# ULTRASONIC NDE IMAGE ENHANCEMENT WITH NONLINEAR FILTERS IN SIGNAL SUBSPACES

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**Abstract**: The objective of this study to examine an effective method to remove speckles for enhancing ultrasonic NDE images. The new method presented is based on Independent Component Analysis (ICA). Firstly, in terms of the characteristic of NDE images, we believe that the main image features in NDE images are constructed by "edges", thus we use "Edge Basis Model" to describe their basis images and propose a new ICA learning algorithm to estimate the model parameters. Then a demixing transform of the original image is employed, and we design nonlinear filters in each signal subspace and obtain our restored image after a mixing transform. Finally, we compare our method with median filtering and Wiener filtering. The experimental results show that the proposed method can remove the speckle noise effectively while at the same time retaining important details without introducing artificial structures. Based on our study, the ICA based ultrasonic NDE image enhancement is better than existing procedures.

**Introduction:** Ultrasonic nondestructive testing is a versatile technique that can be applied to a wide variety of material testing applications. A significant advantage of ultrasonic testing over other material analysis methods is that it can often be performed in process or on-line. However, its main disadvantage often is the poor quality of images, which are degraded by multiplicative speckle noise. Imaging speckle is a phenomenon that occurs when a coherent source and a non-coherent detector are used to interrogate a medium. Its existence is undesirable, since it degrades image quality and affects the task of human interpretation and evaluation. Thus, speckle removal is a key preprocessing step for nondestructive evaluation application.

Classical speckle reduction methods are based on temporal averaging, median filtering, and Wiener filtering. These approaches however can not overcome the tradeoff between noise reduction and preserving significant image details.

In addition, the estimation of an image signal embedded in noise often need to make use of some prior information about the image and the noise. Until recently, most of existing image denoising algorithms are based on additive or multiplicative Gaussian white noise model. In a real world, some complex systems like ultrasonic C-Scan system, due to their nonstandard image acquisitions, such models are often found inapplicable. Moreover, to build a corresponding noise model for these systems is often ad-hoc and difficult.

In this paper, we extend a novel ICA-based method proposed earlier [1] to remove the speckle noise in ultrasonic NDE image. It is organized as follows. The adaptive basis search with ICA is introducted first. Then our edge basis model is defined. The learning algorithm and nonlinear filtering operation are presented in detail in the subsequent sections. Computer experiments are then presented and our new denoising algorithm is compared with the traditional algorithms.

**Adaptive Basis Search with ICA:**

Let $X = (x[i] : 0 \le i < n)$ be a discrete-time signal of length $n$, which can be viewed as a vector in $R^n$. In order to analyze and describe it, we often represent it as a superposition of simple, elementary objects, which is called "bases". It is clear that there does not exist a single universal basis which is well adapted to describe all those signals at the same time [2]. Over the last twenty years, there has been an explosion of interest in alternatives to traditional signal representations.

Compared with other linear transforms, instead of being limited to some fixed bases, ICA seeks the bases in which the coefficients lead to the most independent possible representation of the underlying image data. The obtained basis vectors give features that are localized in space, frequency, and orientation. Experience shows that this kind of local adaptivity is very helpful and important for image restoration application [3].

In our previous research, we assume that the speckle noise comes from another signal source, which accompanies but is independent of the "true signal source" (their statistical characteristics are not the same), thus the speckle removal problem can also be described as "signal source separation and enhancement" problem. Then we classify the basis images that span into two different subspaces, namely "true signal subspace" and "speckle subspace". Finally we build different nonlinear estimators in each subspace to recover the original image.

But there exists another problem. In our current method, we train the basis functions (or basis images) from the original noisy image with FastICA algorithm, and the obtained basis images also include some noise, which means that we do not separate "signal subspace" and "noise subspace" completely and "signal subspace" also contains the vectors of noise process in addition to the clean signal. Thus when we reconstruct the image with these noisy basis functions, the noisy information is still kept inside, which affects the final performance of our algorithm.

