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Research Article

Application of Image Fusion Techniques on Medical Images

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Abstract

Image fusion finds numerous applications in remote sensing, satellite imaging, medical imaging etc. In medical science, in order to diagnose a disease, it is required that the image obtained from a particular modality should be highly informative and should have high accuracy and also it should have high spatial as well as high spectral resolution. However, most of the available modalities alone are not capable of doing it convincingly. To solve this problem, a technique called image fusion has been evolved, in which two or more images are fused together to make a new image. In medical image fusion two or more images obtained from different modalities are fused together to give us a desired image. Selection of fusion rule should be such that it must provide us all the relevant information and at the same time does not introduce any undesired features to the resulting image. In this paper we have proposed a method for fusing CT (Computed Tomography) and MRI (Medical Resonance Imaging) images based on second generation curvelet transform. Proposed method is compared with the results obtained after applying the other methods based on Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), and Discrete Cosine Transform (DCT). Entropy, Standard Deviation, Peak Signal to Noise Ratio (PSNR), Percentage Fit Error (PFE) and Spatial Frequency (SF) are used as performance metric evaluators.

Keywords: *Image fusion, CT, MRI, Second Generation Curvelet Transform, DWT, PCA, Entropy, SD, PSNR, PFE, SF***.**

1. Introduction

Basic meaning of the image fusion is to fuse two or more images obtained from different modalities to produce a new image that is more informative than the source images. An image consists of different features. We can broadly categorize them into textures and edges. Image obtained from one modality is good at providing some specific information. For example CT image provides information about dense hard tissues whereas MRI provides information about soft tissues. So, in order to get multiple information in a single image, image fusion is done. A good image fusion technique should be capable of providing complementary information and discarding the redundant one. Broadly there are two classifications of image fusion algorithms. First one is spatial domain methods like IHS (Intensity Hue Saturation) [Hongbo Wu, Yanqiu Xing, *et al*, 2010], Brovey transform, PCA(Principal Component Analysis)[V.P.S. Naidu and J.R. Raol, *et al*, 2008] etc. In these methods image fusion is performed by directly manipulating the pixels of the respective images. Second one is transform domain methods, in which image is first transformed into frequency domain and then further processing is done. DWT (Discrete Wavelet Transform) [Angoth, CYN Dwith, Amarjot Singh, *et al*, 2013; Hongbo Wu, Yanqiu Xing , *et al*, 2010; Deepika.L , Mary Sindhuja.N.M . Deepika.L, *et al*, 2014], Curvelet transform [Sweta Mehta, *et al*, 2002; Kiran Parmar , Rahul Kher, *et al*, 2012], pyramid transform [V.P.S. Naidu, *et al*, 2013] are examples of transform domain methods. In order to obtain better results, hybrid methods have been evolved to exploit the benefits of different methods [Guruprasad S, M Z Kurian, H N Suma *et al*, 2015]. In this paper we have applied different fusion methods on the test given in [V.P.S. Naidu, *et al*, 2013]. Test data is a multifocus image containing two aircrafts. Different fusion methods have been applied and then results are compared with that of the proposed method, which provides us better results. After this the same methods have been applied on two sets of medical images. In this paper two sets of CT and MRI images of brain are taken and then different fusion methods have been applied on them to have more informative fused image.

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2. Fusion Methods

In this section we have described image fusion methods based on DWT, PCA, DWT-PCA, DCT and Curvelet transform.

2.1 Discrete Wavelet Transform (DWT)

Wavelet is a waveform of limited duration having zero average value and nonzero norm. Wavelet transform applied on a signal decomposes the signal into scaled (dilated or expanded) and shifted (translated) versions of the chosen mother wavelet. The term mother wavelet implies that the other window functions are derived from this function. Wavelet transform is applied in two domains viz continuous and discrete. CWT (Continuous Wavelet Transform) is the correlation between the wavelet at different scales (inverse of frequency) and the signal and is computed by changing the scale of the analysis window each time, shifting it, multiplying it by the signal. Mathematical equation is given by

$$\psi_x(\tau,s)=\frac{1}{\sqrt{s}}\int X(t)\cdot\psi*\left(t-\frac{\tau}{s}\right)dt \tag{1}$$

