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RIPPLET TRANSFORM BASED MULTISENSOR IMAGE FUSION

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ABSTRACT

In this paper, we propose a simple but efficient image fusion method based on Ripplet transform. To check the efficiency of Ripplet transform type -1, we employ multi sensor image fusion. The performance of image fusion is evaluated by Q AB/F metric.

KEYWORDS: image fusion, Ripplet transform, multi sensor.

INTRODUCTION

Image fusion is process of combining & integrating redundant and complementary information from the source images and form fused image. Since the source images have information in limited domain so it is necessary to fuse them for joint analysis. The first step in integrating is image registration[1-4] and second step is image fusion.[5-7] Image fusion is used in applications like (a) concealed weapon detection (b) remote sensing (c) medical diagnosis (d) military surveillance (e) defect detection. Different types of image fusion methods are (a) multi temporal (b) multi focus (c) multi sensor (d) feature based (e) symbol based (f) pixel based. In order to check the efficiency of Ripplet transform type -1 on image fusion, we propose image fusion method based on Ripplet transform (RT). Taking into consideration new image fusion metric Q AB/F[6] (amount of information transferred from source images to fused image).

LITERATURE ON IMAGE FUSION

Lot of techniques on image fusion has been reported in the last decade . some of efficient are as follows - In 2013 , Dr. Rui-shen proposed a method of medical image fusion based on MSD using inter scale and intra scale consistencies.[6] In 2011 , Xudong xang proposed a technique using image matting to focus the focused region of each source images and finally fuse them.[8] In 2014, Wei-whang proposed a technique for image fusion using direction-lets (AWT).[9] IN 2011, Jing-tian & his co workers proposed a efficient technique image fusion using a bilateral gradient based sharpness criterion.[10] In 2012, Li-chen proposed a multi focus image fusion method using wave-let based sharpness measure.[11]

RIPPLET TRANSFORM

This transform is proposed by Dr. Dapeng Oliver Wu with collaboration with Jun Xu . The mathematical representation of Ripplet transform type - 1 is derived in.[12-13] This transform has following properties (1) multi resolution (2) good localization (3) high directionality (4) scaling with arbitrary degree & support (5) anisotropy (6) fast coefficient decay.

OBJECTIVE EVALUATION METRIC FOR IMAGE FUSION

The performance evaluation for image fusion can done by QAB/F.[6] This metric don't require any reference image. It usually measures the amount of edge information transferred from source images to fused image. This is effective evaluation metric than the traditional ones.

PSNR & MSE FOR IMAGE QUALITY

The PSNR[14] computes the peak signal-to-noise ratio, in decibels, between two images. This ratio is often used as a quality measurement between the original and a compressed image. The higher the PSNR, the better the quality of the compressed, or reconstructed image.

The Mean Square Error (MSE)[15] and the Peak Signal to Noise Ratio (PSNR) are the two error metrics used to compare image compression quality. The MSE represents the cumulative squared error between the compressed and the original image, whereas PSNR represents a measure of the peak error. The lower the value of MSE, the lower the error.

To compute the PSNR, calculates the mean-squared error using the following equation:

$$MSE = \frac{\sum_{M,N}[I_1(m,n)-I_2(m,n)]^2}{M*N}$$

M and N are the number of rows and columns in the input images, respectively. Then computes the PSNR using the following equation:

$$PSNR = 10 \log_{10}\left(\frac{R^2}{MSE}\right)$$

METHODOLOGY

First digital images acquired by different sensors will be reconstructed by Ripplet transform type 1 at different coefficients. The image results at different coefficients will be combined avoiding the other image operations like using spatial & frequency domain filters for image enhancement[15-17] or image denoising[18] etc. We avoided the other operations on sources images as our aim is to measure the precise information transferred from source images to fused images based on the operation by Ripplet transform only. The algorithm used is depicted in figure 1.

