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Image Fusion of Brain Images using Redundant Discrete Wavelet Transform

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ABSTRACT
Image fusion has the very wider scope in medical sciences. Medical Images are obtained form different type of equipments and are of different modalities, each of them carries altogether different information. Especially study of brain images and its features is of greater interest for doctors since several centuries. Now because of radiology and evolution computers made this possible to look in to head online. This posed several challenges for software engineers to produce the good quality images or stream of images. Since medical images are from different modalities, which made it difficult to produce a single image from all these images. With the help of several image processing algorithms it is now possible to fuse the images. This gave rise to another challenge for producing efficient algorithm. This paper proposes the Redundant discrete wavelet transform (RDWT) based algorithm for image fusion, and compares with the other DWT based methods. These methods are assessed on the basis of statistical measures such as entropy, mean and standard deviation. According to the assessment made, it is found that the proposed method is giving better results. The Brain atlas based images are considered as input.

General Terms
Image Fusion, Image Analysis, Image processing.

Keywords
Multimodal Image Fusion, DWT based image fusion, Pixel level image fusion, RDWT based image fusion method**.**

1. INTRODUCTION
It is observed that, single image is not enough in analysing the medical image. It may require more images and their combination in to single image. Image fusion is the image processing technique, which merges several input images of the same organ in to a single image with complimentary information from all images [1]. There could be several Image fusion methods, which are useful for different types of applications. This paper first takes an overview of DWT based pixel level image fusion methods, and then aims to find the best method in terms of more information.

2. CATEGORIES OF IMAGE FUSION
Image Fusion can be categorised, as multiview fusion, multifocus fusion, multitemporal fusion and multimodal fusion [2]. Multimodal and multi temporal image fusion methods are widely used in medical image analysis.

2.1 Multimodal Fusion:
Medical images are of different modalities such as: PET, CT, MRI, ultraviolet, etc. These images are fused together to get better quality single image with more and more complimentary information using multimodal image fusion. Its aim is to fuse these images to get better quality output image with maximum information from both the images. Image Fusion has majorly three steps such as image acquisition, image registration and then image fusion [5].

2.2 Image acquisition:
Multimodal images are acquired by the medical instruments such as X-ray, CT, MRI, PET etc. These instruments capture images using different radio frequencies, which limits there penetration level. Because of this the doctors depend on several instruments. One can obtain several images of the same organ using these instruments. These several images carry different information.

2.3 Image registration:
Image registration, which brings the input images to spatial alignment, and combining the image functions (intensities, colors, etc). It works usually in four steps [4] such as i) Feature detection ii) Feature matching iii) Transform model estimation and iv) Image re-sampling and transformation. Images to be considered for registration should be of equal size. Superposition based registered images of CT and MRI are considered for this implementation of image fusion [10].

2.4 Image Fusion:
In practice, the fusion process can be carried out on data and images at four different levels such as signal, pixel, feature and decision level. Multi modal images can be very well fused using Pixel level image fusion methods [5].

Pixel-level image fusion means fusion at the lowest processing level referring to the merging of measured physical parameters. It generates a fused image in which each pixel is determined from a set of pixels of various images, and serves to increase the useful information content of an image [3]. This can be carried out by selecting minimum, maximum or average of inputs.

Pixel Level Image fusion methods can be broadly classified into two that is spatial domain fusion and frequency domain fusion [6]. Averaging, Brovey method, SVR, IHS & Principal Component Analysis (PCA) [6] [7], are spatial domain methods. Gaussian, Laplacian Pyramid [11][12]. Ratio-of-low-pass Pyramid, Gradient Pyramid, FSD Pyramid and Morphological Pyramid and Discrete Wavelet based methods etc. are of frequency domain [8].

3. DWT BASED MULTI MODAL IMAGE FUSION

Wavelet transforms are multi-resolution image decomposition tool that provide low and high frequency components separated. The low frequency components normally denote the background of an image and can be used to smooth the image. The high frequencies represent details of an image since details correspond to high frequencies. It also responds to noise in an image, since noise usually is located in the high frequencies. The image fusion using DWT is carried out as below [9] [11].

- Load the Image $\mathbf{I}_1$ and $\mathbf{I}_2$
- Apply wavelet transformation separately to each source image to establish various images of wavelet tower shaped transformation.
- Fuse images at the end of transformation level.
- Apply inverse Wavelet transform on fused wavelet pyramid.
- Save the Fused Image IF.

