

Brian Image Fusion of MRI-CT Multimodality Systems Using DWT and Hybrid Enhancement Fusion Algorithms

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Abstract

This paper focus on the fusion of the enhancement brain images come from different multimodality systems ((Magnetic Resonance Image, MRI) and (Computed Tomography, CT Scanner)) at the same position section and dimension. The Two-Dimension of Discrete Wavelet Transform and Inverse Discrete Wavelet Transform theories of Daubechies 2 used to separate the low and high frequencies of the taken images and the sophisticate hybrid enhancement fusion algorithm used pixel by pixel maximum selection rule, for approximate information (low frequency) and details information (high frequency) which was enhancement by (*unsharp masking filter*), which were programmed in MATLAB to get more information image, So the decision of Physician will be more accuracy in the diagnostic diseases field.

Keywords: Discrete Wavelet Transform, Hybrid Enhancement Fusion Algorithms, *unsharp masking filter*, Maximum Selection Rule and MATLAB M-File.

الخلاصة

هذا البحث يركز على عملية اندماج الصور المأخوذة لمنطقة الدماغ من جهازي الرنين المغناطيسي والمغراس الحلووني لنفس موقع الفحص ونفس الابعاد. وبذلك تم استخدام نظريات التحويلات الموجية المنفصلة ثنائية الابعاد في فصل الترددات العالية والواطئة للصورة المأخوذة وكذلك استخدام برامج التداخل المشترك المتخصص في عملية اختيار اكبر قيمة بين العناصر لكلتا الصورتين مع استخدام المرشح لتوضيح الحدود والحواف الموجودة في الصورة والتي تم برمجتها بلغة (MATLAB) للحصول على صورة ذات معلومات كثيرة ودقيقة ومشاركة ليصبح قرار الطبيب اكثر دقة في مجال تشخيص الامراض.

1. Introduction:

The development of new imaging sensors has brought with it a need for image processing techniques that can effectively fuse imaging from different modality into composite for interpretation. For example, MRI and CT images may be fused as an aid to medical diagnosis. Dependent on the merging stage, multimodality imaging fusion can be performed at three different levels, namely pixel level, feature level, and decision level. In this paper, the multisensor image fusion is the pixel level fusion, which denotes a fusion process generating a single image containing more accuracy than any other individual source image [Manjunath and Mitra 1996, Vekkot and Shukla 2009].

Multiresolution wavelet transform can be providing good localization in the both frequency and space domains. DWT is more compact, and able to provide directional information in the low-low, high-low, low-high, and high-high bands, and contain unique information at different resolution [Hai-Hui Wang 2004]. This paper proposes a hybrid architecture algorithm for wavelet based image fusion combining the principle of pixel rule and unsharp filter mask.

2. Wavelet Based Hybrid Image Fusion and Enhancement:

The algorithm consist three stages of processing starting from Discrete wavelet analysis stage, the enhancement filter stage and the fusion of the enhancement sours images stage.

2.1 Discrete Wavelet analysis Stage:

The term "wavelet" as it implies means a little wave. This little wave must have at least a minimum oscillating and fast decay to zero, in both the positive and negative direction, of its amplitude. Wavelets can be described by using two functions, the scaling function $\phi(t)$ also known as 'father wavelet' and the wavelet function $\psi(t)$ or 'mother wavelet', which are associated with low pass and high pass filters, respectively.

Wavelets transform (including decomposition and reconstruction) with single mother wavelet functions. One of their main properties is the time-frequency localization property of wavelet functions. The wavelet function can be expressed as a weighted sum of shifted, double-resolution scaling functions [Rao and Bopardikar 1998, Burrus and Guo 2006]:

$$\psi(t) = \sum h_{\psi}(t) \sqrt{2} \phi(2t - n) \quad (1)$$

where the $h_{\psi}(t)$ are called the wavelet function coefficients.

The scaling functions of any subspace can be built from double-resolution copies of themselves:

$$\phi(t) = \sum h_{\phi}(t) \sqrt{2} \phi(2t - n) \quad (2)$$

where the $h_{\phi}(t)$ are called the Scaling function coefficients.

The scaling and wavelet function subspaces are related by [Goswami and Chan 2004].

$$V_{j+1} = V_j + W_j \quad (3)$$

In this paper the most commonly used 2D DWT and IDWT of The Daubechies wavelet with 2 coefficients. It is built with separable orthogonal mother wavelets, having a given regularity. At every iteration of the DWT, the rows of the input image MRI and CT (obtained at the end of the previous iteration) are low-pass filtered with a filter having the impulse response H_o and high-pass filtered with the filter G_o . Then the lines of the two images obtained at the output of the two filters are decimated with a factor of 2. Next, the columns of the two images obtained are low-pass filtered with H_o and high-pass filtered with G_o . The columns of those four images are also decimated with a factor of 2. Four new sub-images (representing the result of the current iteration) are generated. The first one, obtained after two low-pass filtering, is named approximation sub-image (or LL image). The others three are named detail sub-images: LH, HL and HH. The LL image represents the input for the next iteration as shown in the bellow equations and diagrams.