In the above equation τ(translation) and s(scale) are variables required for transforming the signal x(t). Psi (Ψ) is the transforming function known as mother wavelet. In DWT (Discrete Wavelet Transform) a 2D signal (image) I(x, y) is first filtered through low pass and high pass finite impulse response filters (FIR), having impulse response h[n] in horizontal direction and then decimated by factor of 2. This gives first level decomposition. Further the low pass filtered image is again filtered through low pass and high pass FIR filters in vertical direction and then again decimated by 2 to obtain second level decomposition. Filtering operation is given by the convolution of the signal and impulse response of signal.

$$x[n]*h[n]=\sum_{k=-\infty}^{\infty}x[k]\cdot h[n-k] \tag{2}$$

Distortions in the fused image increase with the increase in the number of decomposition levels. So they should not be increased after desired levels. Now to perform inverse wavelet transform, first upsample the subband images by factor of 2 column wise and then filter them through low pass and high pass FIR filters. Repeat the same process in next step row wise. Now add all the images to get the original image.

Fusion algorithm is as follows:

We have two source images $I_1(x, y)$ and $I_2(x, y)$ obtained from CT and MRI scan of brain respectively.

1) Take two source images.
2) Resize both of them to 256 x 256.
3) Convert both the images into grayscale if required.
4) Apply 2D- DWT on both the images and obtain its four components viz: one approximation and three detail ones.
5) Now apply the fusion rule as per the requirement. Here we have experimented with different fusion rules viz:

a. Maximum pixel selection rule (all max): By selecting all maximum coefficients of both the images and fusing them.
b. Mean : By taking the average of the coefficients of both the images.
c. Mix : By taking the average of the approximate coefficients of both the images and selecting the maximum pixels from detail coefficients of both the images.

6) Now apply IDWT to obtain the fused image.

2.2 Principal Component Analysis (PCA)

Principal Component Analysis (PCA) is one of the famous techniques used for dimension reduction, feature extraction, and data visualization. In general, PCA is defined by the transformation of a high dimensional vector space into a low dimensional space. This property of PCA is helpful in reducing the size of medical image data which is of large size without losing important information. In this method a number of correlated variables are transformed into uncorrelated variables called principal components. Each principal component is taken in the direction of maximum variance and lie in the subspace perpendicular to one another.

Fusion algorithm is as follows:

1) Convert the two source images into column vectors and make a matrix 'M' using these two column vectors.
2) Calculate the empirical mean vector along each column and substract it from each of the columns of the matrix.
3) Compute the covariance matrix 'C' of the resulting matrix.
4) Compute the eigen values D and eigen vectors V of the covariance matrix.
5) Select the eigenvector corresponding to larger eigenvalue and divide its each element by mean of that eigenvector. This wil give us first principal component P_1. Repeat the same procedure with eigenvector corresponding to smaller eigenvalue to get second principal component P_2.

$$P_1=\frac{V(1)}{\sum V} \qquad P_2=\frac{V(2)}{\sum V}$$

6) Fused image is obtained by

$$I_f(x,y)=P_1I_1(x,y)+P_2I_2(x,y) \tag{3}$$

2.3 Hybrid algorithm (DWT-PCA)

This method is hybrid of both DWT and PCA applied on the source images.

1) Obtain the wavelet coefficients of the two source images.
2) Convert the wavelet coefficient matrices into column vectors.

3) Compute the covariance matrix using these vectors such that each matrix has first column vector obtained through first image and second column vector obtained through second image.mIt will give us four sets of covariance matrices.
4) Compute the eigen values D and eigen vectors V of the covariance matrices.
5) Select the eigen vector corresponding to larger eigen value and divide its each element by mean of that eigen vector. This wil give us first principal component P_1. Repeat the same procedure with eigenvector corresponding to smaller eigenvalue to get second principal component P_2. Do this for all four sets of covariance matrices.
6) Multiply the normalised eigen vector values with the suitable wavelet coefficient matrix (P_1 with approximate coefficient matrix of first image and P_2 with approximate coefficient matrix of second image)
7) Do this for both approximate and detail coefficients of both the images.
8) Now apply IDWT to these manipulated coefficient matrices .