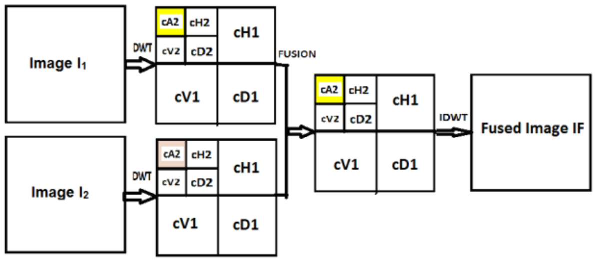

Fig.1. Wavelet based Image fusion.

In the above Fig.1, $\mathbf{I}_1$ and $\mathbf{I}_2$ are input images of different modality. Once the DWT is applied we get cA1 (approximation component), cH1 (horizontal components), cV1 (vertical components) and cD1 (detailed components). The cA1 is considered for the next level of decomposition. This process is carried out till the desired level say j. Then the fusion process is carried out. Fusion can be done by selection of max, min or average of the two images. At the end inverse transform is applied to get fused image.

3.1 Haar based DWT algorithm:

Among the Wavelet Transforms Haar transform is considered to be the basic and very first wavelet. A standard decomposition of a two dimensional signal (image) is done by first performing a one dimensional transformation on each row followed by a one dimensional transformation of each column. Image fusion is carried out by averaging the coefficients of transformed images. [13] At the end inverse transform is applied to get fused image.

When k=0, the Haar function is defined as a constant

$h_0(t) = 1/\sqrt{N}$

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When k>0, the Haar function is defined by

$$h_k(t) = \frac{1}{\sqrt{N}} \begin{cases} 2^{p/2} & (q-1)/2^p \le t < (q-0.5)/2^p \\ -2^{p/2} & (q-0.5)/2^p \le t < q/2^p \\ 0 & \text{otherwise} \end{cases} \quad \text{....(2)}$$

From the definition, it can be seen that p determines the amplitude and width of the non-zero part of the function, while q determines the position of the non-zero part of the function.

The 2x2 Haar matrix is given by H2 = {1,1; 1,-1}.
The filters considered are F1 = {*, 0.5, *, 0.5, *} and F2 = {*, 0.5, *, -0.5, *}.

Entropy of the image is given by

$$S = -\Sigma\,(p) \times \log\,(p). \quad \text{....... (3)}$$

Mean of an image is given by

$$M = \Sigma^{n}_{i=1} X_i /n \text{ and} \quad \text{........ (4)}$$

Standard deviation is given by

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \quad \text{........ (5)}$$

Haar transform is also known as db1; here value of N is 2. It is giving lesser entropy than other DWT methods, where as mean is par with db2 and sym2 and standard deviation is also high.

3.2 Daubechies DWT based Image Fusion:

The Daubechies wavelet (db2) can be decomposed to n level based on the size of the image. Here first level of decomposition is considered for image fusion. Daubechies wavelets are a family of orthogonal wavelets and asymmetric in nature. The two dimensional DWT leads to a decomposition of approximation coefficients at level j in four components: the approximation at level j+1, and the details in three orientations (horizontal, vertical, and diagonal) at j+1. Image Fusion is carried out by averaging the contents. Image reconstruction process is performed using inverse of DWT (IDWT). IDWT uses the wavelet 'db2' to compute the single-level reconstruction of fused Image IF, based on approximation matrix (cA) and detailed matrices cH, cV and cD (horizontal, vertical and diagonal respectively).

Daubechies db2 is giving entropy results better than Haar, but unable give better than SIDWT and RDWT. To get better entropy one has process to the higher level of decomposition.

3.3 Symlet based Image Fusion

Symlet based image fusion similar to 'db2'. The steps are exactly same as the 'db2'. Even the results are almost same.

The problem with the DWT based transforms is that, these are shift variant transform. Shift variance results from the use of critical sub-sampling (down-sampling) in the DWT. In this way, every second wavelet coefficient at each decomposition level is discarded [1]. This is done both to reduce the amount of data that has to be analysed and to enforce the implicit time frequency uncertainty of the analysis. This critical sub-sampling however, results in wavelet coefficients that are highly dependent on their location in the sub-sampling lattice. This can lead to small shifts in the input waveform causing large changes in the wavelet coefficients, large variations in the distribution of energy at different scales, and possibly large changes in reconstructed waveforms.