**Edge Basis Model:**

In order to obtain the clean basis, we need to build a prior basis model to describe them. In our ultrasonic NDE images the most important image feature is "edge". "Ridgelet" function provides an effective approach to represent the objects with singularities along lines [4].

Here we pick a smooth univariate function $\psi : R \to R$ with sufficient decay and satisfying the admissibility condition

$$\int \frac{\left|\hat{\psi}(\xi)\right|^2}{|\xi|^2} d\xi < \infty$$

thus for a $N \times N$ "Edge" basis, our edge model can be defined as

$$c\psi\left(\frac{x\cos\theta + y\sin\theta - b}{a}\right) \qquad (1)$$

where $a$ defines the edge scale and resolution, $c$ is the normalization coefficient.

$$c = \frac{1}{\sum_{x,y\in[0,N]} \psi(\frac{x\cos\theta + y\sin\theta - b}{a})}$$

The model is oriented at the angle $\theta$, constant along the lines $x\cos\theta + y\sin\theta = const$ and get the maximum at the lines $x\cos\theta + y\sin\theta = b$.

Figure 1 shows some examples with different parameters.

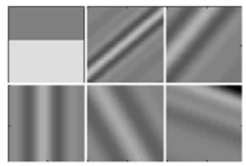


Figure 1 Some Examples for Edge Basis Model

**Learning Agorithm:**

Given the ICA demixing model

$$S_{m\times 1} = W_{m\times n} X_{n\times 1}$$

where $m$ is the number of independent components, $n$ is the dimension of the image data and $W$ is the demixing matrix. Use the above "Edge" basis model, $W$ can be written as:

$$W = \begin{bmatrix} w_1 & w_2 & \dots & w_{m-1} & w_m \end{bmatrix}^T = \begin{bmatrix} w_1(\phi_1) & w_2(\phi_2) & \dots & w_{m-1}(\phi_{m-1}) & w_m(\phi_m) \end{bmatrix}^T$$

Our objective for learning is to adjust the parameters $\phi_i$ to make the coefficients $S$ as independent as possible.

Then our learning optimization algorithm is as follows:

1. Select a criterion to measure the independence of random variables.
   It has been shown that the estimation of the ICA data model can be reduced to the search for uncorrelated directions in which the components are as nongaussian as possible. Each local maximum gives one independent component [3].
   A good choice to measure the nongaussian is kurtosis.
   $$J = kurt(y) = E(y^4) + 3(E(y^2))^2$$
2. Center the data to make its mean zero and whitening the data to give $y$.
   For the whitened data $y$, we have $E(y^2) = 1$, then the kurtosis can be reduced to
   $$J = kurt(y) = E(y^4) - 3$$
3. Choose the number of "Edge Components" $m$.

4. Initialize the parameter $\phi_i = \left[a_i, b_i, \theta_i\right]$ $i \in [1, m]$, then we obtain the ith "Edge" basis $w_i(\phi_i)$.

5. Do a step iteration with gradient descent algorithm on every parameter $\phi_i$ :

$$a_i(t) = a_i(t-1) - \alpha(t)\frac{\partial J}{\partial a_i} = a_i(t-1) - \alpha(t)E(w^T x)^3 \sum_{x1, y1 \in [1, N]} E(x(x1, y1))\frac{\partial w_i(x1, y1)}{\partial a_i}$$

$$= a_i(t-1) - \alpha(t)E(w^T x)^3 \sum_{x1, y1 \in [1, N]} E(x(x1, y1))\psi'(\frac{x1\cos\theta_i + y1\sin\theta_i - b_i}{a_i})\frac{d(-\frac{b_i}{a_i})}{da_i}$$

$$= a_i(t-1) - \alpha(t)E(w^T x)^3 \psi'(\frac{x1\cos\theta_i + y1\sin\theta_i - b_i}{a_i})(-\frac{b_i}{a_i^2})$$