For the 1st decomposed level:

$$O/P \text{ image}(L)(\downarrow 2) = I/P \text{ image} * \text{Filter}(H_o) \quad (4)$$

$$O/P \text{ image}(H)(\downarrow 2) = I/P \text{ image} * \text{Filter}(G_o) \quad (5)$$

$$\text{Approximate}(LL^1)(\downarrow 2) = [O/P \text{ image}(L)]^T * \text{Filter}(H_o) \quad (6)$$

$$\text{Details}(LH^1)(\downarrow 2) = [O/P \text{ image}(L)]^T * \text{Filter}(G_o) \quad (7)$$

$$\text{Details}(HL^1)(\downarrow 2) = [O/P \text{ image}(H)]^T * \text{Filter}(H_o) \quad (8)$$

$$\text{Details}(HH^1)(\downarrow 2) = [O/P \text{ image}(H)]^T * \text{Filter}(G_o) \quad (9)$$

For the 2nd decomposed details level $[LL^2, LH^2, HL^2 \text{ and } HH^2]$ will be get, and so on. Where the (*) mean the convolution and the H_o and G_o are the Low pass and high pass filters respectively for the decomposed level and the H_1 and G_1 are the low pass and high pass filters respectively for the recomposed level as shown in fig(1) and fig(2) [Goswami and Chan 2004].

$$H_o = \begin{bmatrix} -0.0915 \\ 0.1585 \\ 0.5915 \\ 0.3415 \end{bmatrix}, \quad H_1 = \begin{bmatrix} 0.6830 \\ 1.1830 \\ 0.3169 \\ -0.1830 \end{bmatrix}, \quad G_o = \begin{bmatrix} -0.3415 \\ 0.5915 \\ -0.1585 \\ -0.0915 \end{bmatrix} \text{ and } G_1 = \begin{bmatrix} -0.1830 \\ -0.3169 \\ 1.1830 \\ -0.1830 \end{bmatrix}$$

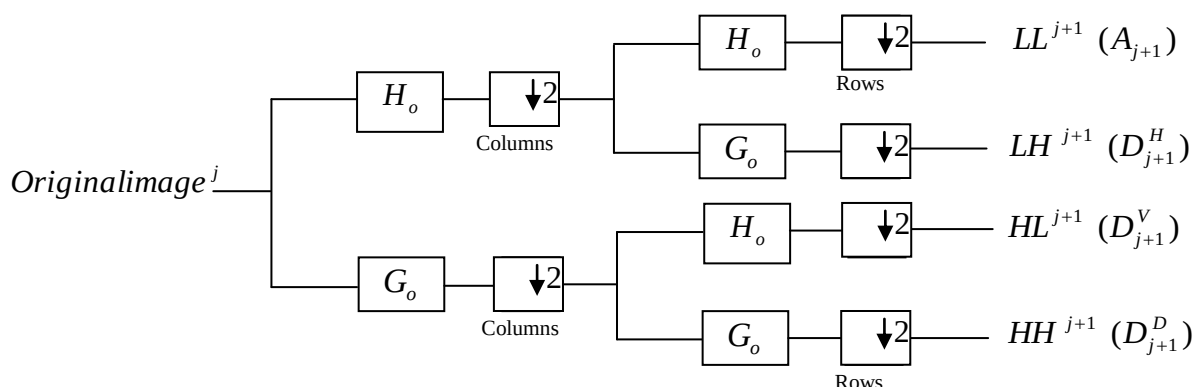


Fig. (1) Two Dimension Wavelet Transform Image Decomposed Diagram.

Where $(j \geq 0)$ according to level of image decomposed.