3.4 Shift invariant discrete wavelet transform for image fusion (SIDWT):

There are a number of possible solutions to the shift variance problem, which we describe in more detail below. These techniques attempt to eliminate or minimize the amount of aliasing that occurs by a combination of relaxing the critical sub sampling criteria and/or by reducing the transition bandwidth of the mother wavelets [14]. SIDWT image fusion scheme overcomes this disadvantage of shift variance. Considering some characteristic of the approximation wavelet coefficients of SIDWT, an approximation scale based wavelet coefficient maximum selection rule for image fusion was presented. At each stage, SIDWT splits the input image into the detail coefficient cD(n), and the approximation coefficient cA(n) which serve as input for the next decomposition level. The filters g(2i.k) and h(2i.k) at level j are obtained by inserting appropriate number of zeros between filter taps of the prototype filters g(k) and h(k). The reconstruction of the input signal is performed by inverse SIDWT.

SIDWT has produced entropy better than DWT methods. But the mean and standard deviation is lesser than DWT methods.

3.5 Redundant discrete wavelet transforms (RDWT):

Is another variant of wavelet transform, is used to overcome the shift variance problem of DWT. RDWT can be considered as an approximation to DWT that re-moves the down-sampling operation from traditional critically sampled DWT, produces an over-complete representation, and provides noise per-sub band relationship. Objective of using RDWT is to investigate the utility of RDWT in medical image fusion and to introduce RDWT based image fusion algorithm to fuse properties of medical images of different modalities such as brain proton density (PD) and T1 brain images. Finally, IRDWT is applied on the fused sub bands to generate the fused medical image [1][5].

RDWT based Image fusion Algorithm

1. Let $\mathbf{I}_1$ and $\mathbf{I}_2$ be the registered brain images of different modalities.
2. Three levels of RDWT decomposition is applied on both the images to obtain the detail and approximation wavelet bands.
3. Let $\mathbf{I}_{cA1}$, $\mathbf{I}_{cV1}$, $\mathbf{I}_{cH1}$, and $\mathbf{I}_{cD1}$ be the RDWT sub bands from $\mathbf{I}_1$.
4. *Let* $\mathbf{I}_{cA2}$, $\mathbf{I}_{cV2}$, $\mathbf{I}_{cH2}$, and $\mathbf{I}_{cD2}$ be the RDWT sub bands from $\mathbf{I}_2$.
5. To preserve the features from both the images, coefficients from approximation band of $\mathbf{I}_1$ and $\mathbf{I}_2$ are averaged,
6. $\mathbf{I}_{cA}F = mean(\mathbf{I}_{cA1} , \mathbf{I}_{cA2})$
7. Where $\mathbf{I}_{cA}F$ is the approximation band of the fused image.
8. For the three detailed sub bands, each band is divided into blocks of size 3 x 3 and the entropy of each block is calculated.
9. Using the higher entropy values, the detail sub bands for the fused image $\mathbf{I}_{cV}F$, $\mathbf{I}_{cH}F$ and $\mathbf{I}_{cD}F$ are generated.
10. For fused image block **IF**, RDWT coefficients from $\mathbf{I}_1$ are selected if the entropy of block from $\mathbf{I}_1$ image is greater than the corresponding block from the $\mathbf{I}_2$ image, otherwise $\mathbf{I}_2$ is selected.
11. Finally, IRDWT is applied on the four fused sub bands to generate the fused medical image **IF** .
12. **IF** = IRDWT ($\mathbf{I}_a F$, $\mathbf{I}_v F$, $\mathbf{I}_d F$, $\mathbf{I}_h F$)

RDWT is giving the better than DWT and SIDWT methods. This proves that RDWT is able incorporate more information from both the images. These results are obtained at very first level. So it can be useful for medical image fusion.