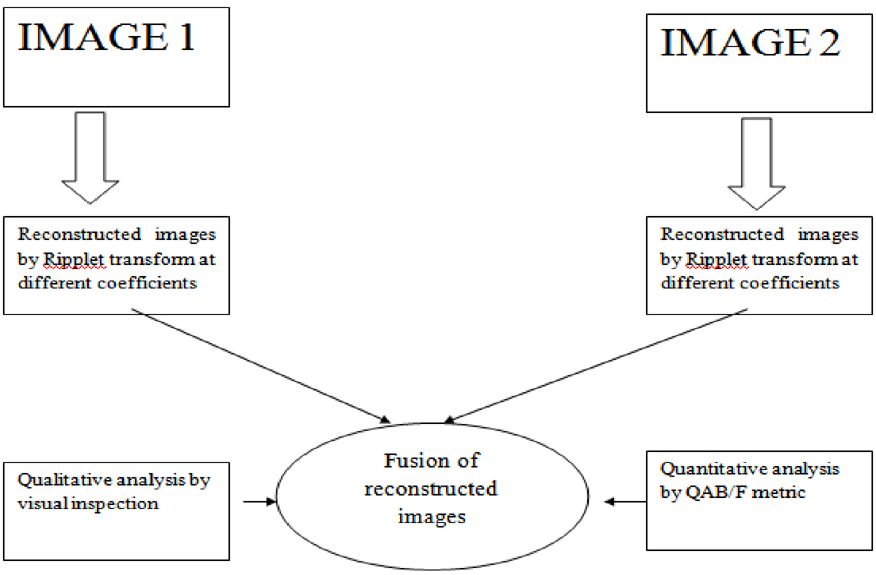
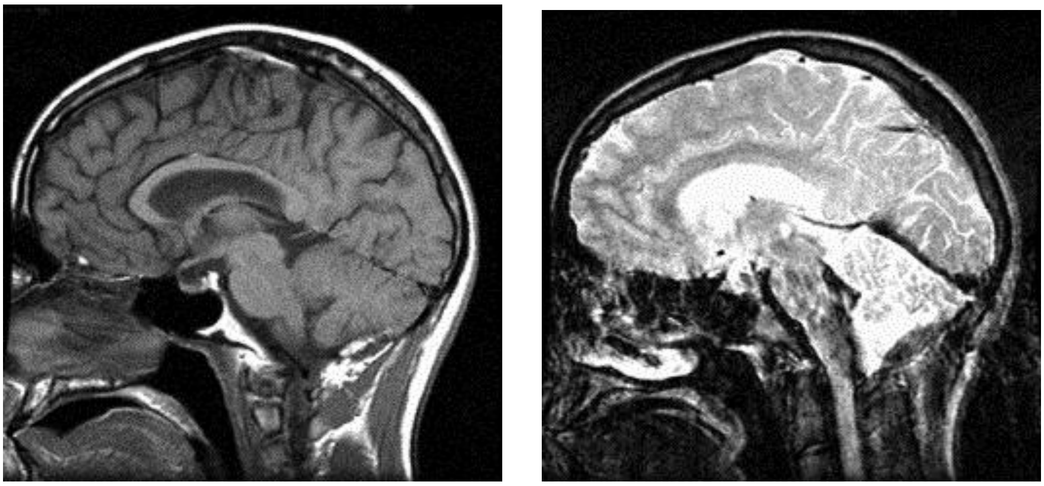


Figure1: Multi sensor image fusion.

