IMAGE FUSION FOR MEDICAL IMAGE PROCESSING APPLICATION USING UNDECIMATED WAVELET TRANSFORM

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Abstract: *Image fusion has become important part of medical diagnosis. This paper gives introduction to image fusion methods based on various wavelet transforms. Fusion of CT scanned images and MRI images using multi resolution wavelet transform with necessary pre-processing of it is proposed. It also compares the performance of the various types of wavelet transform, families used and the different fusion rules with some important evaluation parameters that are Mutual information, Entropy, edge association.*

Index Terms - Image fusion, wavelet transform, CT and MRI Image, fusion Rules, Mutual information, Entropy, edge association.

1. INTRODUCTION

The process of combining the relevant information from a set of images into a single superior quality fused image is called as image fusion. This high quality fused image needs to have better spatial and spectral information, than any of the input images. Image fusion method can be broadly classified into two groups

1. Spatial domain fusion method
2. Transform domain fusion.

In spatial domain techniques, the pixel values are manipulated to achieve desired result. The Spatial domain fusion methods are averaging, Brovey method, principal component analysis (PCA), Intensity Hue saturation (HIS) based methods and high pass filtering based technique. The spatial domain approach is that tend to produce spatial distortion and Spectral distortion in the final fused image, so it has a disadvantage. In transform domain methods the image is first transferred into another domain, say frequency domain and the fusion operations is performed on the transform of the image and then the inverse transform is performed to get the resultant fused image. Spatial distortion can be very well handled by frequency domain approaches on image fusion. The discrete wavelet transform is now becoming a very important tool for fusion. Image Fusion techniques play crucial role in medical image processing application, military application, microscopic imaging, remote sensing, computer vision and robotics. In medical application, the different modalities like CT scan, MRI Scan, X-rays, PET, nuclear medicine and other modalities are used to examine the organs of body have their own advantages and disadvantages. Major advantage of the CT is its capability to image bone and blood vessels all at the same time. In the CT scanned image of the brain hard tissue like the skull bone is clearly seen but the soft tissue like the membranes covering the brain are less visible and hence CT is not sensitive in detecting inflammation of the membranes in the brain. In the MRI scanned image of the same brain we observe the soft tissue like the membranes covering the brain can be clearly seen but the hard tissue like the skull bones cannot be clearly seen. These are the demerits of the CT and MRI scans. Combination of CT and MRI scanned images of the brain then yields an image in which both hard tissue like skull bones and the soft tissue like the membranes covering the brain can be clearly visible. The main purpose of medical image fusion is to obtain a high resolution image which contains as much details as possible for the sake of diagnosis. So if these two images of the same organ are fused then the fused image contains considerably more amount of information for diagnosis of that organ, as compared to the non-fused images.

1.1 Discrete Wavelet Transforms

Wavelets are finite duration oscillatory functions with zero average value. They have finite energy and hence are suited for analysis of transient signal. Wavelets can be described by using two functions namely the scaling function f(t) or father wavelet and the wavelet function ψ(t) or mother wavelet. A number of basis functions can be used as the mother wavelet for Wavelet Transformation. The mother wavelet through translation and scaling produces various wavelet families which are used in the transformation. The wavelet families are given by following Eq.1,

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right), (a, b \in R), a > 0 \ldots\ldots \quad ---(1)$$

The Haar, Daubechies, Symlets and Coiflets are compactly supported orthogonal wavelets. These wavelets along with Meyer wavelets are capable of perfect reconstruction. The Meyer, Morlet and Mexican Hat wavelets are symmetric in shape. The wavelets are chosen based on their shape and their ability to analyze the signal in a particular application. The Discrete Wavelet Transform has the property that the spatial resolution is small in low-frequency bands but large in high-frequency bands. This is because the scaling function is treated as a low pass filter and the mother wavelet as high pass filter in DWT implementation. The wavelet transform decomposes the image into low-high, high-low, high-high spatial frequency bands at different scales and the low-low band at the coarsest scale which is shown in figure 1. The lowlow image has the smallest spatial resolution and represents the approximation information of the original image. The other sub-images, on the contrary show the detailed information of the original image. There are different levels of decomposition which are shown in Figure 1. After one level of decomposition, there will be four frequency bands, as listed above. The next level decomposition is just applied to the LL band of the current decomposition stage, which forms a recursive decomposition procedure. Thus, N-level decomposition will finally have 3N+1 different frequency bands, which include 3N high frequency bands and just one LL frequency band.

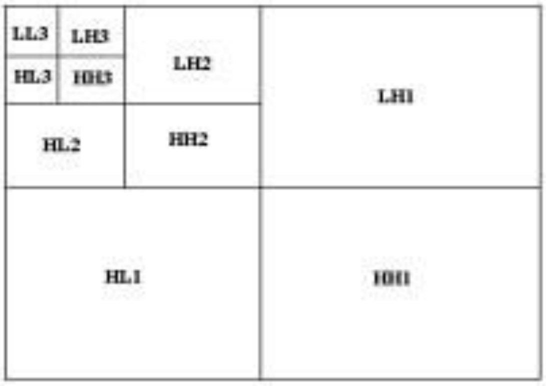
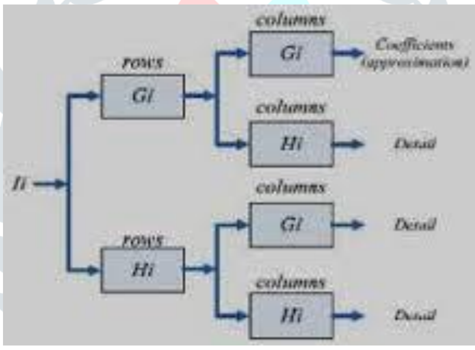


