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An Approach for Embedding and Retrieving the Data in Medical Image Using Contourlet Transform

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Abstract: Data hiding in medical images has wide applications in the medical field. The medical images of different modalities like CT, MRI , with Patient medical Report (PMR) can be sent to the clinicians residing at any corner of the globe for the diagnosis. This has the advantage of data security, attachment of patient data with the medical image which saves the space in hospital digital database. The main requirements of general data hiding method are robustness to attack, high hiding capacity and maintaining Region of Interest (ROI) of the image during their processing. Hence, the comparison of wavelet transform and contourlet transform for data hiding in the medical image(CT-BRAIN) is performed in this work.

***Key Terms* –** Contourlet Transform, Multidimensional Filter Banks and Nonsubsampled Filter Banks.

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1. INTRODUCTION

The contourlet transform [6] is proposed as a directional multiresolution image representation that can efficiently capture and represent the smooth object boundaries in medical images. Its efficient filter bank construction as well as low redundancy make it an attractive computational framework for various image processing applications.

The main challenge in exploring the images comes from the discrete nature of the data. The various approaches like wavelets, and many more approaches develop a transform in the continuous domain and then discretize for sampled data. Contourlet starts with a discrete-domain construction and then its convergence the continuous domain.

The contourlet transform [3] is constructed as a combination of the Laplacian pyramid and the directional filter banks (DFB), the flow of operation is illustrated in Fig 1(a), where the Laplacian pyramid iteratively decomposes a 2-D image into lowpass and highpass subbands, and the DFB are applied to the highpass sub- bands to further decompose the frequency spectrum. Using ideal filters, the contourlet transform will decompose the 2-D frequency spectrum into trapezoid-shaped regions as shown in Fig 1(b).

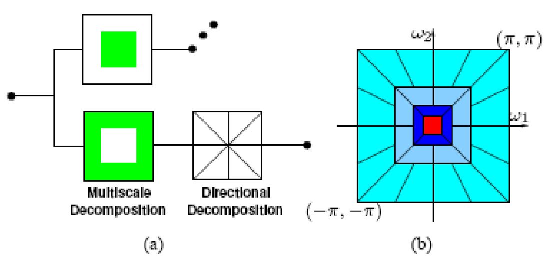

Fig.1. The original contourlet transform.
(a) Block diagram (b) Resulting frequency division.

Contourlet possesses the important properties of directionality and anisotropy which wavelets do not possess and so it outperforms wavelets in many image processing applications. Also contourlet provides a much richer set of directions and shapes than wavelets and thus is more efficient in capturing smooth contours. Due to the presence of both downsamplers and upsamplers in both Laplacian Pyramid and Directional Filter Bank, contourlet transform is not shift-invariant. Shiftinvariance property helps in better detection of edges. Since Contourlet transform is not shift invariant, new derivative of contourlet transform called Non-subsampled Contourlet Tranform (NSCT) is proposed in this work.

This proposed transform can thus be divided into two parts that are both shift-invariant: (1) A nonsubsampled pyramid structure that ensures the multi-scale property and (2) A nonsubsampled DFB structure that gives directionality property.

2. NONSUBSAMPLED CONTOURLET AND FILTER BANKS

The contourlet transform [3],[8] employs Laplacian pyramids for multiscale decomposition, and directional filter banks (DFB) for directional decomposition. To achieve the shift-invariance, the nonsubsampled contourlet transform is built upon nonsubsampled pyramids and nonsubsampled DFB.

2.1. Nonsubsampled Pyramids(NSP)

The multi-scale property of the NSCT[3],[8] is a shiftinvariant filtering structure that achieves a subband decomposition similar to that of the Laplacian pyramid. The solution is obtained by using two-channel nonsubsampled 2-D filter banks. Fig 2.1 illustrates the proposed nonsubsampled pyramid (NSP) decomposition with J = 3 stages. Such expansion is conceptually similar to the 1-D nonsubsampled wavelet transform computed with the 'a trous' algorithm and has J +1 redundancy, where J denotes the number of decomposition stages.