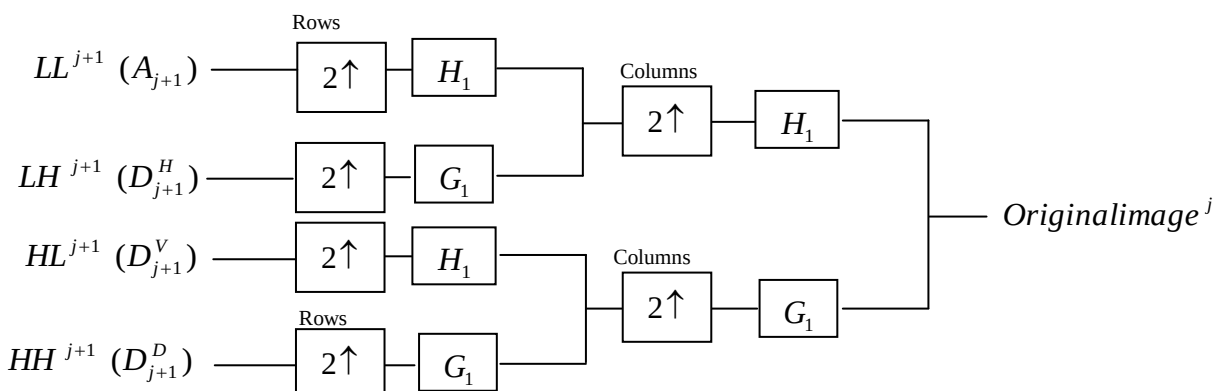


Fig. (2) Two Dimension Wavelet Transform Image Recomposed Diagram.

2.2 Enhancement Image stage:

One of the spatial filters of interest is the highpass filter, which is sometime referred to as an unsharp filter. This filter sharpens a blurry image by enhancement the high frequencies (details information or sharpness information) extract from sours images. The spectral components of an image can be divided into low frequency $f_{lowpass}(x, y)$ and high frequency $f_{highpass}(x, y)$ components.

$$f(x, y) = f_{lowpass}(x, y) + f_{highpass}(x, y) \quad (10)$$

Given that the mean filter is a lowpass filter and effectively remove high frequency components from an image, Equation (10) can be rewritten as

$$f(x, y) = f_{mean}(x, y) + f_{highpass}(x, y) \quad (11)$$

where $f_{mean}(x, y)$ is the mean filter image. Solving for the highpass filter output yields

$$f_{highpass}(x, y) = f(x, y) - f_{mean}(x, y) \quad (12)$$

Which is the highpass filter image.

In any many instance, it is desired to enhance the high frequency components of an image (details information (LH, HL and HH)) without attenuate the low frequency components to sharps a blurred image (approximate information (LL)). In this paper, it is desired to add a proportional a mount of the high frequency components to the original image $f(x, y)$. Multiplying equation (12) by a gain term G and adding this quantity to $f(x, y)$ yields

$$f_{highpass}(x, y) = (1 + G) f(x, y) - G f_{mean}(x, y) \quad (13)$$

For $G=0$ equation (13) reduces to the original image, and as G increase, the high frequency components are enhanced, improve the overall sharpness of the image. Typical values for G are in the range of 0 to 2 as shown in fig (3) [Arthur R weeks 1996, Tinku A. 2005], and from the testes, found that the suitable value of G for medical imaging application is 1.6.

$\frac{-1}{9}$	$\frac{-1}{9}$	$\frac{-1}{9}$
$\frac{-1}{9}$	$\frac{+8}{9}$	$\frac{-1}{9}$
$\frac{-1}{9}$	$\frac{-1}{9}$	$\frac{-1}{9}$

(a)

$\frac{-G}{9}$	$\frac{-G}{9}$	$\frac{-G}{9}$
$\frac{-G}{9}$	$\frac{9+8G}{9}$	$\frac{-G}{9}$
$\frac{-G}{9}$	$\frac{-G}{9}$	$\frac{-G}{9}$

(b)

Fig. (3) Represent 3x3 Filter Mask Coefficients (a) Implementation of Equation (12) and (b) Implementation of quation (13).

2.3 Image fusion stage

The advent of multiresolution wavelet transforms gave rise to wide developments in image fusion research. Several methods were proposed for various applications utilizing the directionality, orthogonality and compactness of wavelets. Fusion process should conserve all important analysis information in the image and should not introduce any artefacts or inconsistencies while suppressing the undesirable characteristics like noise and other irrelevant details. Fusion can be performed on pixel, feature or decision level. The complexity of pixel algorithms is less than other methods. So the fusion process, between the MRI image which has the more information about the soft tissue such that brain tissue, fluid and so on and the CT Scan image which has the more information about the hard tissue such that bone, mass and so on, to produce image has both properties to be more clear and significant in the field of the medicine diagnostic. Select the pixel base algorithm for approximate and details information at each level which involves fusion based on

taking the maximum value pixels from both source images as shown in fig(4) [Vekkot and Shukla 2009].

$$LL_f^L = \text{Maximum}(LL_{f(MRI)}^L(i, j), LL_{f(CT)}^L(i, j)) \quad (14)$$

Where, LL_f^L is the fused and $LL_{f(MRI)}^L$ and $LL_{f(CT)}^L$ are the input images, i and j represent the pixel positions of the subimages, and L is the level decomposed.