$$b_i(t) = b_i(t-1) - \alpha(t)\frac{\partial J}{\partial b_i} = b_i(t-1) - \alpha(t)E(w^T x)^3 \psi'(\frac{x1\cos\theta_i + y1\sin\theta_i - b_i}{a_i})(-\frac{1}{a_i})$$

$$\theta_i(t) = \theta_i(t-1) - \alpha(t)\frac{\partial J}{\partial c_i} = \theta_i(t-1) - \alpha(t)E(w^T x)^3 \psi'(\frac{x1\cos\theta_i + y1\sin\theta_i - b_i}{a_i})(\frac{y1\cos\theta_i - x1\sin\theta_i}{a_i})$$

6. Do a symmetric orthonormalization.

   We have known that the basis vectors $w_i$ corresponding to different independent components are orthogonal in the whitened space. Thus in order to prevent different vectors from converging to the same local maxima we must orthogonalize the vectors $w_1 \quad w_2 \quad \ldots \quad w_{m-1} \quad w_m$ after every iteration.

7. If not converged, go back to step 4.
8. Go back to step 3 until the number of the learned bases is equal to $m$.
   When the learning process can not converge in step 4-7, which means $m$ is too big, the correct number of "Edge" bases should be the number of the bases we have learned now. Under this state, our learning process will stop. Thus our algorithm can also learn the number of the "Edge" basis images.

**Nonlinear Filtering:**

We now apply nonlinear contrast stretching in each "Edge" component to enhance the image features. Here, adaptive gain through nonlinear processing is generalized to incorporate hard thresholding in order to avoid amplifying noise and remove small noise perturbations [5]. The generalized adaptive gain (GAG) operator (Fig. 2) is defined as:

$$f(v)=\begin{cases}0 & \text{if } |v|<T_1 \\ \mathrm{si\,gn}(v)T_2+\bar{a}(sigm(c(u-b))-sigm(-c(u+b))) & \text{if } T_2\le |v|\le T_3 \\ v & \text{otherwise}\end{cases}$$

where $v\in[-1,1]$, $u=sign(v)(|v|-T_2)/(T_3-T_2)$, $b\in(0,1)$, $\bar{a}=a(T_3-T_2)$, $0\le T_1\le T_2\le T_3\le 1$, $c$ is a gain factor, and $a=\dfrac{1}{sigm(c(1-b))-sigm(-c(1+b))}$, $sigm(v)=\dfrac{1}{1+e^{-v}}$.

where parameters $T_1, T_2, T_3, b, c$ are tuning parameters which must be adjusted experimentally for each class of images. The interval $[T_2, T_3]$ decides the sliding window for feature selectivity, which can be adjusted to emphasize coefficients within a specific range of variation, *c,b* determine the shaper of thw windows. By selecting a pari of appropriate values we can achieve "fouces" enhancement effects.

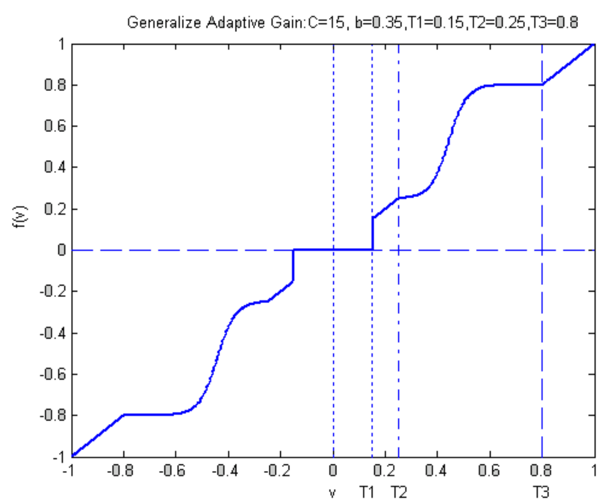



Figure 2 An example of a generalized adaptive gain function

Thus our nonlinear enhancement is very easy to realize. After the demixing transform (only including the "Edge" components), we apply our GAG operator to enhance the image feature. Then our restored image can be obtained after a mixing transform. Figure 3 shows the flow chart of the entire operation.

