Study on Medical Image Processing Algorithm based on Contourlet Transform and Correlation Theory

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Abstract

In recent years, processed medical image becomes more and more important to diagnosis. Anamorphic image may result in wrong judgment on state of an illness, even leads to fateful danger. Meanwhile, more efficient data transportation and storage are required with the development of high-resolution photography. Therefore, thousands of researchers work on the field of medical image processing. In this paper, contourlet transform, which may provide with tight bracing and mutli-scale analysis, is introduced. And a new medical image processing algorithm based on contourlet transform and correlation theory is presented. This algorithm possesses some excellent performances such as multi-scale analysis, time-frequency-localization and multi-directions. Especially, this algorithm has excellent performance when describing anisotropic 2-D data. So high-quality medical image can be reconstructed even though a relative few coefficients are employed.

To verify the algorithm, some medical images were processed. The experimental results show that this algorithm has better performance in compression and denoising than that of wavelet transform.

Index Terms - Contourlet Transform. Correlation Theory. Medical Image. Image Processing.

1. Introduction

Medical Imageology is a cross-discipline to study imaging technology of biomedicine. And it is an important part of iatrology diagnosis technology. In iatrology, the image has very significant sense for people understanding disease. Every new imaging technology will greatly drive iatrology forward once it applies in medicine. Although all kinds of imaging technology have respective theory and method, their diagnosis value and limit is also respectively different, but all their objectives are finding out people's physiology function state and pathology variation so as to diagnose illness by observing image of internal structure and organ of human [1].

Nowadays, medical image not only extends examination scope of human disease and enhances diagnosis level, but also treats some diseases. It has become an important backbone of medical treatment. Along with the development of science and technology, medical imageology may be used surveying morphological variation as well as giving functional diagnosis today. Therefore, medical imageology has become an important studying objective in the world and obtained great progress.

The history of medical imageology can trace to 1895. In that year, germen roentgen discovered X-ray in CRT experiment. Consequently radiology, which may diagnose internal organs of human based on image, was established. And the basis of medical imageology was settled too. Now, with the rapid development of medical technology, the medical image plays an important role in clinical diagnosis, therapy, teaching and researching. These imaging modalities include computerized tomography (CT), magnetic resonance imaging (MRI), ultrasound image (USI), X radiographs, electronic endoscope image (EEI), Electrocardiogram (ECG) and Electroencephalography (EEG) etc., where some image can provide flexible means of reviewing anatomical cross-sections and physiological states meanwhile may reduce patient radiation doses and examination trauma [2]. But due to some reasons, the use of this information is greatly limited. With the increasing mature of computer and image processing technology, these technologies has gradually entered medical field and made the quality of medical image and vision method has greatly improved, and the level of diagnosis and therapy have

978-0-7695-3507-4/08 $25.00 © 2008 IEEE
DOI 10.1109/CSIE.2009.1010

been greatly improved by using image operation and analysis.

2. Image processing technologies of medical imageology

In general, many images processing technology, such as image reinforcing, edge detection, image denoising and image compression etc, may apply in medical fields.

2.1. Necessity of image compression technology in medical image

Because numberized medical image has higher resolution, it needs more storage space. To meet the demand for high-speed transmission of image in image storage and remote treatment, the efficient image compression is necessary. Compression may be lossy or lossless, depending on system requirements. Lossless compression ensures complete data fidelity, but it is typically limited to compression ratios of between 2:1 and 3:1. Hence, lossless techniques only a modest reduction file size. Lossy compression methods are required to reduce significantly transmission and storage cost, but losses must not be diagnostically significant. In recent years, some American industrial standards such as ACR and NEMA, and DICOM have been established.

2.2. Some algorithms of image compression technologies

Recently, medical image encoding methods have been developd rapidly. Many new methods have been proposed, such as full frame DCT [3], JPEG [4], motion compensation DCT [5], vector quantization [6], segmentation-based encoding, Fractal Image Compression Encoding and wavelet transform (WT) [7]. Among which, WT is the up to date one. Here, WT is used as the standard of comparison.

2.3. Denoising technology of medical image

Some medical images may contain strong background noises, such as US image, ECG image and EEG image etc. in order to use these images polluted by noise in clinical diagnosis and therapy of doctor. Application of denoising technology is necessary.