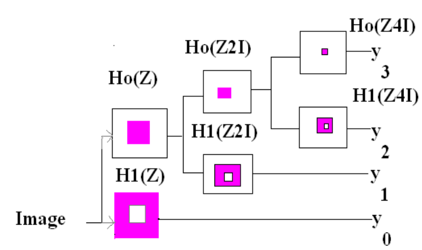

Fig.2.1. Iteration of the two-channel nonsubsampled filter banks in the analysis part of a nonsubsampled pyramid.

The perfect reconstruction condition is given in (Eq 1),

$$H_0(z)G_0(z) + H_1(z)G_1(z) = 1. \qquad (1)$$

this condition is much easier to satisfy the reconstruction condition for critically sampled filter banks, and thus allows better filters to be designed.

The proposed pyramid is not only the 2-D pyramid with J +1 redundancy. Specifically, the NSFB is built from a given lowpass filter $H_0(z)$. One then sets $H_1(z) = 1 - H_0(z)$, and $G_0(z) = G_1(z) = 1$. This perfect reconstruction system can be seen as a particular case of this work with more general structure. The advantage of this construction is that it is less restrictive and as a result, better filters can be obtained.

2.2. Nonsubsampled Directional Filter Banks (NSDFB)

The nonsubsampled DFB[3],[8] is a shift-invariant property of the critically sampled DFB in the contourlet transform. The building block of a nonsubsampled DFB is also a two-channel nonsubsampled filter bank which is shown in Fig 2.2. To obtain the finer directional decomposition, a nonsubsampled DFB's is performed. For the next level, it upsample all the filters by a quincunx matrix given in (Eq 2),

$$Q = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \qquad (2)$$

The NSDFB is constructed by eliminating the downsamplers and upsamplers. This is equivalent to switching off the downsamplers in each two-channel filter bank in the DFB tree structure and upsampling the filters accordingly. This results in a tree composed of two-channel nonsubsampled filter banks.

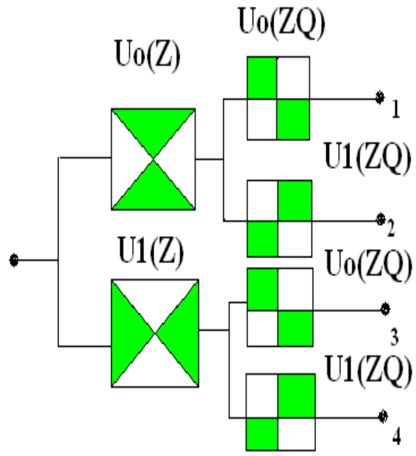

Fig.2.2.A four-channel nonsubsampled directional filter bank constructed with two-channel fan filter banks.

2.3. Nonsubsampled Contourlet Transform

The NSCT [3] is constructed by combining the NSP and the NSDFB as shown in Fig 1 (a). Nonsubsampled pyramids provide multiscale decomposition and nonsubsampled DFB's provide directional decomposition. This scheme can be iterated repeatedly on the lowpass subband outputs of nonsubsampled pyramids. In a typical 5-scale decomposition, it upsample by $2I$ the NSDFB filters of the last two stages. Filtering with the upsampled filters does not increase computational complexity.

Thus, the complexity of the NSCT is dictated by the complexity of the building-block NSFB's. If each NSFB in both NSP and NSDFB requires L operations per output sample, then for an image of N pixels the NSCT requires about BNL operations where B denotes the number of subbands.

For example, if L = 32 Bit for CT--BRAIN abnormal Image, a typical decomposition with 4 pyramid levels, 16 directions in the two finer scales and 8 directions in the two coarser scales would require a total of 1536 operations per image pixel.

In particular, it satisfy the anisotropic scaling property in establishing the expansion nonlinear approximation behavior. This property is ensured by doubling the number of directions in the NSDFB expansion

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at every other scale. The NSCT has redundancy given by, $1+\sum_{j=1}^{J} 2\,lj$ where lj denotes the number of levels in the NSDFB at the j-th scale.

3. WAVELET TRANSFORM

3.1. Introduction

The wavelet transform [5],[7] is an efficient image processing tool. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of a set of such wavelets or basis functions. The result of a separable extension from one-dimensional (1-D) bases, wavelets in higher dimensions can only capture very limited directional information. For example, 2-D wavelets only provide three directional components, namely horizontal, vertical and diagonal.