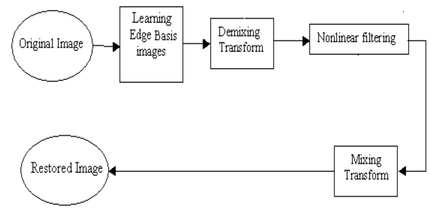



Figure 3 Flow chart for the proposed method

**Experimental Results and Concluding Remarks:**

Fig. 4 shows the basis images of Fig. 5a. We compare the proposed method with two other approaches (Wiener filtering and median filtering). The results that are shown in Figure 5 demonstrate that with our method the speckle noise is efficiently removed while at the same time important details (edges in particular) are retained without introducing artificial structures. We further calculate the ratio of standard deviation to mean (SD/Mean) for each image and use it as a criterion for image quality.

In general, smaller values in standard deviation to mean ratio imply less noise in the image and better quality. The results are shown in Table 1. From both the figures and the table, we can conclude that our method outperforms the others in terms of both visual quality and performance criterion.

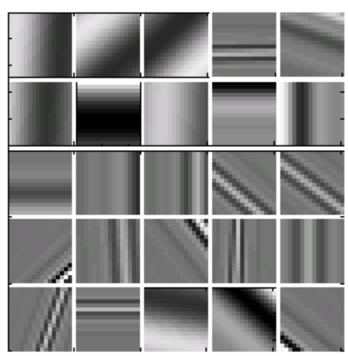
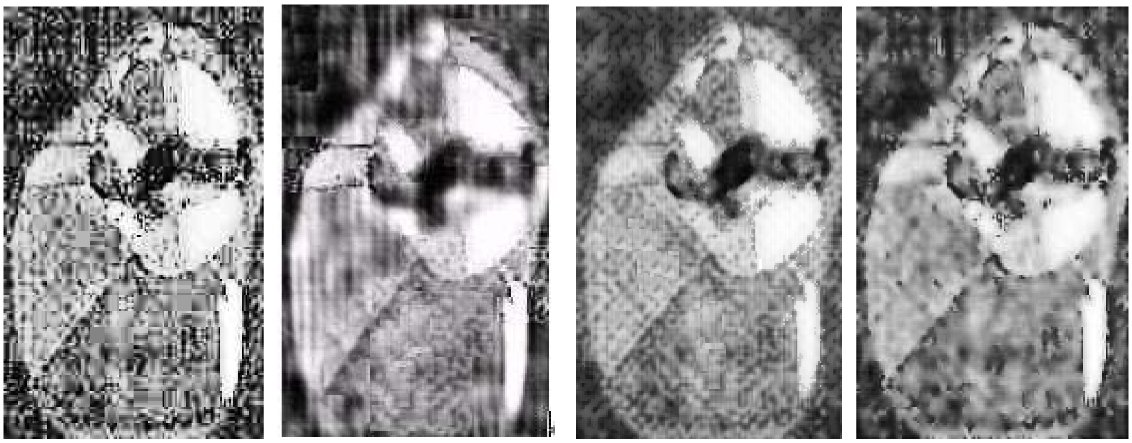


Figure 4 The Basis Images after Convergence



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

Figure 5 (a)Original Image (b) The restored image with the proposed method (c) The restored image with Wiener filter (d) The restored image with median filter

TABLE 1 Ratio comparison

| | (a) | (b) | (c) | (d) |
|---|---|---|---|---|
| SD/Mean (Fig. 5) | 0.5250 | 0.4246 | 0.4434 | 0.4614 |

**Future Work:** Our method as presented performs well but can be computationally more demanding. It does have potential to become a general approach for NDE image enhancement and restoration.

Our immediate future work will focus on how to build a more accurate model to describe the basis functions. We will also look into the performance of the proposed method on the laser ultrasound images, which also have significant amount of speckle noises.

**References:**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