Medical Image Fusion using Ridge let Transform

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ABSTRACT

Image fusion is one of the most modern, accurate and useful diagnostic techniques in medical imaging today. The Fusion of Computed Tomography (CT) image and Magnetic Resonance (MR) image forms a new image with improved information content for diagnosis. The fused image can significantly benefit medical diagnosis and also the further image processing in computer aided diagnosis. The maximum frequency fusion rule is used for fusing the coefficients of ridgelet transform. The simulation results show that the performance of ridgelet transform is better than the wavelet transform in the fusion of CT and MR images from visual quality, Entropy and PSNR points of view.

Key words
CT, MR, Wavelet, Ridgelet, Entropy, PSNR.

1. INTRODUCTION

The use of image fusion techniques has gained significant popularity over the past decade. It is improved with the development of digital image processing and image analysis technology. For many applications, image fusion provides a pleasing perceptual display for the user to make better decisions which drives research in medical applications, geo-spatial displays and military situational awareness [1]. The exploration of image fusion techniques relies on interplay between the user and the system to augment the feature and content of the image. Image fusion algorithms can be categorized into different levels: low, middle, and high; or pixel, feature, and Symbolic levels [8]. The Pixel Level image fusion is to take the average of the two images pixel by pixel. The feature-level algorithms typically segment the image into contiguous regions and fuse the regions together using their properties. The features used may be calculated separately from each image or they may be obtained by the simultaneous processing of all the images. Symbolic level Fusion algorithms combine image descriptions to the fused image, such as in the form of a relational graph. So the main objective of image fusion is to obtain a better visual understanding of certain phenomena, and to introduce or enhance intelligence and system control functions [9]. Medical image fusion is the process of combining relevant information from several images into one image. The final output image can provide more information than any of the single images. It contains various potential applications for medical data collection and diagnosis and assists physicians in extracting features that may not be normally visible in images produced by different modalities. There are numerous medical examples presented of image fusion for registering and combining magnetic resonance (MR) and computer tomography (CT) into composites to aid surgery. In each of these examples, there are numerous opportunities for image fusion success in bringing together images from different images to help in decision making and diagnostics [3].

2. IMAGE FUSION

The task of image fusion is to make many salient features in the new image such as regions and their boundaries [7]. Several situations in image processing require high spatial and high spectral resolution in a single image. However, the instruments are not capable of providing such information either by design or because of observational constraints. One possible solution for this is image fusion. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. During the process of fusion, input images A and B are combined in to a new fused image F by transferring, ideally all of their information into F [13]. This is illustrated graphically using a simple Venn diagram in Fig.1.

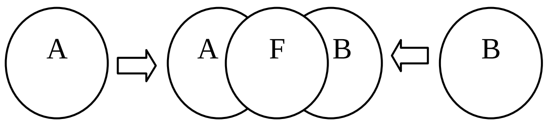


Fig.1. Graphical representation of the image fusion process

The combination of images from different modalities leads to additional clinical information which is apparent in the separate imaging modality. For this reason radiologists prefer multiple imaging modalities to obtain more details [1]. Imaging is performed to extract all the useful information from the individual modality and integrate from source images in to the result, without introducing any artifacts or inconsistencies.

CT images [4] are mainly employed to visualize dense structures such as bones. So, they give the general shapes of objects and few details. On the other hand, MR [10] images are used to depict the morphology of soft tissues. So, they are rich in details. Since these two modalities are of a complementary nature, our objective is to merge both images to obtain as much information as possible.

3. FUSION USING WAVELET TRANSFORM

As with wavelet transforms, a key advantage it has over Fourier transforms is temporal resolution i.e., it captures both frequency and location information [5]. The most common form of transform type image fusion algorithms is the wavelet fusion algorithm due to its simplicity and its ability to preserve the time and frequency details of the images to be fused [7]. A schematic diagram of the wavelet fusion algorithm of two registered images $I_1(X_1,X_2)$ and $I_2(X_1,X_2)$ is depicted in Fig.2.

