$$

Here in step (3), g(**y**) is the operator or the function of the shrinkage, which is used to reduce the noise. In medical images, the noise is signal-dependent Poisson noise, thus, we mainly aim to reduce Poisson noise in images. In the next section, based on Poisson noise's special property, we will give an efficient shrinkage scheme, which can be obtained directly from the noisy data.

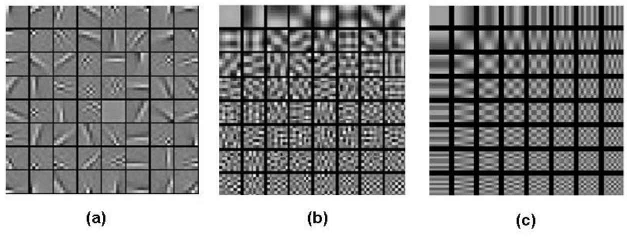

Fig. 2 Basis functions of ICA (a), PCA (b) and DCT (c).

2. 4 Shrinkage for Poisson noise

In this paper, we proposed a shrinkage function based on cross-validation algorithm [11] for Poisson noise. In our method, we can estimate noise level for ICA-domain coefficients in Poisson noise images. It is thus suitable for noise removal in Poisson noise images. The shrinkage function g(**y**) is given by

$$g(\mathbf{y}) = \mathbf{y}' = \mathbf{y}\,\frac{\mathbf{y}^2 - \boldsymbol{\delta}^2}{\mathbf{y}^2} \qquad (11)$$

where δ^2 is the power of Poisson noise. The noise power of *i*-th component can be estimated by

$$\boldsymbol{\delta}_i^{\,2} = (\mathbf{W}_i . \mathbf{W}_i)\,\mathbf{x} \qquad (12)$$

We can obtain noise power in each sample of noise data in ICA-domain and then denoise each data sample according to the SNR. Usually, we can interpret the shrinkage function as the following: Because the ICA transform matrix **W** can be considered as a local directional filter, after ICA transformation, the ICA-domain coefficient can be thought as the projections of the image onto localized “details”. For the noise power estimate, we project the image onto the square of the corresponding transformation matrix, which effectively computes a weighted average of local intensity in the image. This will be an approximation of noise power according to the property of Poisson noise. It is clear that the estimate of noise power can adapt to local variations in the signal or noise..

3. Multiscale filter

Multiscale filter was proposed for vessel enhancement by Frangi et al in 1998 [6]. The flowchart of a multiscale filter is shown in Fig.3. The basic idea of the multiscale filter is that the second order derivative of a Gaussian kernel at scale *s* generates a probe kernel that enhances the contrast between the regions inside and outside the range (-*s*, *s*) in the direction of the derivative. The local orientation of vessel can be obtained by eigenvalue analysis of the Hessian Matrix. The idea behind eigenvalue analysis of the Hessian is to extract the principal directions in which the local second order structure of the image can be decomposed. Table 1 summarizes the relations that hold between the eigenvalues of the Hessian and different structures.

Table 1. eigenvalues patterns in 2D and 3D. (H=high, L=low, N=noisy)

2D	2D	Orientation Pattern
λ_1	λ_2	
N	N	noisy, no preferred direction
L	H-	tubular structure(bright)
L	H+	tubular structure(dark)
H-	H-	blob-like structure(bright)
H+	H+	blob-like structure(dark)

Since we want to enhance the bright vessel structure, which is a tubular-like structure, the eigenvalues of Hessian matrix should satisfy the condition: $\lambda_1 = \text{Low}$ and $\lambda_2 = -\text{high}$.

R_B is defined as the ratio for distinguishing between blob-like and tubular-like structures since it will be zero only for tubular-like structures:

$$R_B = \frac{|\lambda_1|}{|\lambda_2|} \qquad (13)$$

‘‘Second order structureness’’ measure is defined as,

$$E = \sqrt{\lambda_1^2 + \lambda_2^2} \qquad (14)$$

The final vesselness measure can be calculated:

$$I(s) = \begin{cases} 0 & \text{if} \quad \lambda_2 > 0, \\ \exp(-\frac{R_B^2}{2\beta^2}(1-\exp(\frac{E^2}{2c^2})) & \end{cases} \qquad (15)$$

β and c are thresholds, which can control the sensitivity of the filter measures of R_B and *E*.