Fox example, EEI contains plentiful stomach information which has great value in clinical diagnosis. EEI has many background noises which need to be suppressed. There are many methods for EEI denoising, and new method continually emerges too. Gramatikov [8] has suggested that WT is prospective and potential in EEI denoising.

Morlet use WT to extract high-resolution of medical image in post-infarction patients. In 2003, Sun Guangyao [9] present that signals was filtered by Mallet Algorithm using the dyadic spline WT, and disturbances were eliminated.

By dynamical changing the size of frequency window, the wavelet analysis provides space and time locating capability which can not been provided from base function derived from sine signal or pulse function. Nevertheless, in 2-D data processing, wavelet analysis meets difficulty too. The cause is that wavelet is decomposed just in horizontal and vertical direction. And in higher dimension information, direction of the useful data is complicated. Thus, the efficiency and veracity of wavelet analysis is damaged. In order to solving this problem, many new methods are put forward.

On the basis of recent development of image processing technology, we further explore high-resolution and multi-scale analysis method. The contourlet transform (CT) is introduced into the fields of medical image analysis. Consequently, the inherent shortcoming of traditional analysis method is solved and exactly extraction on medical image information is realized.

3. Main title Contourlet transform

3.1. comparing with WT

WT would take many wavelet coefficients to accurately represent even one simple 2-D curve, so CT were developed as an improvement over WT in order to resolve this inefficiency. The CT has the multiscale and time-frequency-localization properties of WT; meanwhile it offers a high degree of directionality and anisotropy. Precisely, CT involves basis functions that are oriented at any power of two's number of directions with flexible aspect ratios. With such richness in the choice of basis functions, CT can represent any 1-D smooth edges with close to optimal efficiency. Fig. 1 shows that compared with WT, CT can represent a smooth contour with much fewer coefficients [10].

3.2. Pyramidal directional filter bank and Iterated directional filter banks

Contourlets are implemented by the pyramidal directional filter bank (PDFB) that is a cascade of a laplacian pyramid (LP) and a directional filter bank

(DFB) [11]. Due to this cascade structure, multiscale and directional decomposition stages in the CT are independent of each other. We can decompose each scale into any arbitrary power of two’s number of directions, and different scales can be decomposed into different numbers of directions.

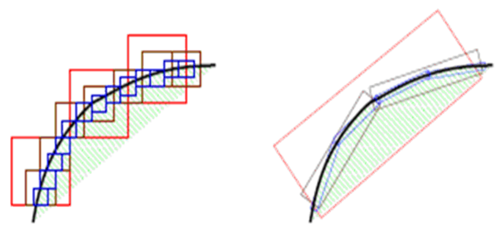


Fig. 1. Wavelet versus Contourlet: illustrating the successive refinement by the two systems, where Contourlet using fewer coefficients than wavelet.

Bamberger and Smith [12] constructed a 2-D directional filter bank (DFB) that can be maximally decimated while achieving perfect reconstruction. To obtain the desired frequency partition, a complicated tree expanding rule has to be followed for finer directional subbands [13]. In [14], a new construction was proposed for the DFB that avoids modulating the input image and has a simpler rule for expanding the decomposition tree. This DFB is intuitively constructed from two building blocks. The first building block is a two-channel quincunx filter bank [15] with fan filters (see Fig. 2) that divides a 2-D spectrum into two directions: horizontal and vertical. The second building block of the DFB is a shearing operator, which amounts to just reordering of image samples.

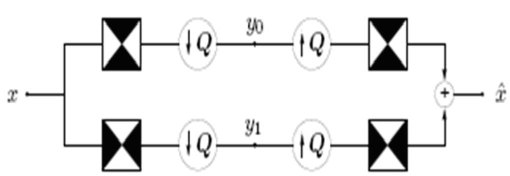


Fig. 2. 2-D frequency partition using quincunx filter banks with fan filters. The black regions represent the ideal frequency supports of each filter. Q is a quincunx sampling matrix.

4. building discriminant for filtering

Essentially, CT filters noise from signal by means of limited iterative decompositions and reconstructions. But the levels of decomposition and the threshold value of reconstruction is very dependent on individual experience. Therefore, there is strongly subjectivity when the data is processed. According to relational theories of that signal is not correlated with noise, an objective filtering rule is proposed in this paper. Generally, the signals containing noise are processed as Fig. 3.