RESULT AND DISCUSSION

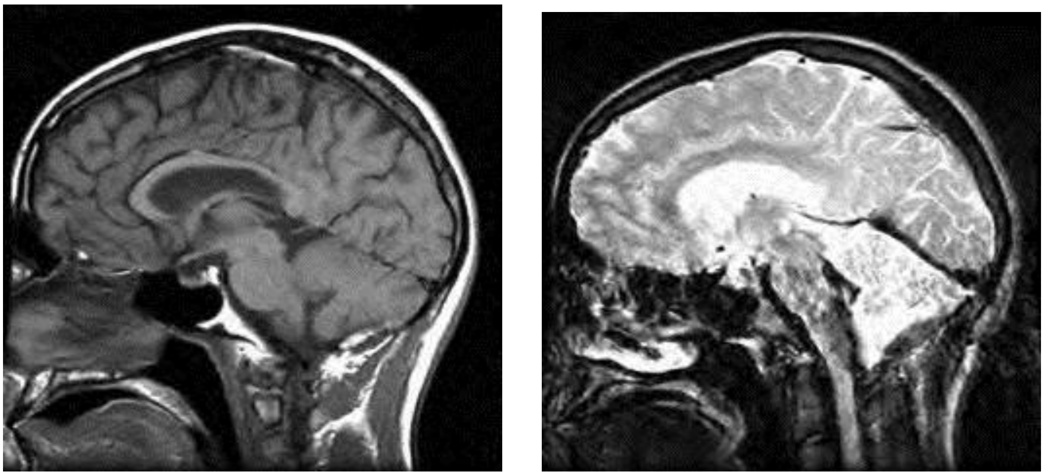
Source images are taken from Yiu Liu homepage,[19] then imply Ripplet transform type-1 on these images at different coefficients 10000,20000,30000,40000,50000. The original source images are depicted in figure 2 and reconstructed images are depicted in figure 3. Fusion results are shown in figure 4.The PSNR, MSE & QAB/F calculation are shown in table 1 ,table 2 & table 3. For fusion of the multi sensor modalities alpha factor can be varied to show the proportion of fusion. If alpha factor = 0.5 then two images are mixed equally. if alpha factor < 0.5,then contribution of source image 1 will be more and if a alpha factor >0.5

but less than 1, then contribution of source image 2 will be more. We use alpha factor 0.5 for equal mixing of images.