It uses only 1-D operations. Thus, the systems as the directional filter bank involve nonseparable filtering and sampling and have high computational complexity.

The 1-D wavelet transform can be extended to a 2-D wavelet transform using separable wavelet filters. It is computed separately for different segments of the time-domain signal at different frequencies. The decomposed image for 2-D DWT is shown in the Fig.3.1.

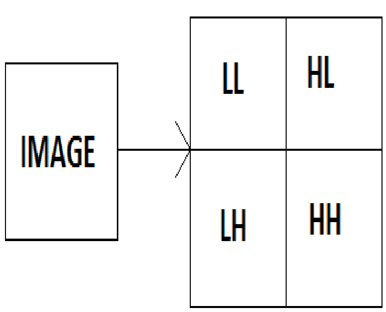

Fig.3.1. 2-D DWT Level of Decomposition

The duration of the wavelet is determined by the bandwidth of subbands and the frequency of the wavelet is determined by the carrier (mid frequency point of subband) of subband. The desired sampling frequency (time resolution) of the wavelets is obtained by the successive down-sampling in the subband filter bank system.

3.2.Wavelet Vs contourlet

The main difference between the wavelet transform and contourlet transform is discussed in the Table I.

TABLE-I

WAVELET	CONTOURLET
It offers less set of directions and shapes.	It offers richer set of directions and shapes.
It is less effective in capturing smooth contours and geometric structures in images.	It is more effective in capturing smooth contours and geometric structures in images.
It starts with continuous domain.	It starts with discrete domain.

4. PROPOSED METHOD

4.1 EMBEDDING ALGORITHM

1.Choose the medical image according to user defined, and decompose the image by using NSCT block.

2.Set the threshold value for data security purpose.

3.Generate the pseudo noise sequence.

4.Ex-OR the PN-Sequence and message Bit, given to mixer for shifting property.

5.embed_ vec (i , j)=embed_ vec (i , j)+ alfa * mes _ ss (k), by using this equation information is hidden, (where alfa=0.8).

6.Repeat steps 3 to 5 until all the information is embedded.

7.Apply INSCT to obtain the embedded image.

This is the approach for embedding the data in the CT-BRAIN abnormal image. By this approach it can store number of patient information which will give the data security and avoids the information loss. This is the major advantage in embedding process.

4.2 RETRIEVING ALGORITHM

1.Apply NSCT to the Embedded Image.

2.Select the threshold value for retrieving the data.

3.Generate the pseudo noise sequence.

4.Org_bin=double(xor (rec_mix1,pn_sequence)), by using this equation the hidden data is retrieved from an image.

5.Repeat steps 3 and 4 until the data is retrieved.

These are the proposed method for data embedding and retrieving in medical image using the Contourlet transform. By this approach it is expected many medical images of different modalities with Patient Medical Report (PMR) attached to them can be sent to the clinicians residing at any corner of the globe for the diagnosis.

5.RESULTS AND CONCLUSION

5.1.Results Of Wavelet and Contourlet Transform

The CT-BRAIN image is given as the input with a resolution of 256X256 gray scale , 32 bit image is shown in the Fig.5.1(a).

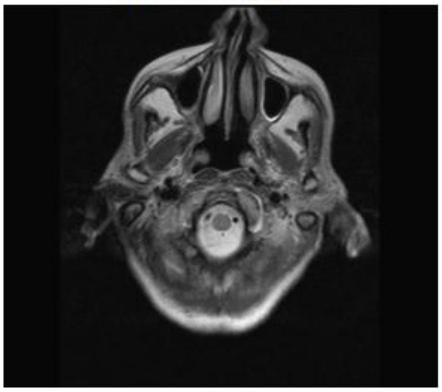

Fig.5.1(a). Input Abnormal image - CT BRAIN.

The wavelet transform using HAAR-DWT decomposed image is shown in Fig5.1(b). The image gives four subbands namely LL, LH, HL,HH. LL is low resolution approximate image other three bands contain edge information of three directions (Vertical, Horizontal, and Diagonal). The main drawback of this method is the directions and its shape. Due to this drawback, data hiding is not efficient in the medical image. Hence, the contourlet transform is proposed .