The vesselness measure is analyzed at different scales *s* of Gaussian kernel. The response of the filter will be maximized at one scale, at which Gaussian kernel will approximately matches the size of the vessel to be detected. We fuse the vesselness measure provide by the filter response at different scales to obtain the final measure of noduleness:

$$I = \max_{s_{\min} \le s \le s_{\max}} I(s) \qquad (16)$$

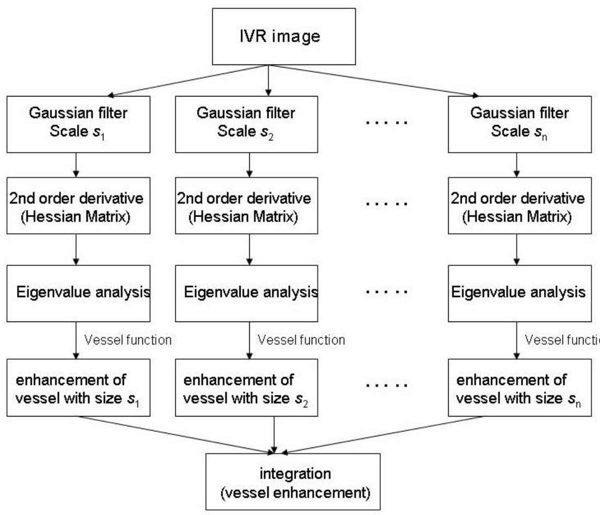

Fig.3 The flowchart of multiscale filter.

4. Experiment Results

The effectiveness of the proposed method has been validate by using real medical IVR images. One typical IVR image, which was collected on Shimadzu Digital Angiography System "Bransist Safire", is shown in Fig.4(a). The result by ICA shrinkage filter is shown in Fig.4(b). It can be seen that the noise is significantly reduced by ICA shrinkage filter with less blurring. But the vessel structures were not significantly enhanced. The result by multiscale filter is shown in Fig.4(c). It can be seen that only vessels were enhanced or extracted. The limitation is that non-vessel signals like bones were suppressed. In this paper, we propose to combine the ICA shrinkage result with the inversion of multiscale filter result as Eq.(17).

$$I = \frac{I_{ICA} + \alpha \cdot (255 - I_{multiscale})}{1+\alpha} \qquad (17)$$

where I_{ICA} is the result by ICA shrinkage filter and $I_{\text{multiscale}}$ is the result by multiscale filter, (255- $I_{\text{multiscale}}$) is the inversion of $I_{\text{multiscale}}$. α is a scaling factor. In this paper, α is 0.1, which is obtained by several test runs. The combined result is shown in Fig.4(d). It can be seen that simultaneous noise reduction and vessel enhancement have been achieved.

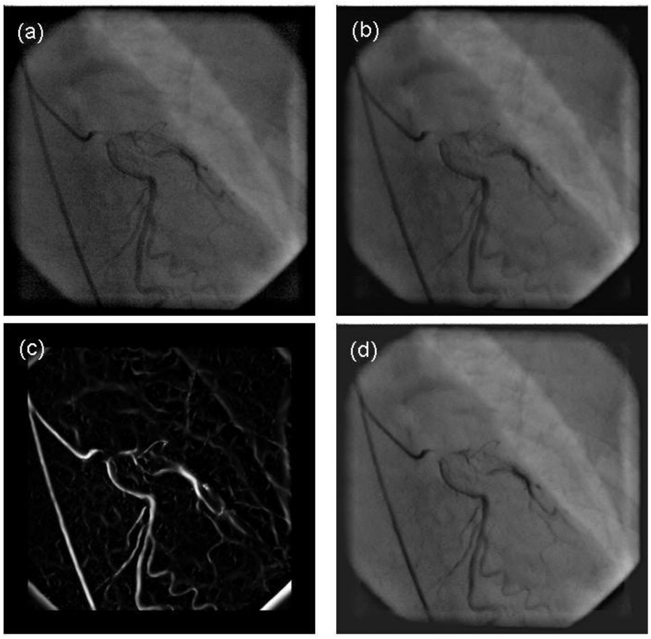

Fig.4 (a) Original IVR image; (b) ICA Shrinkage result; (c) multiscale filter result; (d) the combined result.

5. Conclusions

We proposed to combine an ICA Shrinkage filter with a multiscale filter for enhancement of IVR images. The ICA shrinkage filter is used for noise reduction and the multiscale filter is used for enhancement of vascular structure. Experimental results show that the quality of the IVR image can be dramatically improved without any blurring in edge by the proposed method. Simultaneous noise reduction and vessel enhancement have been achieved.

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