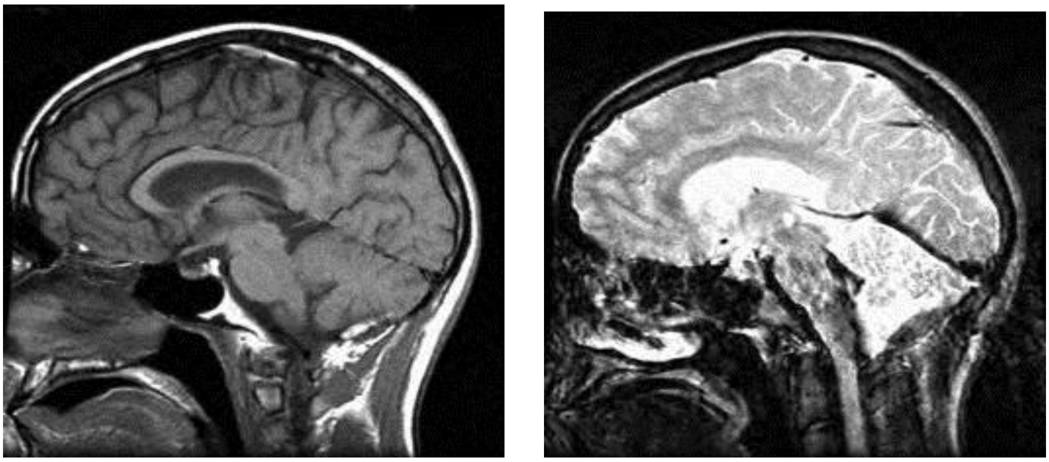


(a) **(b)**

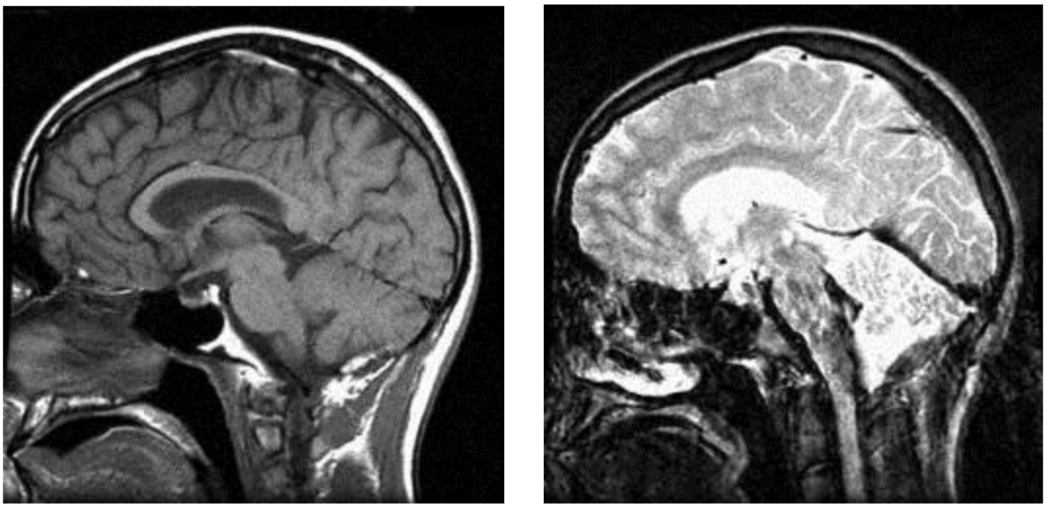
Figure 2: original images



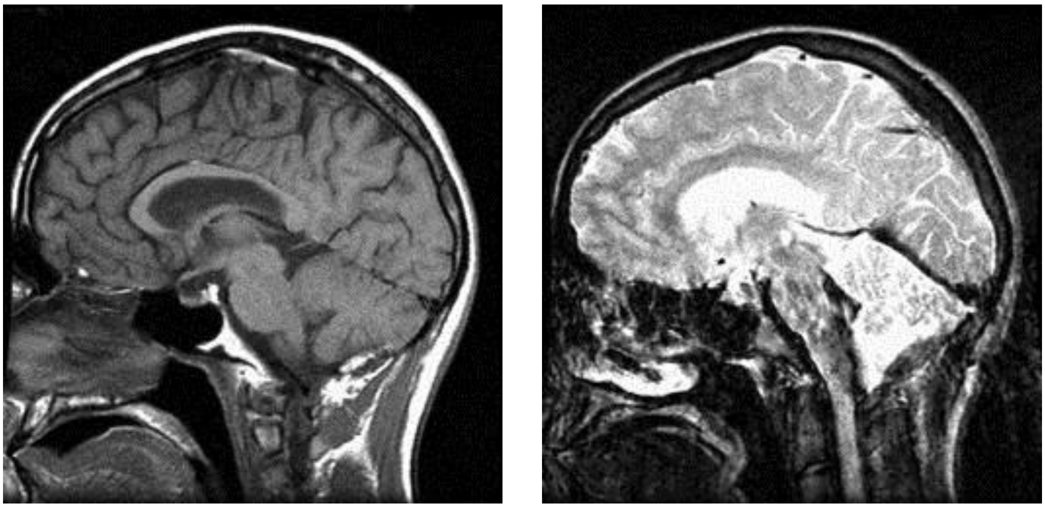
Reconstructed images at 10000 Ripplet coefficients



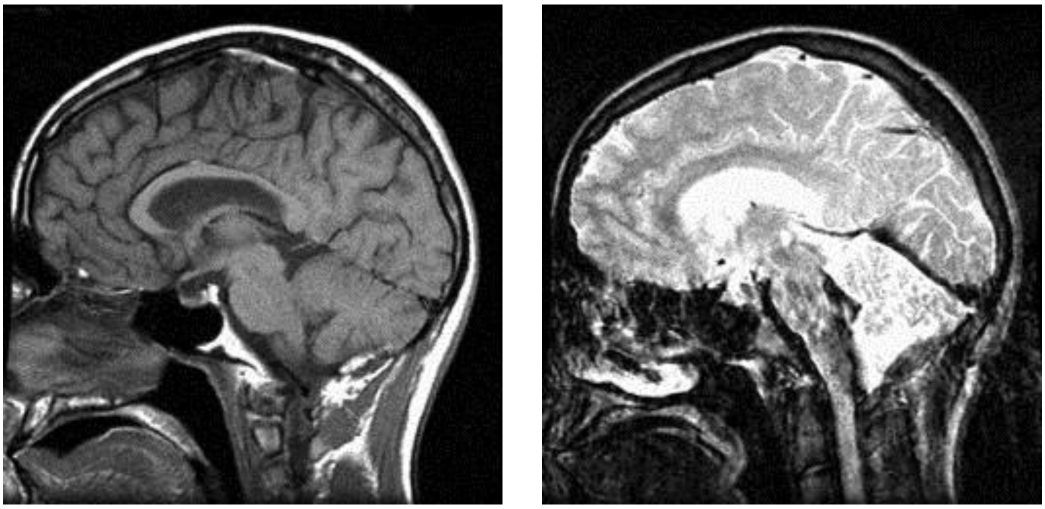
Reconstructed images at 20000 Ripplet coefficients