2.4 Discrete Cosine Transform (DCT-1D)

Discrete Cosine transform (DCT) as the name implies transforms finite set of data points into cosine functions. DCT is a Fourier related transform like Discrete Fourier Transform (DFT) with the only difference that the former uses only cosine functions while the latter uses both sine and cosine functions. DCT has one of the interesting property of energy compaction. DCT is applied on both 1D and 2D signals. 1D DCT of a vector S(x) of size N is given by

$$S(u) = a(u)\sum_{x=0}^{N-1} s(x)\cos\left(\frac{\pi(2x+1)u}{2N}\right),\ 0 \le u \le N-1 \tag{4}$$

Inverse 1D DCT is given by

$$S(x) = \sum_{x=0}^{N-1} a(u)s(u)\cos\left(\frac{\pi(2x+1)u}{2N}\right),\ \ 0 \le x \le N-1 \tag{5}$$

Where

$a(u) = \frac{1}{\sqrt{N}}, u = 0$ and

$\sqrt{\frac{2}{N}}, 1 \le u \le N-1$

u is a discrete frequency variable and x is pixel index. DCT has various variants. Two among them are Frequency Partition DCT (FPDCT) and Multiresolution DCT (MDCT). Both are discussed in the further sections.

Fusion algorithm:

1) Take the two source images of equal size say MxN.
2) Divide the first 2D image into rows and link them together in a chain form to have a 1D row vector R of size MN.
3) Divide the second 2D image into columns and link them together in a chain form to have a 1D column vector C of size MN.
4) Apply DCT on both R and C separately and then apply averaging operation on the vectors.
5) Apply inverse DCT on the resulting vector.
6) Convert 1D vector into 2D image.

2.5 Frequency Partition DCT (FPDCT)

1) Repeat the first three steps of algorithm described in section 2.4.
2) For each vector divide the DCT coefficients into low frequency and high frequency compoents using partition factor f. Low frequency coefficients lie in the range 0 ≤ L ≤ MNf-1 and high frequency components lie in the range MNf ≤ L ≤ MN.
3) Average the pixels of low frequency coefficients of both the vectors and form a low frequency vector (LF).
4) Apply maximum pixel selection rule for high frequency coefficients of both the vectors and form a high frequency vector (HF)
5) Now form vector V of size 1x2 having LF and HF as two components.
6) Apply inverse DCT.
7) Convert the 1D vector into 2D image.

2.6 Multiresolution DCT (MDCT)

MDCT is one of the variants of DCT which is very similar to wavelets. The only difference is FIR filters are replaced by DCT. In this method at first 1D-DCT is applied on the source image and divide the points into two halves. In first half and second half apply IDCT to obtain low pass image L and high pass image H. Now again apply 1D-DCT on H and L images and then divide their respective points into two halves. On each half apply IDCT to obtain HH, HL, LH and LL images. The same process can be continued further to obtain other sub band images.

Fusion algorithm:

1) Take the source images and apply the preprocessing steps as mentioned in above methods.
2) Now apply MDCT to obtain sub band images of each source image.
3) Now fusion rule is such that it will select maximum value of the two detail set of coefficients (sharpening operation) and for approximate set of coefficients apply averaging (smoothing) operation.
4) To obtain the fused image inverse MDCT has to be applied which is the reverse of the process as that of MDCT.

2.7 Curvelet Transform

Curvelet Transform is basically an extension of Wavelet Transform and they are becoming popular day by day in the field of image processing because of their ability to provide good representation of edges in an image. In First generation curvelet transform image is first splitted into small overlapping tiles followed by Ridgelet transform on each tile. To understand digital curvelet transform we have to start with continuous curvelet transform. Consider two windows V(t) and W(r) known as corner window and radius window respectively which are supported in t ∈ [-1,1] and r ∈ [1/2,2]. Permitting condition for them is

$$\sum_{j=-\infty}^{\infty} W^2\left(2^j(r)\right)=1, \qquad r\in(3/4,3/2);$$

$$\sum_{t=-\infty}^{\infty} V^2(t-l)=1, \qquad t\in(-1/2,1/2);$$

For scales j ≥ j_0, Fourier domain window is given by

$$U_j(r,\theta)=2^{-3j/4}W\left(2^{-j}r\right)V\left(\frac{2^{[j/2]}\theta}{2\pi}\right) \tag{6}$$

j/2 implies j/2 rounding operations. U_j represents wedge window in polar coordinates shown in the fig.1 l