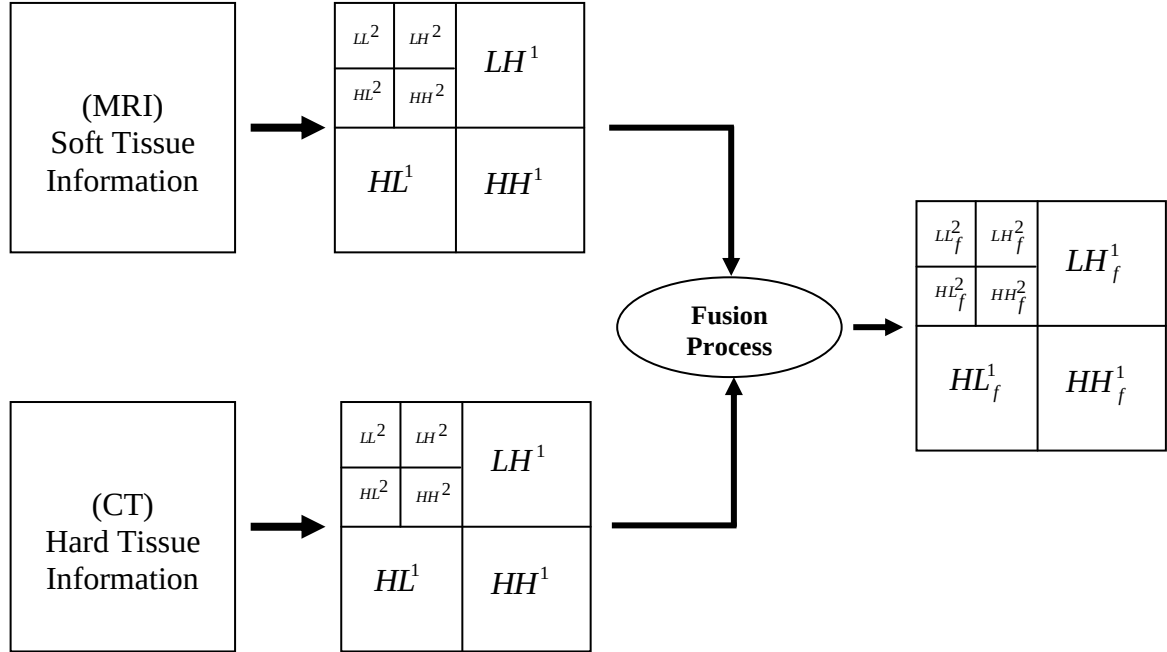


Fig. (4) Image Fusion Process for the MRI and CT Images source which were Decomposed at level two.

3. Hybrid Enhancement Fusion Algorithms:

In this paper, the decomposition the MRI and the CT sours images was done in two levels, to separate the image into two main components low frequency which is represent the main body information and high frequency which is represent the borders and sharpness information. The sophisticated 3x3 filter mask (unsharp filter) using to enhancement the borders information for each decomposed level and the fusion algorithm applies for each decomposed level of both sours images. Finally the IDWT was applied for fusion subimages to get on the enhancement, clear and significant image. All the equations mention above can be shown as a flow chart as shown in fig (5).