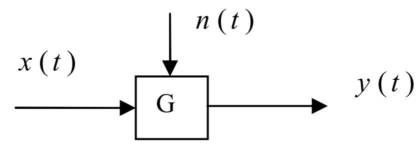


Fig. 3 Signals flow chart.

Where $x(t)$ is input signals, $n(t)$ is noise, G represents processing system and $y(t)$ is output signals.

Thus, the cross correlation function of input signals and output signals is:

$$r_{xy}(t) = \int_{-\infty}^{+\infty} [x(t)+n(t)] * y(t-\tau)dt \tag{1}$$

Unwrapping expression (1), the cross correlation function may be written as following:

$$r_{xy}(t) = \int_{-\infty}^{+\infty} x(t) * y(t-\tau)dt + \int_{-\infty}^{+\infty} n(t) * y(t-\tau)dt \tag{2}$$

The autocorrelation function of output signals is:

$$r_{y^2}(t) = \int_{-\infty}^{+\infty} y(t) * y(t-\tau)dt \tag{3}$$

In the ideal case that noise may be fully filtered out and the direct current part of both signal and noise are also taken out, the first part of the expression (2) is an autocorrelation function of output signals, and the second part is zero. The difference between expression (1) and expression (2) is described with e (t), thus,

$$\begin{aligned} e(t) = r_{xy}(t) - r_{y^2}(t) = \int_{-\infty}^{+\infty} x(t) * y(t-\tau)dt + \\ \int_{-\infty}^{+\infty} n(t) * y(t-\tau)dt - \int_{-\infty}^{+\infty} y(t) * y(t-\tau)dt = 0 \end{aligned} \tag{4}$$

Based on above expressions, the levels of decomposition and reconstruction may be controlled; consequently, noise may be filtered from signal according to our demand.

The main title (on the first page) should begin 1-3/8 inches (3.49 cm) from the top edge of the page, centered, and in Times 14-point, boldface type. Capitalize the first letter of nouns, pronouns, verbs, adjectives, and adverbs; do not capitalize articles, coordinate conjunctions, or prepositions (unless the title begins with such a word). Leave two 12-point blank lines after the title.

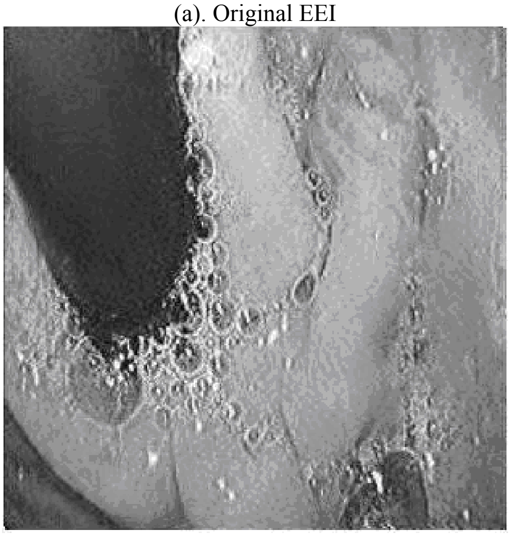
5. Experiment and analyses

Two experiments have been done in this study. In experiment 1, an EEI was respectively processed with CT and WT so as to verify their denoising performance. In experiment 2, a series of experiments of cerebral CT image were done to test compression performance of CT.

5.1. experiment 1: denoising

Based on above mentioned algorithm, we rewrote some codes and processed a 512*512 gray-scale EEI. The result is shown as following:

(a). Original EEI



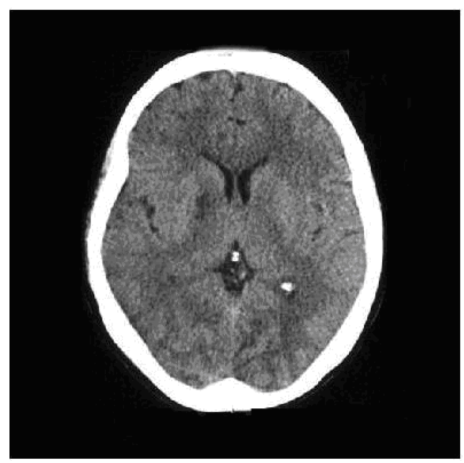
(b). Denoising using WT (SNR=13.52dB)

(c). Denoising using CT (SNR=14.00dB)