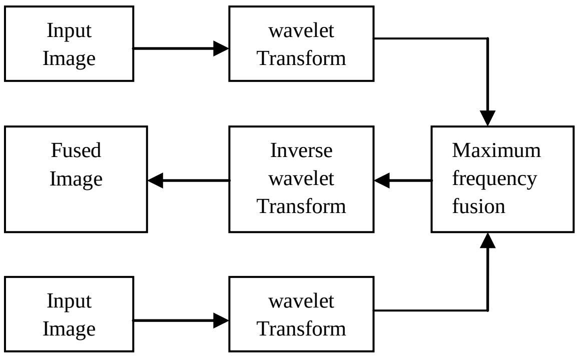


Fig.2. Block diagram of Image fusion using Discrete Wavelet Transform

Two images, $I_1(X_1,X_2)$ and $I_2(X_1,X_2)$ are registered. Wavelet transform is applied on two images. It can be represented by the following equation,

$$I(X_1,X_2) = W(I_1(X_1,X_2)), W(I_2(X_1,X_2))))$$

where W is the wavelet transform operator.

Wavelet coefficients are fused using the fusion rule. IDWT is applied on the fused wavelet coefficients to obtain the fused image $I(X_1,X_2)$ given by

$$I(X_1,X_2)=W^{-1}(\varphi(W(I_1(X_1,X_2)), W(I_2(X_1))))$$

Where W^{-1} and φ are the Inverse Discrete Wavelet Transform operator and fusion operator.

There are several wavelet fusion rules, that can be used for the selection of the wavelet coefficients from the wavelet transform of the images to be fused [13]. The most frequently used rule is the maximum frequency rule which selects the coefficients that have the maximum absolute values. The Wavelet Transform concentrates on representing the image in multiscales and it's appropriate to represent linear edges. For curved edges, the accuracy of edge localization in the Wavelet Transform is low [5,3]. So, there is a need for an alternative approach which has a high accuracy such as the Ridgelet Transform.

4. FUSION USING RIDGELET TRANSFORM

The Ridgelet Transform [2,4] belongs to the family of discrete transforms employing basis functions. To facilitate its mathematical representation, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool for shape detection. So, the Ridgelet Transform is primarily a tool of ridge detection or shape detection of the objects in an image [6].

The Ridgelet basis function is given by,

$$\Phi_{a,b,\theta} = (x_1,x_2) = a^{-1/2}\,\Phi((x_1\cos\theta + x_2\sin\theta - b)/a)$$

for each $a>0$, each $b \in \mathbf{R}$ and each $\theta \in [0, 2\pi)$. This function is constant along with lines $x_1\cos\theta + x_2\sin\theta$ = constant. Thus, the ridgelet coefficients of an image $f(x_1, x_2)$ are represented by:

$$R_f(a,,\theta) = \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} \varphi_{a,b,\theta}(x1,x2)\, f(x1,x2)\, da\, db\, d\theta}{4\pi a}$$

This transform is invertible and the reconstruction formula is given by:

$$f(x_1,x_2) = \int_0^{2\pi}\int_{-\infty}^{\infty}\int_0^{\infty} \frac{R_f(a,b,\theta)\,\varphi_{a,b,\theta}(x1,x2)\, da\, db\, d\theta}{4\pi a}$$

Hence, the Ridgelet Transform [11] is the application of the 1D-Wavelet Transform to the slices of the Radon transform where the angular variable θ is constant and it is varying. To make the Ridgelet Transform discrete, both the Radon transform and the Wavelet Transform have to be discrete.

First the 2D Fast Fourier Transform (FFT) of the given image is computed. Then the resulting function in the frequency domain is to be used to evaluate the frequency values in a polar grid of rays passing through the origin and spread uniformly in angle. When applying 1D-FFT for the rays, a variant of the Radon transform is obtained, where the projection angles are not spaced uniformly [5].

A by-product of this construction is the fact that the transform is organized as a 2D array with rows containing the projections as a function of the angle. Thus, processing the Radon transform in one axis is easily implemented [12]. To complete the ridgelet transform, a one-dimensional wavelet transform (WT1D) along the radial variable in Radon space has to be taken. Assembling all above ingredients together gives the flowchart of the discrete ridgelet transform (DRT) depicted in Fig.3.