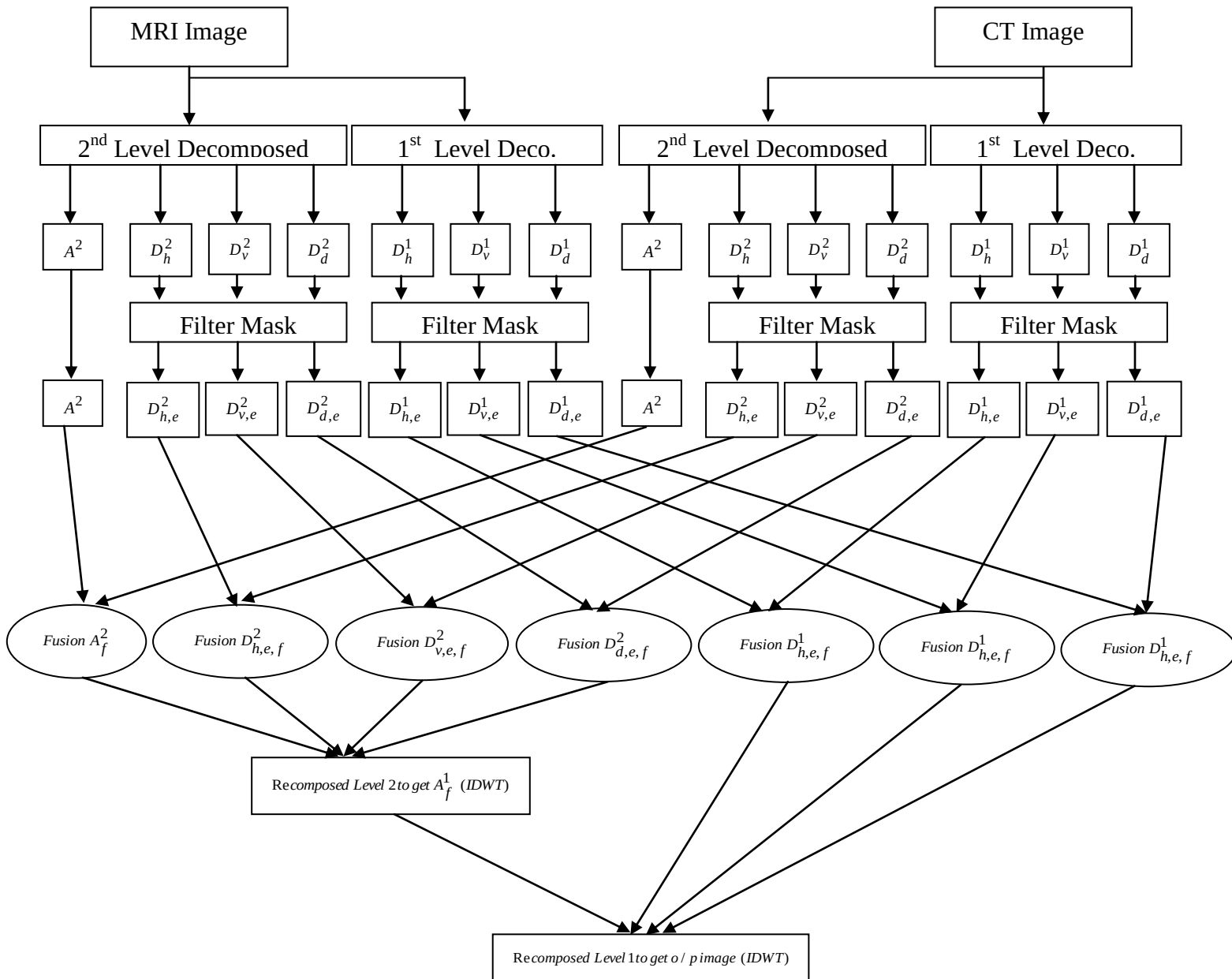


Fig. (5) The Policy of Hybrid Enhancement Fusion Architecture.

4 Experimental Results

One of the main challenges in the field of the radiological department is how to improve the image and how to fusion between the multimodality system such as (MRI-PET), (PET-CT) and (MRI-CT) to get more accuracy and clear image which be significant in the medical decision. The off line data which were used in this paper taken from the 1.5T MRI of Al-Hilla Surgical Hospital and 16 Slice CT Scan of Mergan Hospital. The initial conditions for the images fusion are the Sours images of MRI and CT should be taken from the same patient, position (Slice location) and size. Where the MRI system show the information about the soft tissue such as (Brian, Blood, Vesselsetc) and the CT system show the information about the hard tissue such as (Bone, Stone, Clottingetc). The fusion can be study in the different region (Brian, Liver, Cardiacetc), This paper deals the fusion occur in the brain as follows:

A) Reading the Sours Images as shown in fig (6):



Fig. (6) Sours Images (256x256) (a) MRI Images Represent the Soft Tissue (b) CT Images Represent Hard Tissue.

B) Decomposed the sours images to the 1st and 2nd Level as shown in fig (7, 8):

