FASTICA FOR ULTRASOUND IMAGE DENOISING USING MULTISCALE RIDGELET TRANSFORM

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ABSTRACT

Ultrasoundography is widely used and it is considered to be the safest technology in medical imaging. As the images are noisy with speckle which are the outcomes of interference between coherent waves and are backscattered by targeted surfaces. Finally at the sensor, they arrive out of phase. This limits the extraction of fine details from the image. Here, a new algorithm using Multi-scale Ridgelet Transform (MRT) by using Fast Independent Component Analysis (FastICA) is proposed for ultrasound image denoising. The proposed algorithm is extended from the existing FastICA algorithm which is not suitable for the noisy signals. For solving this problem, we sum up the two method i.e. image denoising and source separation on ultrasound images under noise conditions. The results of the proposed method i.e. improvement in Peak Signal to Noise Ratio (PSNR) as compare to FastICA conclude that it can separate every independent component effectively under different noise conditions.

KEYWORDS: FastICA, Multiscale Ridgelet Transform, Radon Transform, Ultrasound Image

I. INTRODUCTION

Medical diagnosis collects information from various sources like clinical tests, patient history, histological reviews, and imaging techniques for getting proper conclusions towards diseases. In this regard Ultrasound imaging is one of the safest and easily available techniques which become popular because of its characteristics like non invasive, portable, relatively inexpensive, and provides a real –time image. The technique is based on the principle of reflected sound waves and to form an image of the tissue it utilizes the interaction of sound waves with living tissue. Finally, each & every information from the target organ can be analyzed through these real time images. The poor quality is the basic problem of ultrasound images i.e. caused by the multiplicative speckle noise. To identify the particular part which experts want to examine, the process takes considerable time to get the image and this causes a discomfort to the patient. Thus, the major issues are delay in diagnosis and lack of clarity of image.

This paper focus on the enhancement of the ultrasound imaging systems with the help of improved PSNR to enhance the visualization of Images. This research has given rise to the development of many methods aiming to solve this problem [1], [2]. An interesting aspect of this emerging field, which is still open to more research, is the fact that the theoretical development evolves in pair with the real-world application specifications and requirements. Extracting components and time courses of interest from fMRI data [3], [4] is a representative illustration of this statement. BSS (Blind Source Separation) can be evaluating with dual strategies: Source reconstruction problem or Source decomposition problem. In the first strategy, one assumes that during an experiment E, the collected data $x_{t,x} = \{x_1, \ldots, x_T\}$ are not a faithful copy of the original process of interest $s_{t,x}$.

$$x_{t,x} = F(s_{t,x}) \cup n_{t,x}$$

(1)

i.e. $s_{t,x}$ the observed data are some transformation F of the sources $s_{t,x}$ corrupted with a Stochastic noise $n_{t,x}$ which reflects either the modelling incertitude or the superposition of real unwanted
signals. Here $\Delta$ is the operator modelling the noise superposition and our aim is to recover the original sources $S_{1...T}$ from the observed data. The second strategy deals with the source separation problem which is to be considered as decomposition. The decomposition approach can be considered to be dual to the reconstruction approach (Fig. 1). For instance, principal component analyses (PCA) rely on the decorrelation between the decomposed components, and independent component analyses (ICA) rely on their statistical independence.

The Multiscale Ridgelet transform [5] is proposed to overcome the limitations of Fast ICA Algorithm, by improving the threshold for preserving and enhancing the ultrasound images. The performance of each algorithm will be compared using PSNR.

This paper includes:
- Section II presents the concise review of FastICA.
- Section III presents the Ridgelet transform.
- Section IV presents the threshold methods for image denoising and proposed work.
- Section V presents the Experimental results and discussions.
- Finally, conclusions are derived based on above work in section VI.

## II. FastICA ALGORITHM

Presently, conventional ICA model estimated algorithm mainly includes 3 factors: Information maximization, Mutual information minimization and Maximum likelihood estimation method. Slow convergence rate and large computing quantity are the main remedy with this algorithm. But FastICA overcome these remedy as it is based on a fixed-point iteration scheme which has most of the advantages of neural algorithms, such as small memory requirements, parallel distribution and fast convergence.