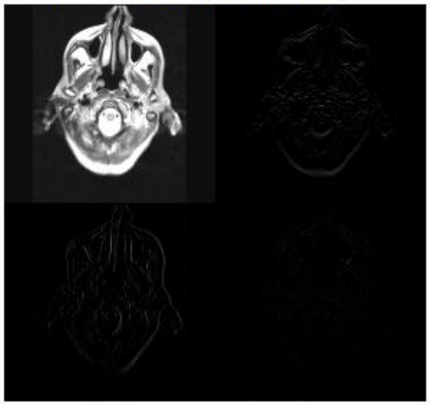

Fig.5.1(b).Wavelet Decomposed Image.

The input image which is shown in Fig.5.1(a) is processed for contourlet coefficient which is discussed in Fig.2.1. The decomposed image for the NSCT is shown in the Fig.5.1(c,d and e) which is the NSCT coefficient.

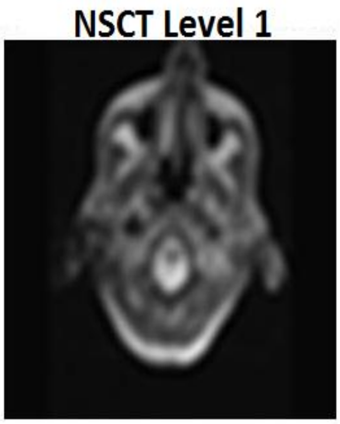

Fig.5.1(c). Decomposed image for NSCT coefficient in level 1.

Fig.5.1(d).Decomposed image for NSCT coefficient in level 2.

Fig.5.1(e).Decomposed image for NSCT coefficient in level 3.

The contourlet transform for various levels and directions which is processed inside the NSCT coefficient are shown in the Fig.5.1(f).

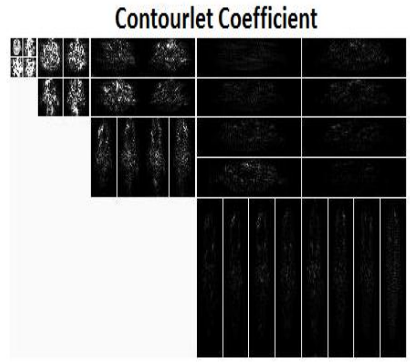

Fig. 5.1(f). Contourlet transform on the CT-BRAIN image. This image is decomposed into two pyramidal levels, which are then decomposed into four and eight directional subbands. Small coefficients are shown in black while large coefficients are shown in white.

The reconstruction of the image is achieved by the inverse NSCT, which is shown in the Fig.5.1(g) .

Fig.5.1(g).Contourlet Reconstructed Image.

Hence, from the above analysis the contourlet transform is more effective than the other transforms for various levels. The result of wavelet transform gives only fewer sets of direction and shape, whereas contourlet gives multi directional set of subbands and shapes. Further the NSCT coefficient of level 3 is used for the data hiding process.

Table 5.1 Tabulation Of Results

Techniq NSCT	CT Normal Input	CT Abnormal Input	MRI Normal Input	MRI Abnormal Input
MSE	0.000047	0.000049	0.000040	0.000039
PSNR	53X10^13	50.5X10^13	61.1X10^13	63.6X10^13

This shows that MSE is very low and PSNR is good for NSCT technique and the reconstructed image is obtained without any loss of information. Hence the work can be extended for classifier technique which will be used to classify the normal and abnormal images.

6. CONCLUSION AND FUTURE WORK

In this project work Medical image obtained from different modalities are used for embedding and retrieving the information without any loss in the data and the original image is reconstructed using the NSCT technique. In this method two techniques were used, to implement the data embedding and retrieving process to reduce the Mean Square Error (MSE) and high peak signal to noise ratio (PSNR). The main drawback in this technique is that it requires more time for embedding and retrieving. The future work can be extended for compression technique to reduce the speed of time and also classifier can be used to distinguish the normal and abnormal medical images.

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