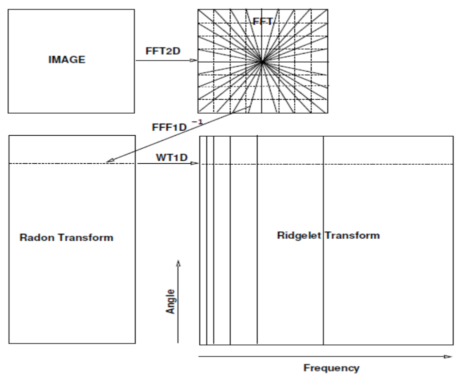


Fig.3. Discrete Ridgelet Transform flow chart

The DRT of an image of size n × n is an image of size 2n × 2n, introducing a redundancy factor equal to 4. Because this transform is made of a chain of steps, each one of which is invertible, the whole transform is invertible, and so has the exact reconstruction property. For the same reason, the reconstruction is stable under perturbations of the coefficients[11]. Last but not least, this discrete transform is computationally attractive. The block diagram of image fusion using the ridgelet transform is shown in the Fig4.

4.1 Fusion Algorithm

- Two images, MR and CT are registered.
- Ridgelet Transform is applied on both the images.
- Ridgelet coefficients are fused using maximum frequency fusion rule which selects the coefficients that have the maximum absolute values.
- Inverse Ridgelet Transform is applied on the fused ridgelet coefficients to obtain the fused image.

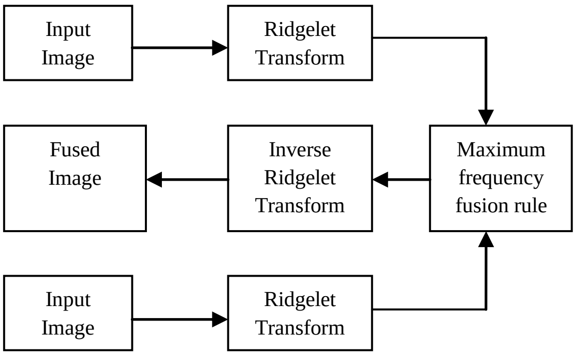


Fig.4. Block diagram of image fusion using Ridgelet transform

5. EXPERIMENTAL RESULTS

The Ridgelet fusion algorithm for the fusion of MR and CT images is tested and compared to the traditional wavelet fusion algorithm. The visual quality of the fused image and the quantitative analysis are used for the evaluation of fusion algorithm using wavelet and ridgelet transforms.

5.1 Entropy

It is used to measure the difference between the source image and the fused image. For better fusion result the entropy should have a smaller value.

Entropy is given by

$$E\,(d, f) = \sum_{i=0}^{L-1} p_d(i)\log_2 \frac{p_d(i)}{p_f(i)}$$

5.2 PSNR

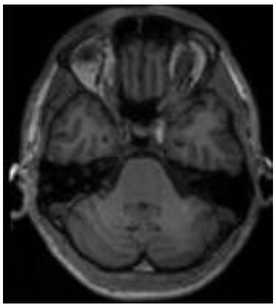
The PSNR of the fusion result is defined as follows:

$$PSNR = 10 \times \log\ (f_{max})^2\ /RMSE^2$$

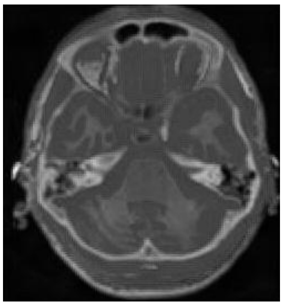
Where f_{max} is the maximum gray scale value of the pixels in the fused image. The higher the value of the PSNR, better the performance of the fusion algorithm.

The Entropy and PSNR values between the source image and the fused image are obtained. The CT and MR scans of the brain are used for the experiment as shown in Figs 4, 5 and 6. And also the wavelet and ridgelet fusion results are obtained as shown in Figs 4, 5 and 6. The Entropy and PSNR values of these results are tabulated in Tables 1, 2 and 3. From these results, it is clear that the ridgelet transform fusion algorithm has succeeded in obtaining better results than the wavelet transform fusion algorithm. The Database consists of 45 volumes of medical images and all the images are tested. The fusion results of some of the sample images are shown below.