### Data Pre-processing

ICA algorithm is usually required an appropriate pre-treatment for the observed data, if it uses a fast fixed-point algorithm for it. Finally the convergence in the calculation process is improved. Here, to whiten the data is the most significant step which refers to a linear transformation of the data. It makes sure the sub-vector of unrelated new vector and the new vector’s covariance matrix is an identity matrix which is called as spatially white, this process is called whiten. Here, we have supposition that $x(t)$ has zero mean, and the pre-whiten treatment for $x(t)$ can achieve under the condition below.

$$P(t) = Qx(t)$$ \hspace{1cm} (3)

Where, $P(t)$ is whiten vector and $Q$ is whiten matrix, and is selected to assure the sub-vector of whiten vector unrelated and have a unit variance. Therefore, correlation matrix (covariance matrix) of $P(t)$ becomes a unit matrix, i.e.

$$E \{PP^T\} = I.$$  

Then, Eq. (3) becomes Eq. (4):

$$P(t) = Qx(t) = QASS(t) = KS(t)$$ \hspace{1cm} (4)

Where matrix $K=QA$ is called separation matrix which is MxM orthogonal matrix, then

$$E \{PP^T\} = KE|SS^T|K^T=I$$ \hspace{1cm} (5)

Therefore,

$$S(t) = K^Tp(t)$$ \hspace{1cm} (6)
Determination of Objective Function

Fast fixed-point algorithm (FastICA) is a rapid neural algorithm by seeking a local extremum of observed variable’s linear combination of fourth-order cumulant (kurtosis coefficient). Then we can use kurtosis coefficient to get separation matrix. Kurtosis coefficient is the higher-order statistics of signal. For a zero-mean random variable $y$, kurtosis coefficient is defined as:

$$Kurt[y] = E[y^4] - 3[E[y^2]^2]$$  \hspace{1cm} (7)

If $y$ is a Gaussian random signal, the kurtosis coefficient is zero. When the random signal is super-Gaussian distribution, its kurtosis is positive; when the random signal is sub-Gaussian distribution, its kurtosis is negative. For two independent random signal $y_1$ and $y_2$, $kurt[y_1+y_2]=kurt[y_1]+kurt[y_2]$, for a scalar constant $\beta$, $kurt[\beta y]=\beta^4 kurt[y]$. We get the vector $P$ as pre-whitening treatment for $x(t)$ which is observation signal. Now, we assume that there is a linear combination $W^T P$, and the norm of $W$ is bounded $\|W\|=1$, finally we can evaluate the greatest or the smallest kurtosis.

$$Kurt (WTP) = Kurt (WTKS) = Kurt (ZTS) = \sum_{ni=1}^n z_i^4 i kurt (si)$$  \hspace{1cm} (8)

Eq. (8) is the objective function what we seek to.

III. MULTISCALE RIDGELET TRANSFORM (MRT)

Radon Transform

The Radon transform of an object $f$ is the collection of line integrals indexed by $(\theta, t) \in [0, 2\pi) \times \mathbb{R}$ given by

$$Rf(\theta, t) = \int f(x_1, x_2) \delta(x_1 \cos \theta + x_2 \sin \theta - t) \, dx_1dx_2$$  \hspace{1cm} (9)

Where $\delta$ is the Dirac distribution.

Multiscale Ridgelet Transform (MRT)

Multiscale ridgelet transform is based on the ridgelet transform and with a spatial band pass filter operation to isolate different scales as shown in [6].

Algorithm

1. Apply the `a trous algorithm with J scales [7].
2. Apply the radon transform on detail sub-bands of J scales.
3. Evaluate the ridgelet coefficients by putting 1-D wavelet transform on radon coefficients.
4. Finalize the multiscale ridgelet coefficients for J scales.