Reconstructed images at 30000 Ripplet coefficients

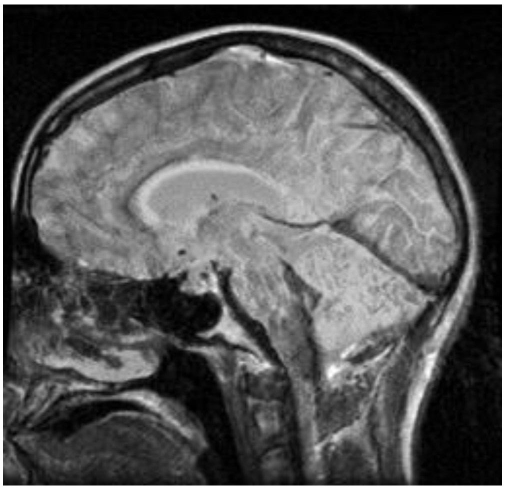
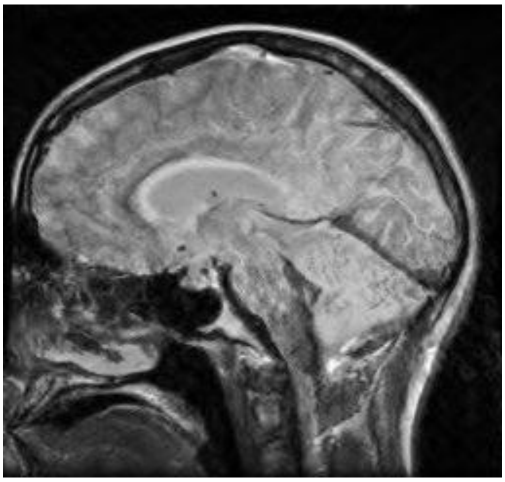


Reconstructed images at 40000 Ripplet coefficients

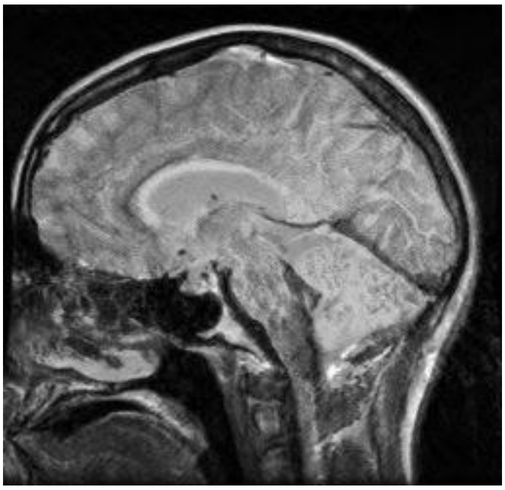
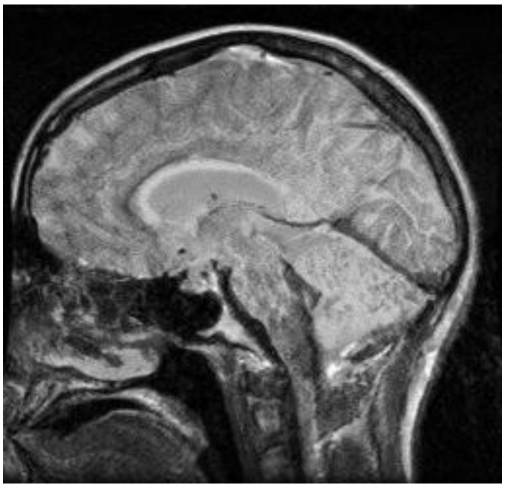