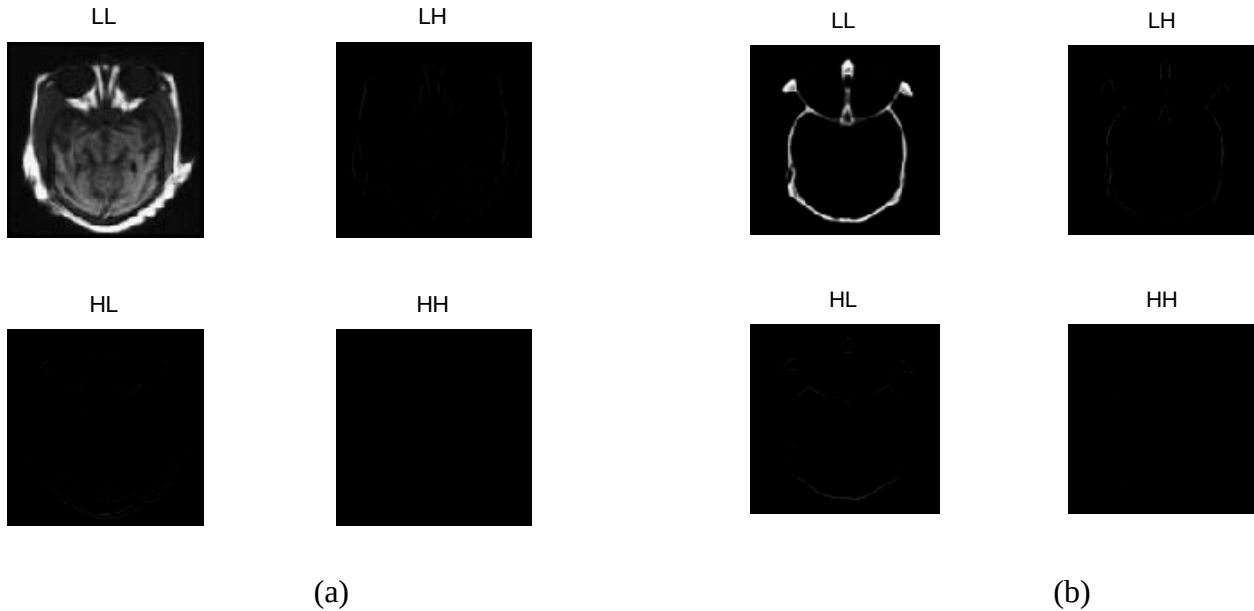


Fig. (7) Decomposed at 1st Level (132x132 pix.) (a) MRI Subimage (b) CT Subimage.

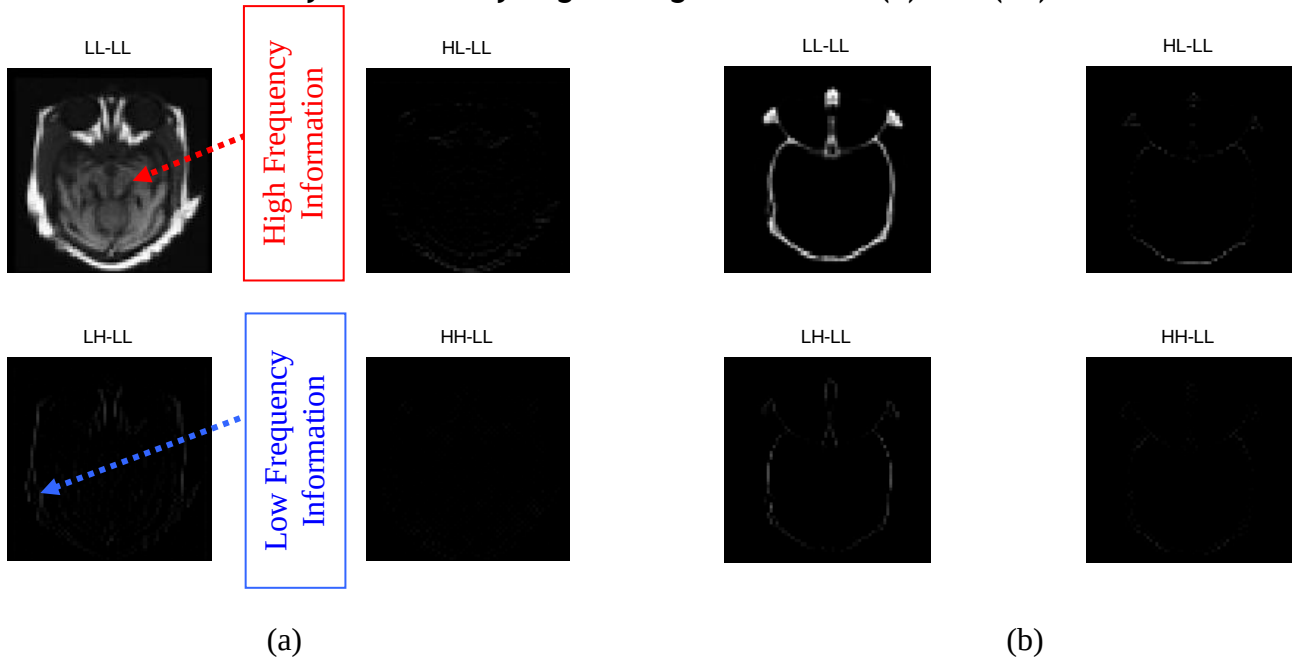


Fig. (8) Decomposed at 2nd Level (68x68 pix.) (a) MRI Subimage (b) CT Subimage.

C) Enhancement 1st and 2nd Decomposed Subimage with Unsharp Filter:

After extract the high frequency information from the source images (LH, HL, and HH), enhance sharpness and border information by convolution and correlation with unsharp filter (3x3) mask mentioned above to get upon clear border as shown in fig (9, 10).