4. EXPERIMENTAL RESULTS

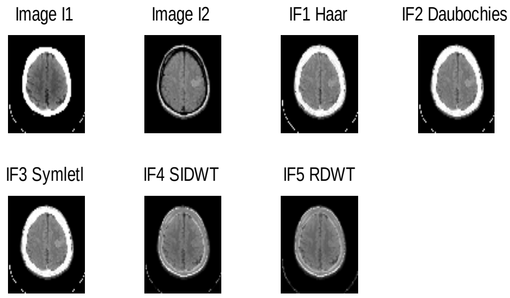

Fig. 1. Result Set 1 I1= CT, I2 = PD

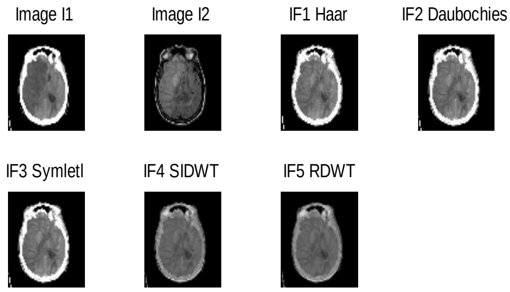

Fig. 2. Result Set 2 I1 = CT, I2 = PD

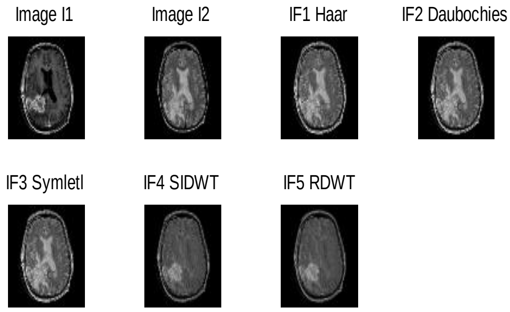

Fig. 3. Result Set 3 I1 = MR-GAD, I2 = MR-T2

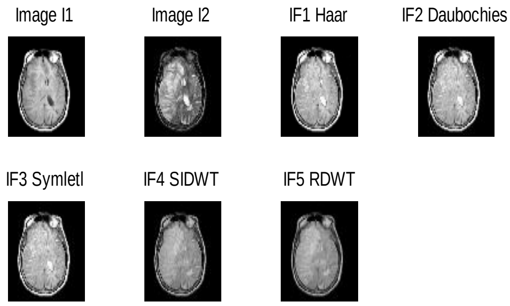

Fig. 4. Result Set 4 I1 = MR-T1, I2 = MR-T2

Table 1. Values of Entropy

	Entropy				
	Haar	DB2	Sym2	SIDWT	RDWT
Image Set 1	0.9814	1.0098	1.0098	1.0741	1.2497
Image Set 2	1.0153	1.1199	1.1199	1.2200	1.3362
Image Set 3	1.0210	1.1511	1.1511	1.2738	1.4695
Image Set 4	1.0228	1.1618	1.1618	1.3022	1.5249

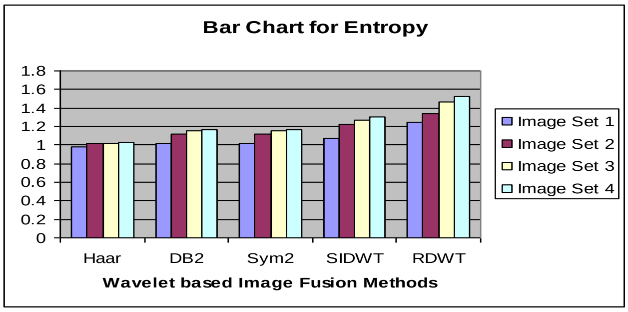

Fig. 5. Bar chart showing Entropy

Table 2. Values of Mean

	Mean				
	Haar	DB2	Sym2	SIDWT	RDWT
Image Set 1	67.2846	67.4358	67.4358	49.5288	49.5326
Image Set 2	67.2040	67.3111	67.3111	48.4266	48.4263
Image Set 3	48.7156	48.8548	48.8548	36.9601	36.9601
Image Set 4	73.4437	73.5492	73.5492	59.3010	59.3009

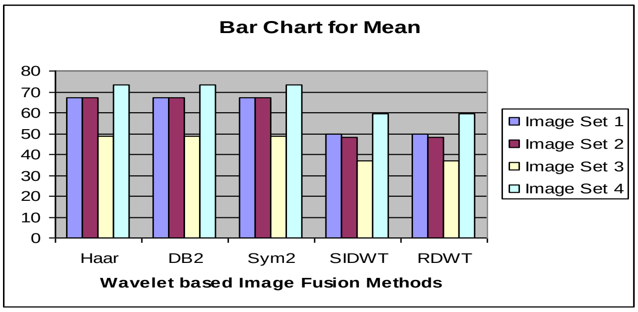

Fig. 6. Bar chart showing Mean

Table 3. Values of Standard Deviation

	Standard Deviation				
	Haar	DB2	Sym2	SIDWT	RDWT
Image Set 1	90.7338	90.5795	90.5795	63.7879	63.1872
Image Set 2	86.4943	86.3881	86.3881	57.7093	57.2065
Image Set 3	57.1669	57.1211	57.1211	42.6585	42.2507
Image Set 4	89.1262	89.0789	89.0789	72.6856	71.8634