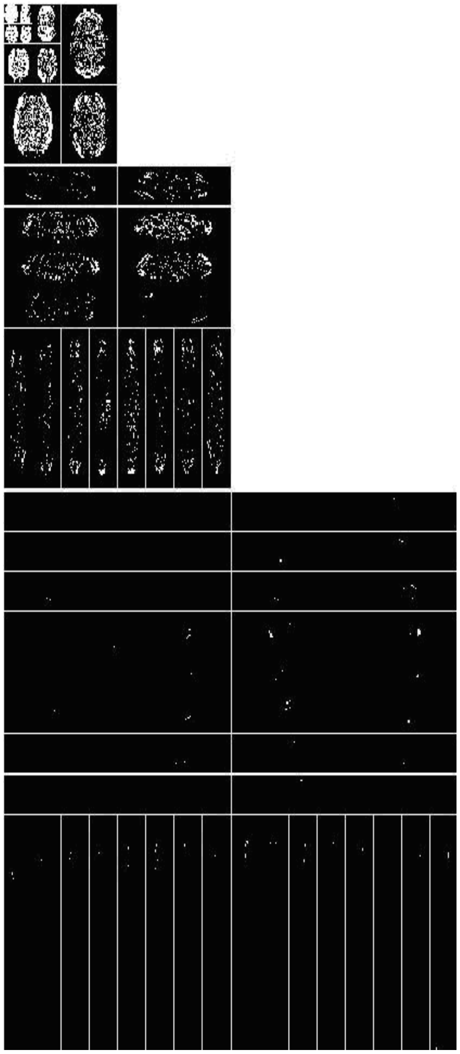
Fig. 3. denoising performance: CT versus WT. The result shows that the CT takes advantages to the WT in 2-D medical image denoising.

5.2. Testing for image compression

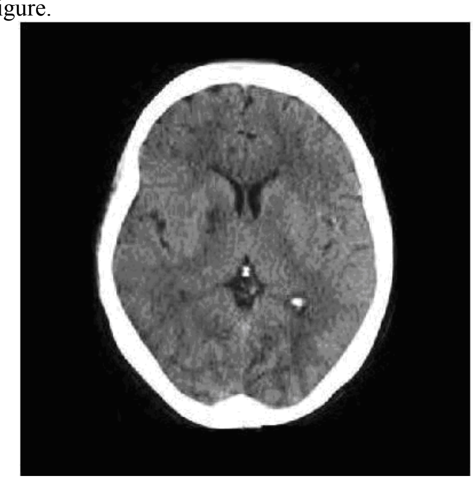
Here, a series of experiments were done. Some of testing results are illustrated as following:



(a). Original cerebral CT image

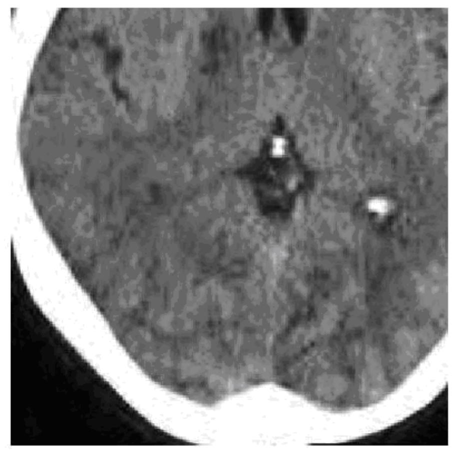


(b). 344064 coefficients are obtained when the original image is decomposed, where 6554 significant coefficients will be retained. These retained coefficients distribute as above figure.



(c). Reconstructed image with contourlet transform (using 6554 coefs; SNR=23.35dB)

(d). Reconstructed image with WT (using 6554 coefs; SNR=22.76dB)



(e) Reconstructed image with contourlet transform (using 6554 coefs; SNR=23.35dB)

Fig. 4. Some experimental results for cerebral CT image compression

6 Conclusion and further work

The results of experiment 1 show that denoising performance of CT is better than that of 2-D WT in processing medical image. And experiment 2 indicates that contourlet compression algorithm has outstanding performance in medical image compression (SNR is 23.35dB when compression ratio is 52.5). In the future, we will continually perfect the algorithm and corresponding evaluation work.

7. Acknowledgements

This work has been supported by National Natural Science Foundation of China (50175037) and Science and Technology Department of Zhejiang Province (2006c21127).

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