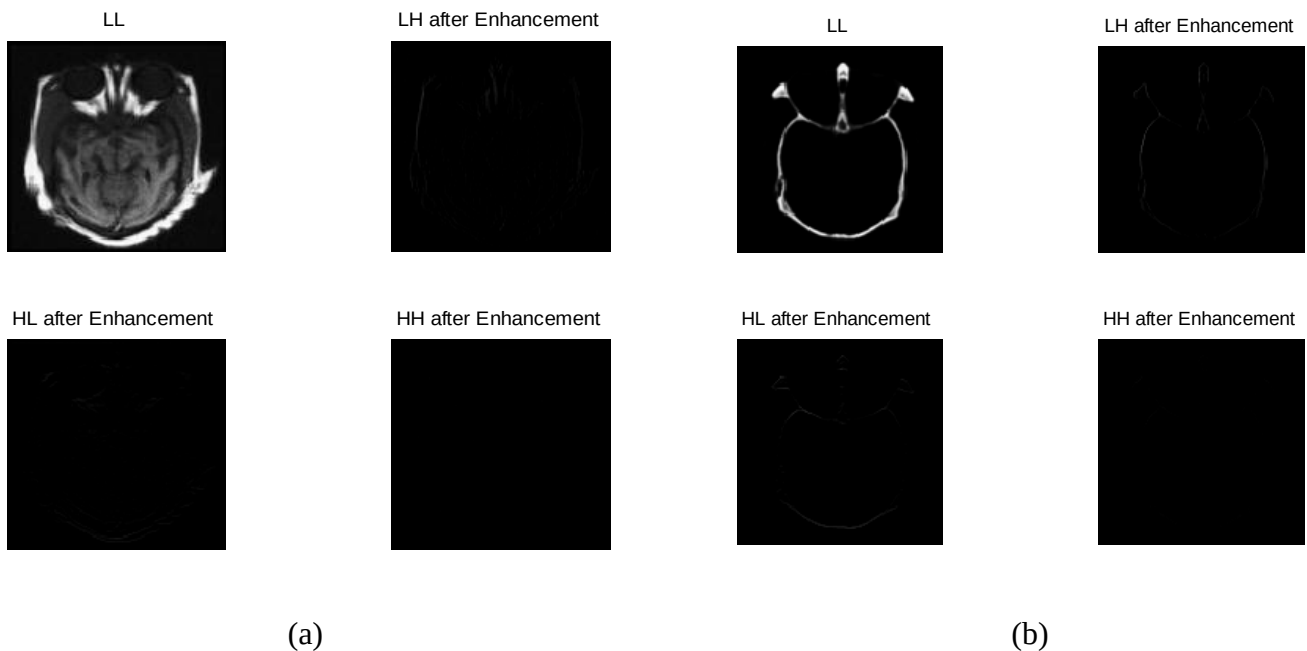


Fig. (9) 1st Level Decomposed Subimage Enhancement (a) MRI Subimage (b) CT Subimage.



(a) (b)
Fig. (10) Enhancement of 2nd Level Decomposed (a) MRI Subimage (b) CT Subimage.

D) Fusion of the 2nd Level Decomposed Stage as shown in fig (11):

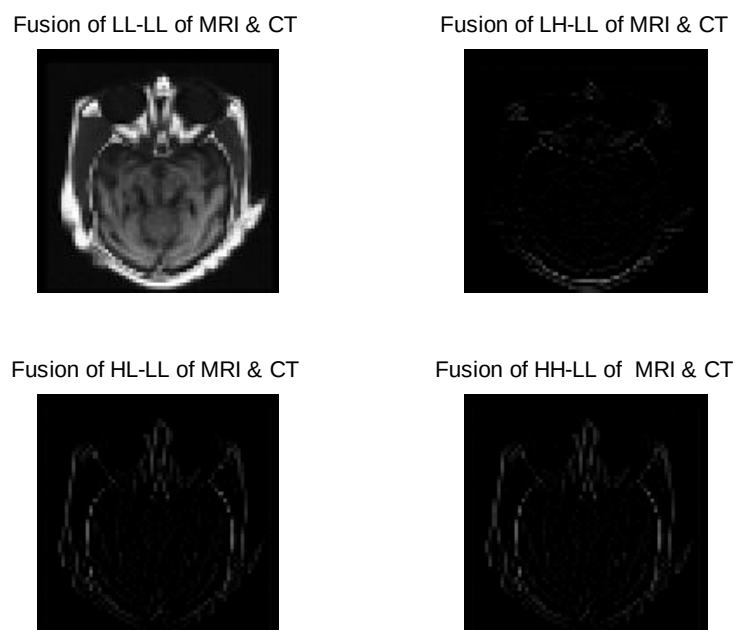


Fig. (11) Fusion of 2nd Level Decomposed of Approximation and Enhancement Details Information of MRI and CT Subimage.