Reconstructed images at 50000 Ripplet coefficients

Figure 3 : Reconstructed images by Ripplet

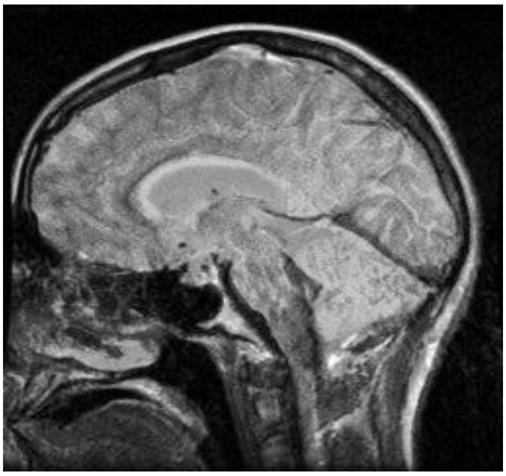
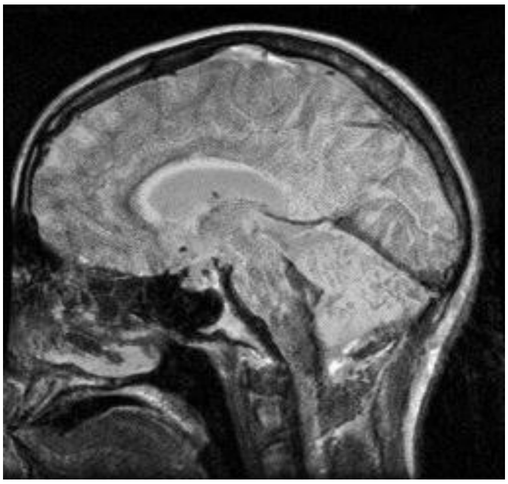
 

Fusion without reconstruction Fusion of images reconstructed at 10000 Ripplet coefficients.

Fusion of images reconstructed at 20000 Ripplet coefficients

Fusion of images reconstructed at 30000 Ripplet coefficients

Fusion of images reconstructed at 40000 Ripplet coefficients Fusion of images reconstructed at 50000 Ripplet coefficients

Figure 4: Fusion results

Table 1: PSNR.

Between original image (a) & reconstructed images at-	PSNR
10000	29.3602
20000	31.0594
30000	31.7669
40000	32.0995
50000	32.2796

Between original image (b) & reconstructed images at-	PSNR
10000	27.4776
20000	29.6009
30000	30.6805
40000	31.2596
50000	31.5824

Table 2: MSE.

Between original image (a) & reconstructed images at-	MSE
10000	75.3459
20000	50.9499
30000	43.2900
40000	40.0985
50000	38.4702

Between original image (b) & reconstructed images at-	MSE
10000	116.2315
20000	71.2833
30000	55.5949
40000	48.6547
50000	45.1689

Table 3: Q AB/F.

FUSION RESULTS	Q AB/F
fusion of original image (a) & (b) without reconstruction	0.1385
fusion of images reconstructed at 10000 Ripplet coefficients	0.7031
fusion of images reconstructed at 20000 Ripplet coefficients	0.6983
fusion of images reconstructed at 30000	0.6961

Ripplet coefficients	
fusion of images reconstructed at 40000 Ripplet coefficients	0.6939
fusion of images reconstructed at 50000 Ripplet coefficients	0.6936

CONCLUSION

On the basis of PSNR & MSE calculated between original and reconstructed images at different Ripplet coefficients, it is depicted that reconstructed images by Ripplet transform showed improved quality as PSNR is increasing and MSE decreasing. The quality of image is further improved when increasing Ripplet coefficients from 10000 to 50000. Q AB/F is very low when no reconstruction is done. Q AB/F factor is increased drastically after reconstruction by Ripplet transform. Q AB/F is approaching to 0.7 out of 1 in every case of fusion. Both image quality & image fusion quality is increased after processing by Ripplet type-1 transform. Ripplet transform provide efficient representation of images with singularities along smooth curves. Ripplet is capable of representing shape of an object, but they are not good representing textures.

FUTURE SCOPE

As Ripplet transform do not represent texture well. So there is necessity to combine Ripplet transform with other image transform which give better texture representation. As a result the whole image can be represented well. Ripplet transform can be used instead to newly proposed Directionlet transform as it contains both anisotropy as well as high directionality property.

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