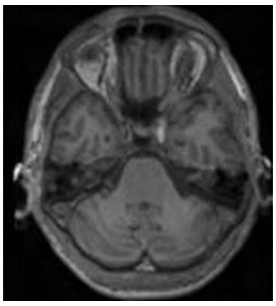
(a)



(b)

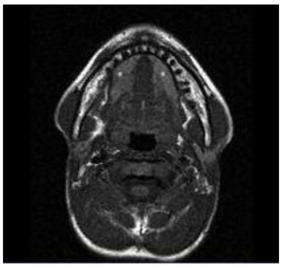


(c)

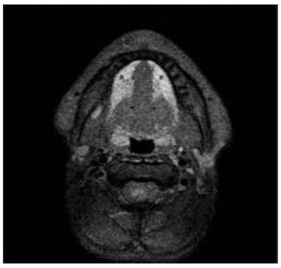


(d)

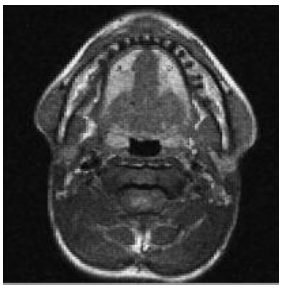
Fig.5. Image fusion. (a) CT Image-Brain1. (b) MR Image-Brain1.(c) Fused Image-Wavelet Transform. (d).Fused Image-Ridgelet Transform.



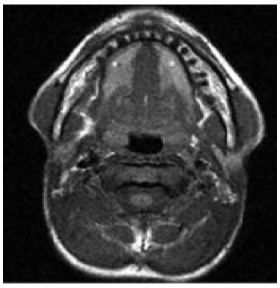
(a)



(b)



(c)



(d)

Fig.6. Image fusion. (a) CT Image- Brain2. (b) MR Image-Brain2 (c) Fused Image-Wavelet Transform. (d) Fused Image-Ridgelet Transform

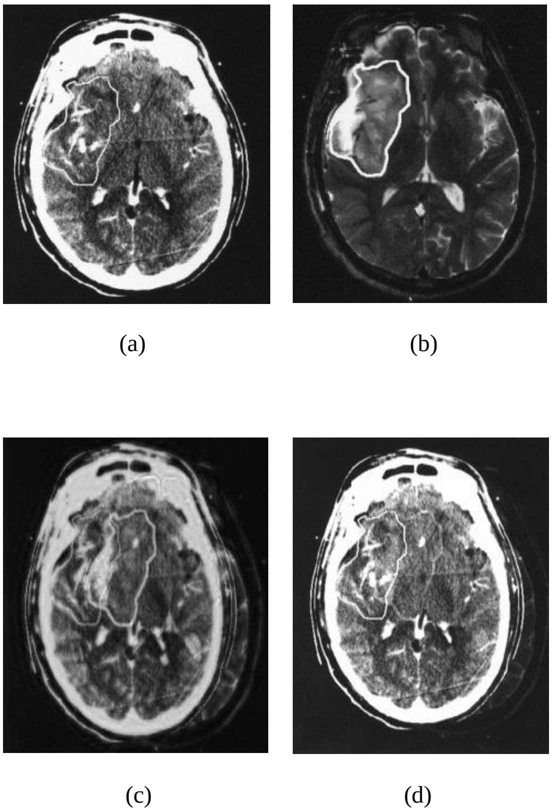


Fig.7. Image fusion. (a) CT Image- Brain3. (b) MR Image- Brain3 (c) Fused Image-Wavelet Transform. (d) Fused Image-Ridgelet Transform

6. QUANTITATIVE ANALYSIS

The Tables 1, 2 and 3 give the Entropy and PSNR values and Fig 8, 9, 10 represent the comparison of wavelet and ridgelet transforms based on the values of PSNR and Entropy for the sample images mentioned above. All the images in the database are analysed and the result of some of the samples are listed in the tables below.