F) First Level Recomposed Process Stage (IDWT) as shown in fig (12):

LL Subimage of first MRI & CT Fused Recomposed

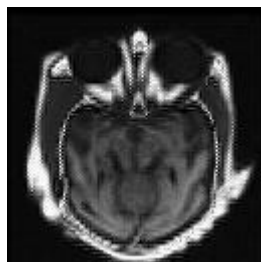
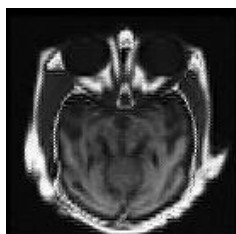


Fig. (12) Approximate Information (LL) Getting from 1st Recomposed Process.

G) Fusion of 1st Decomposed Level Stage as shown in fig (13):

LL Subimage after Recomposed



LH Subimage after Recomposed



HL Subimage after Recomposed



HH Subimage after Recomposed

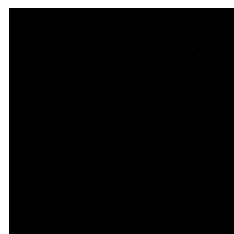


Fig. (13) Fusion of 1st Decomposed Stage of MRI and CT.

H) Second Recomposed Process Stage (IDWT) as shown in fig (14):

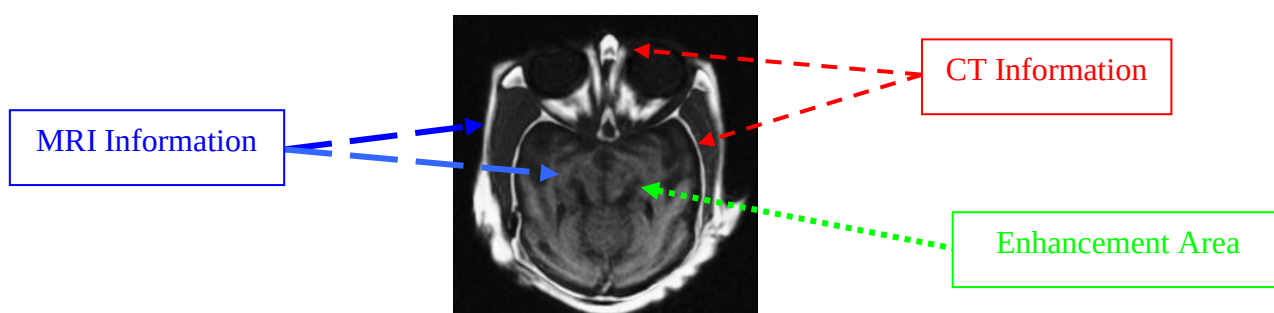


Fig. (14) Final MRI and CT Images Fusion after 2nd Recomposed Stage.

I) Final Image without using DWT and Unsharp Filter:

To show the strong and significant of the work, compare between the final image of its work as shown in the figure (14) and image without the mention above algorithm as shown in the Figure (15).

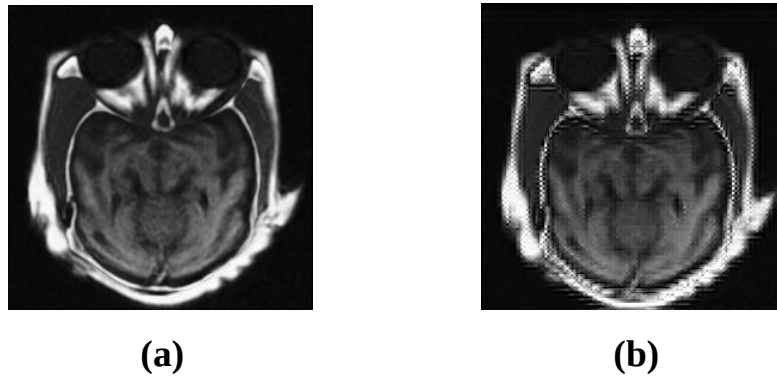


Fig. (15) a) Fusion with Algorithm b) Fusion without algorithm

6. Discussions

DWT was used to separate the image in to two level of frequencies at different stages so from that can be get the body information (low frequency) and the border information (high frequency) separately.

Now used the unsharp filter (high frequency filter) and fusion process to enhanced the border information (when it's separated and decomposed at every stage) to get more significant information. Then IDWT was used to reconstruction the fused low frequencies of two images with the enhanced and fused high frequencies of the mention images to get final more accuracy and clear image.

7. Conclusions

The final results show that the fusion process between MRI and CT Images give a significant anatomical image but if we need a wide application area make the fusion between anatomical MRI and CT images with functional Positron Emission Tomography (PET) or Single Photon Emission Computed Tomography (SPECT) images to be functional-anatomical image.

There are a little difference between the original and final image contrast and resolution while using the unsharp filter because the sours image taken as an off line data from the MRI and CT workstation which was enhanced by the default, So it is prepare to apply this algorithm as an online software program in the workstation during the data acquisition process to achievement the desired results.

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