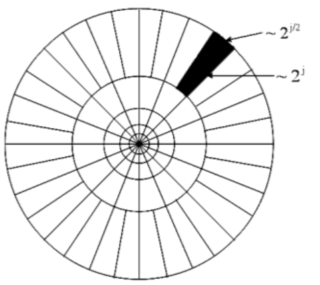


Fig.1 Continuous tiling of frequency domain into wedges

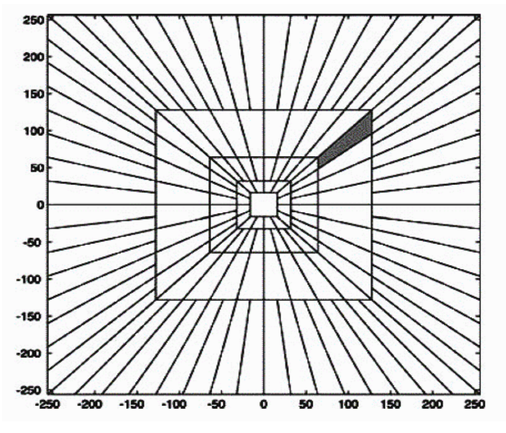


Fig.2 Discrete tiling of frequency domain

In order to define Curvelets at scale 2^{-j}, $j \geq 0$, orientation at $\theta_{j,l}$, and position at $x_k^{(j,l)}=R_{\theta l}^{-1}(k_1\cdot 2^{-j},k_2\cdot 2^{-j/2})$ we will use the following equation

$$\psi_{j,l,k}(x)=\psi_j\left(R_{\theta l}\left(x-x_k^{(j,l)}\right)\right) \tag{7}$$

R_θ denotes the rotation matrix with angle θ. Curvelet coefficients can be obtained by the inner product of f $L^2(R^2)$ *and* $\Psi_{j,l,k}$.

$$C_{j,l,k}=\left\langle f,\psi_{j,l,k}\right\rangle=\int_{R^2} f(x)\overline{\psi_{j,l,k}(x)}dx \tag{8}$$

Since Second generation curvelet transform (FDCT) does not uses Ridgelet Transform hence faster than the First generation curvelet transform. In this transform basis functions used are long ridges and their shape at scale j is of 2^{-j} by $2^{-j/2}$. Curvelets has one of the unique property as they provide optimally sparse representation of objects with edges. FDCT has two methods of implementation. First is based on Unequally Spaced Fast Fourier Transform (USFFT) and the second one based on wrapping algorithm. In this paper wrapping algorithm is used. The local window used is given by

$$U_j(w)=W_j(w)V_j(w) \tag{9}$$

Where

$$W_j(w)=\sqrt{\phi_{j+1}^2(w)-\phi_j^2(w)}$$

$$V_j(w)=V\left(2^{j/2}w_2/w_1\right) \qquad j\geq 0$$

Where

$$\phi_j(w_1,w_2)=\phi\left(2^{-j}w_1\right)\left(2^{-j}w_2\right)$$

Discrete Curvelet is given by

$$\psi_{j,l,k}(x)=2^{3j/4}\psi_j\left(s_{\theta_l}^T\left(x-S_{\theta_l}^{-T}b\right)\right) \tag{10}$$

Where S_θ is the shear matrix

$$S_\theta=\begin{bmatrix}1 & 0\\ -\tan\theta & 1\end{bmatrix}$$

and b quantizes $\left(k_1\times 2^{-j},k_2\times 2^{-j/2}\right)$

Discrete Curvelet Transform is given by

$$C_{j,l,k}=\int f(w)U_j\left(S_{\theta_l}^{-1}w\right)\exp\left[i\left\langle S_{\theta_l}^{-T}b,w\right\rangle\right]dw \tag{11}$$

Since $S_{\theta_l}^{-T}$ is not a perfect rectangle therefore fast fourier transform algorithm cannot be used. Rewrite the above equation as

$$C_{j,l,k}=\int f(w)U_j\left(S_{\theta_l}^{-1}w\right)\exp\left[i\left\langle b,S_{\theta_l}^{-T}w\right\rangle\right]dw$$
$$=\int f(w)U_j\left(S_{\theta_l}^{-1}w\right)\exp\left[i\langle b,w\rangle\right]dw \tag{12}$$

FDCT using wrapping algorithm.

1) Take n x n image f[i_1, i_2].
2) Choose the coarsest decomposition scale, using curvelets or wavelets.
3) Apply 2D-FFT and obtain fourier samples $\hat{f}$[i_1, i_2].
4) For each scale j angle l found the product $\hat{f}$[i_1, i_2]V_N[i_1, i_2].
5) Wrap this product around the origin.
6) Apply the inverse 2D-FFT to the wrapped data to obtain FDCT coefficients.