Table 1. Performance of Wavelet and Ridgelet Transforms for Image-Brain1

Image	Parameters	Wavelet Transform	Ridgelet Transform
Brain1	Entropy	18.8638	6.5554
	PSNR(dB)	38.3533	55.9894

Table 2. Performance of Wavelet and Ridgelet Transforms for Image- Brain2

Image	Parameters	Wavelet Transform	Ridgelet Transform
Brain2	Entropy	18.0600	6.0153
	PSNR(dB)	47.7947	63.7322

Table 3. Performance of Wavelet and Ridgelet Transforms for Image- Brain3

Image	Parameters	Wavelet Transform	Ridgelet Transform
Brain3	Entropy	21.0910	6.4938
	PSNR(dB)	49.2054	59.8669

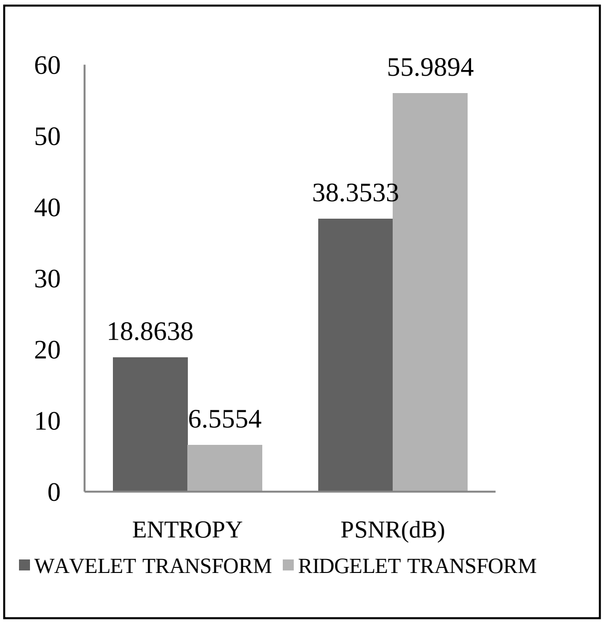


Fig.8.Wavelet Vs Ridgelet fusion result-Brain1

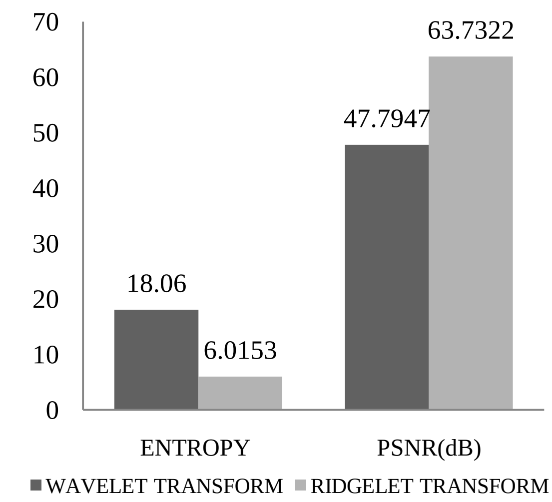


Fig.9.Wavelet Vs Ridgelet fusion result-Brain2

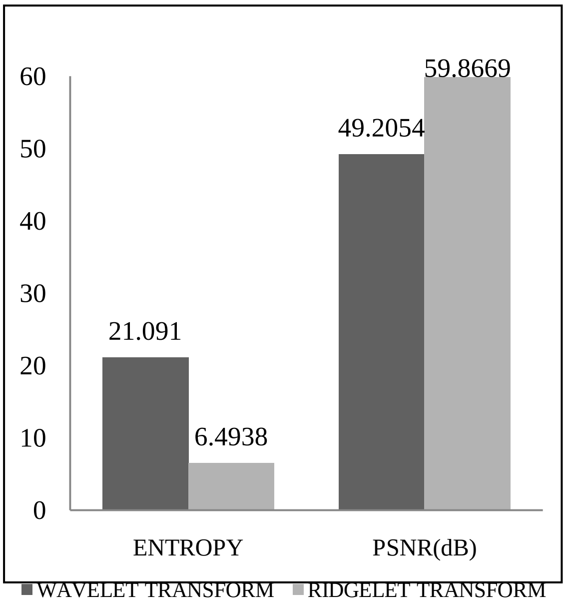


Fig.10.Wavelet Vs Ridgelet fusion result-Brain3

7. CONCLUSION

A comparison study has been made between the traditional wavelet fusion algorithm and ridgelet fusion algorithm. The results obtained show that the ridgelet fusion results have lower entropy and higher PSNR values than the wavelet fusion results. This shows that the application of ridgelet transform in the fusion of CT and MR images of the brain is superior to the application of wavelet transform. And also the visual quality of the fused image is better in the ridgelet fusion results than in the wavelet fusion results.

Further the work can be extended to Curvelet and Contourlret transforms.

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