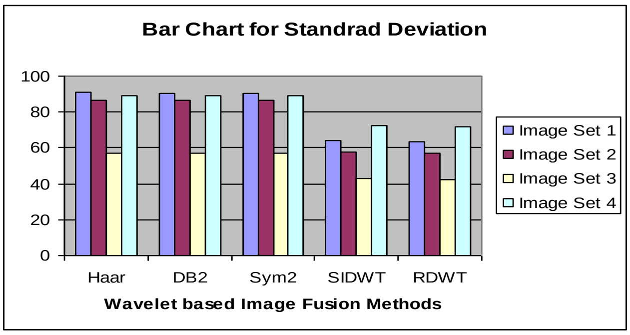

Fig.7. Bar chart showing Standard Deviation

5. SUMMARY AND CONCLUSION

Image fusion has wide range of applications in mage processing. It enhances the quality of images by fusing many images of poor quality. It tries to cater all information from many images into one image. It can be carried out at three levels that is pixel, feature and decision level. Many of the fusion algorithms are useful at pixel level fusion.

Wavelet based image fusion retains most of the advantages for image fusion. In wavelet transformation due to sampling, the image size is halved in both spatial directions at each level of decomposition process thus leading to a multi-resolution signal representation. DWT and SIDWT are giving the good results at higher level of decomposition. This eventually requires more calculation and time required.

The proposed method RDWT is giving better results than DWT and SIDWT at the very first level. This ultimately saves time and number of calculations. RDWT improves reliability by redundant information and improves capability by incorporating complementary information.

6. REFERENCES

[1] Richa Singh, Mayank Vatsa, Afzel Noore “Multimodal Medical Image Fusion using Redundant DiscreteWavelet Transform”, 2009 Seventh International Conference on Advances in Pattern Recognition.

[2] Jan Flusser, Filip ˇSroubek, and Barbara Zitov, Image Fusion: Principles, Methods, and Applications, Tutorial EUSIPCO 2007.

[3] Valdimir S. Petrovoc, Manchester School of Engineering, “Multisensor Pixel-level Image Fusion” , A Thesis of Phd program Feb-2001.

[4] Medha V. Wyawahare, Dr. Pradeep M. Patil, and Hemant K. Abhyankar, Image Registration Techniques: An overview, International Journal of Signal Processing, Image Processing and Pattern Recognition Vol. 2, No.3, September 2009

[5] Jiang Dong, Dafang Zhuang, Yaohuan Huang and Jingying Fu, “dvances in Multi-Sensor Data Fusion: Algorithms and Applications”,*Sensors* **2009**, *9*, 7771-7784; doi: 0.3390/ 91007771

[6] Manjusha Deshmukh and Udhav Bhosale, “Image Fusion and Image Quality Assessment of Fused Images” International Journal of Image Processing (IJIP), Volume (4).

[7] V. Ramachandra and Uttamkumar,” Image fusion in GRDSS for Land use Mapping “www.mapindia.org/2005/papers/pdf/66.pdf.

[8] Uttam Kumar, Anindita Dasgupta, Chiranjit Mukhopadhyay, N. V. Joshi, and T. V. Ramachandra, “Comparison of 10 multi-sensor image fusion paradigms for ikonos images”,

http://wgbis.ces.iisc.ernet.in/energy/paper/ijrrcs_ikonos_fusion/image.htm.

[9] Shivsubramani Krishnamoorthy, Prof. K P Soman "Implementation and Comparative Study of Image Fusion Algorithms" , International Journal of Computer Applications (0975 – 8887) Volume 9– No.2, November 2010.

[10] The Whole Brain Atlas- Harvard Medical School www.med.harvard.edu/aanlib/

[11] Eduardo Fernández Canga, "IMAGE FUSION" Project report for the degree of ME. in Electrical & Electronic Engineering

[12] N. Indhumadhi, G. Padmavathi, " Enhanced Image Fusion Algorithm Using Laplacian Pyramid and Spatial frequency Based Wavelet Algorithm", International Journal of Soft Computing and Engineering (IJSCE) ISSN: 2231-2307, Volume-1, Issue-5, November 2011.

[13] Dennis L. HartmannATMS 552 Notes: Section 9: Wavelets Page 240-258

[14] Andrew P. Bradley Shift-invariance in the Discrete Wavelet Transform Proc. VIIth Digital Image Computing: Techniques and Applications, Sun C., Talbot H., Ourselin S. and Adriaansen T. (Eds.), 10-12 Dec. 2003, Sydney