Proposed fusion algorithm is as follows

1) Apply FDCT wrapping on the source images and obtain the C1{1,i}{1,j} and C2{1,i}{1,j} curvelet coefficients.
2) Choose any one of the methods for selecting the coefficients. Maximum pixel selection (all max), Minimum pixel selection (all min) or mean of the coefficients obtained from the two images.
3) In our proposed fusion method maximum rule has been used since it improves the sharpness of the fused image due to which salient features become more visible and hence image quality improves.
4) Apply inverse FDCT wrapping algorithm to the coefficients to get the fused image

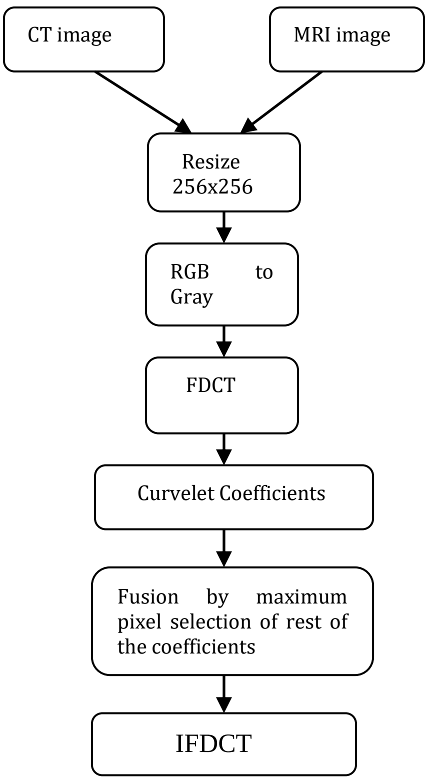


Fig.3 Flow chart of proposed algorithm

3. Performance Evaluation Metrics

3.1 With reference image

1) Percentage Fit Error (PFE)

$$PFE = \frac{norm(I_R - I_F)*100}{norm(I_R)}$$

Its value is high if the difference between the reference image and fused image is more. It should be as low as possible

.

2) Peak signal to noise ratio (PSNR)

$$PSNR = 20\log_{10}\left(\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I_R(i,j)-I_F(i,j))^2}\right)$$

High value of this implies more similarity between the fused image and reference image.

3.2 Without reference image

1) Standard Deviation (SD)

$$\sigma = \sqrt{\sum_{i=0}^{L}\left(i-\bar{i}\right)^2 h_{I_F}(i)}, \qquad \bar{i} = \sum_{i=0}^{L} i h_{I_F}$$

$h_{I_F}(i)$ is the normalized histogram of the fused image and L denotes the number of frequency bins in the histogram. SD indicates the contrast of the image and its value increases with contrast in the image.

2) Spatial Frequency (SF)

$$SF = \sqrt{RF^2 + CF^2}$$

Row Frequency

$$RF = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=1}^{N-1}\left[I_F(i,j)-(i,j-1)\right]^2}$$

Column Frequency

$$CF = \sqrt{\frac{1}{MN}\sum_{j=0}^{N-1}\sum_{i=1}^{M-1}\left[I_F(i,j)-I_F(i-1,j)\right]^2}$$

It tells about the activity level in the image

3) Entropy

$$Entropy = -\sum_{i=0}^{L} h_{I_f}(i)\log_2 h_{I_f}(i)$$

Where $h_{I_f}(i)$ is the normalized histogram of the fused image and L is the number of frequency bins in the histogram. Entropy as a parameter indicates the information content of the image. It is sensitive to noise and high value of entropy indicates high information content in the image.

4. Result and Analysis

In this section we will discuss the results obtained by applying above mentioned algorithms on test data.

Fig.1 (a) Reference image

This is the actual image which we want to recover using fusion of the two multifocus images (fig.1 (b) and fig.1 (c)) obtained from the same image.

Fig.1 (b)

Fig.1 (b) and fig.1 (c) are the images that are obtained by blurring the two aircrafts shown in fig.1 (a) alternately.