![Fig. 1: Relations between transforms.](image)

IV. IMAGE DENOISING

Assume that one is given with noisy data of the form:

$$\overline{I}(x, y) = I(x, y) + \sigma Z(x, y)$$  \hspace{1cm} (10)
Where $Z(x,y)$ is unit-variance and zero-mean Gaussian noise. Denoising a way to recover $I(x,y)$ from the noisy image $I(x,y)$ as proper as possible. Rayudu et al. [29] have proposed the hard thresholds for Ultrasound image denoising as shown below:

Let $y_\lambda$ be the noisy ridgelet coefficients ($y = MRT*I$). They used the following hard-thresholding rule for estimating the unknown ridgelet coefficients:

\[
\hat{y}_k = \begin{cases} 
 y_k ; & \text{if } |y_k|/\sigma \geq k \hat{\sigma}_k \\
 0 ; & \text{else}
\end{cases}
\]  

(11)

In their experiments, they have chosen a scale dependent value for $k$; $k = 4$ for the first scale ($j = 1$) while $k = 3$ for the others ($j > 1$).

**Algorithm**

1. To get the scaling coefficients and multiscale ridgelet coefficients apply multiscale ridgelet transform to the noisy images.
2. Apply thresholding to the multiscale ridgelet coefficients by choosing the threshold with the help of Eq. (11).
3. Reconstruct the threshold scaling coefficients and the multiscale ridgelet coefficients to get the denoised image.

**Proposed Algorithm**

Below is the algorithm for proposed blind source separation under different noise conditions.

1. Load the two images for source mixing.
2. Apply the Gaussian noise of zero mean and 0.01 standard deviation.
3. By using the multi-scale ridgelet transform apply the noise removal algorithm.
4. Finally, by using FastICA algorithm apply the source separation algorithm.

**V. EXPERIMENTS & RESULTS**

In the field of digital image processing removal of noise from the images is a critical task. The PSNR i.e. Peak Signal to Noise Ratio, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupted noise that provides the fidelity of its images. Below table shows the denoising results of two methods on five sample ultrasound images. Here, in fig 4 the first column shows the sample images with Gaussian noise of zero mean and 0.01 variance; second and fifth column shows the combination of mixing images, third, fourth and sixth,seventh columns denote comparison result of FastICA and proposed method i.e. multiscale ridgelet transform respectively. It is clear that our proposed method shows improvement PSNR as compare to the FastICA by which it is concluded that it can separate every independent component effectively under different noise conditions.
Table 1: Performance Comparison between Different Methods

<table>
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<th>Noise Level</th>
<th>Image Name</th>
<th>PM1</th>
<th>PM2</th>
<th>Image Name</th>
<th>PM1</th>
<th>PM2</th>
</tr>
</thead>
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<td>33.3542</td>
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<td>30.753</td>
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<td>5</td>
<td>37.1425</td>
<td>43.5814</td>
</tr>
</tbody>
</table>

PM1: Fast ICA Algorithm  
PM2: Fast ICA Algorithm + Ridgelet Transform  
Above table shows the denoising results of two methods on five sample ultrasound images. In Fig. 4, the first column shows the sample images with Gaussian noise of zero mean and 0.01 variance; second & fifth column shows the two combination of mixing images, third, fourth and sixth seventh columns denote comparison result of Fast ICA and proposed method i.e. multiscale ridgelet transform respectively. It is clear from results that our proposed method shows improvement in PSNR as compare to the FastICA by which it is concluded that it can separate every independent component effectively under different noise conditions.

VI. CONCLUSION

The current findings add substantially to our understanding of Fast ICA in the field of ultrasound imaging. For evaluation of the proposed method, some ultrasound images are selected randomly negotiation between the preservation of useful diagnostic information and noise suppression must be treasured in medical images. In case of ultrasonic images, a special type of acoustic noise, i.e. known as speckle noise, is the major issue of image quality degradation. For effective suppression of speckle noise many denoising techniques have been proposed. Extracting the noise from the original image is still a challenging task for researchers. Here, the Fast ICA based multiscale ridgelet transform denoising algorithm for Ultrasound images is proposed. Based on the results, we can conclude that proposed method can separate every independent component effectively under different noise conditions.

REFERENCES

AUTHORS


Ketaki Solanki: I am having 6+ years of experience. I started my professional career as an Assistant Professor in Electronics & Communication Engineering. I completed M.Tech in Electronics and Communication Engineering. Image Processing and Digital Signal Processing, Algorithm and Data Structure, Operating Systems are my area of Research and Development.