Fig.1 (c)

Table 1 Results obtained for first set of data

S. No	Method	PFE	PSNR	SD	SF
1	DWT all max	5.98	36.71	41.99	12.82
2	DWT mean	4.01	38.44	45.86	9.09
3	DWT mix	3.81	38.67	46.15	12.80
4	PCA	3.98	38.48	45.90	9.13
5	Hybrid	4.18	38.26	45.87	9.94
6	Curvelet mean	4.01	38.44	45.86	9.09
8	Curvelet all max	**0.48**	**47.59**	**49.32**	**16.94**
9	FPDCT	3.09	39.58	48.97	15.40
10	MRDCT	3.05	39.63	47.83	14.77

From the above table we can see that Curvelet by all max method gives the best results. In [V.P.S. Naidu, *et al*, 2013] image fusion is done through six different methods and their results are compared using above mentioned parameters for same set of test data. They have obtained best results using the method dual tree multi-resolution DCT (DTMDCT) followed by Laplacian pyramid (LP2D) based method. Table below shows the results they have obtained and compared with the results from our proposed method.

Table 2 Comparison with the proposed method

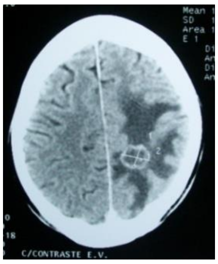
S. No	Method	PFE	PSNR	SD	SF
1	DTMDCT	1.07	44.17	49.66	16.93
2	LP2D	0.52	47.0	50.1	17.0
3	Curvelet all max	**0.48**	**47.59**	**49.32**	**16.94**

We can see that proposed method improves PFE and PSNR and also results of SD and SF are very close to their results.

Fig 1 (d) Fused image by curvel*et al*l max

Now we have applied same methods on two sets of medical data. Medical data consists of CT and MRI images of brain.

First set of data



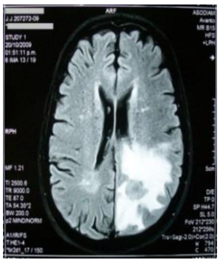


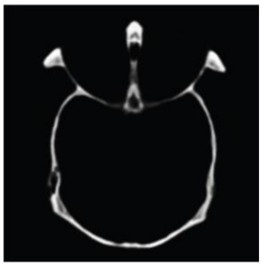
Fig 2 (a) CT image **Fig 2 (b)** MRI image

Table 3 Results of fused image for data set 1

S. No	Method	Entropy	SD	SF
1	DWT max	7.4555	0.3391	0.1748
2	DWT Avg	7.2773	0.2583	0.0955
3	DWT mix	7.2937	0.2669	0.1536
4	PCA	7.2197	0.2627	0.0894
5	Hybrid	7.4185	0.2589	0.0994
6	Curvelet mean	7.2766	0.2583	0.0955
8	Curvelet all max	**7.6292**	**0.3468**	**0.1823**
9	FPDCT	7.2783	0.2583	0.0955
10	MRDCT	7.1679	0.3007	0.1661

Fig 2(c) Fused image

Second set of data



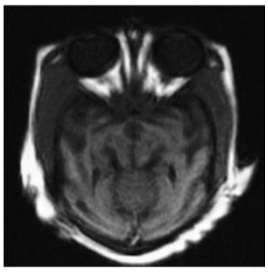


Fig 3 (a) CT image **Fig 3 (b)** MRI image

Table 4 Results of fused image for data set 2

S. No	Method	Entropy	SD	SF
1	DWT all max	6.7892	0.2514	0.1059
2	DWT Avg	5.9184	0.1502	0.0809
3	DWT mix	5.9666	0.1510	0.0845
4	PCA	6.4129	0.1994	0.0839
5	Hybrid	5.0361	0.1435	0.0871
6	Curvelet mean	5.9245	0.1502	0.0809
8	Curvelet all max	**7.2147**	**0.2398**	**0.1060**
9	FPDCT	5.9284	0.1502	0.0809
10	MRDCT	6.2623	0.2031	0.1066

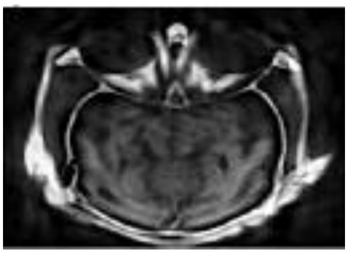


Fig 3(c) Fused image

From table 3 and table 4 we can see that Curvelet with maximum selection rule provides best results.

Conclusion

We have applied various fusion methods on three sets of data and it is observed that fusion by Curvelet using maximum selection rule provides better results when compared with those of other methods.

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