Fig.1: Recursive decomposition

1.2 Stationary Wavelet Transform:

The Discrete Wavelet Transform is not a time- invariant transform. The way to restore the translation invariance is to average some slightly different DWT, called un-decimated DWT, to define the stationary wavelet transform (SWT). It does so by suppressing the down-sampling step of the decimated algorithm and instead up-sampling the filters by inserting zeros between the filter coefficients. Algorithms in which the filter is upsampled are called “à trous”, meaning “with holes”. As with the decimated algorithm, the filters are applied first to the rows and then to the columns. In this case, however although the four images.
produced (one approximation and three detail images) are at half the resolution of the original; they are the same size as the original image. The approximation images from the undecimated algorithm are therefore represented as levels in a parallelepiped, with the spatial resolution becoming coarser at each higher level and the size remaining the same. Stationary Wavelet Transform (SWT) is similar to Discrete Wavelet Transform (DWT) but the only process of down-sampling is suppressed that means the SWT is translation-invariant. The 2D SWT decomposition scheme is illustrated in Figure 2.



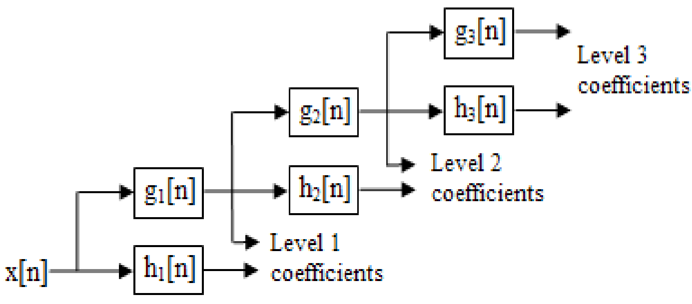


Fig.2: SWT decomposition scheme

The 2D Stationary Wavelet Transform (SWT) is based on the idea of no decimation. It applies the Discrete Wavelet Transform (DWT) and omits both down-sampling in the forward and up-sampling in the inverse transform. More precisely, it applies the transform at each point of the image and saves the detail coefficients and uses the low frequency information at each level. The Stationary Wavelet Transform decomposition scheme is illustrated in Figure 2 where Gi and Hi are a source image, low pass filter and high-pass filter, respectively. Figure 2 shows the detail results after applying SWT to an image using SWT at 1 to 4 levels.

2. Image Fusion Using UWT

2.1 Preprocessing for Image Fusion

The multimodal images which are needed to be fused need to be processed prior to application of fusion algorithm. [8] The pre-processing includes image registration, image resizing

2.1.1. Image Registration

The images which are obtained by different modalities might be of different orientations and hence are needed to be registered before they are fused.

2.1.2. Image Resizing

Also the sizes of the images might vary so before fusion, the images are needed to be resized so that both the images are of the same size. This is done by interpolating the smaller size image by rows and columns duplication.

2.1.3 Image Enhancement

If both or any of the images are not of grayscale then it is desired that it is converted to grayscale. The next step which follows this is equalization of the histograms of the images so that the contrast of the image is enhanced and that both the images have similar range of values for wavelet coefficients.

2.2 Image Fusion Algorithm

The steps in the algorithm for image fusion using UWT as shown in Figure 3 are as follows:
(1) Read the input images (MRI & CT Scanned).
(2) Resample and register both these images.
(3) Apply 2D- wavelet transform to these images which decompose it into four sub-bands (LL, LH, HL and HH).
(4) The Wavelet coefficients obtained from both the images are fused using the rules for fusion.
(5) The final fused image is reconstructed by applying inverse wavelet transform to fused image.

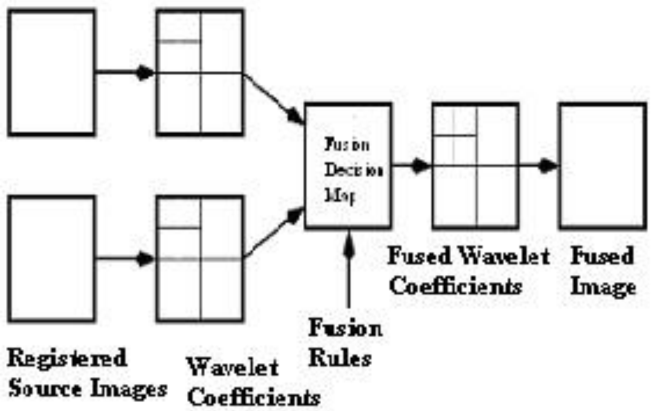


Fig.3: Fusion Algorithm

2.3 Fusion Rules

By application of Wavelet Transforms to the images we obtain the Wavelet Coefficients which are called as approximation coefficients, horizontal detail coefficients, vertical detail & diagonal detail coefficients. These corresponding coefficients of each of the image are to be fused together in a particular manner.

3. Performance Metrics to Evaluate

3.1 Image Fusion Techniques:

The image fusion process should preserve all valid and useful information from the input images, so also it should not introduce undesired artifacts. Various metrics are used in order to evaluate the performance of Image Fusion techniques.
As for the combination of the input image pairs, a wide range of fusion rules can be found in the literature. In general, these rules vary greatly in terms of their complexity and effectiveness. The spectral factorization method proposed here can be employed together with any fusion rule. Therefore, in order to assess the effectiveness of the proposed method, we applied four different fusion rules.

The first investigated combination scheme is the simple “choose max” (CM) or maximum selection fusion rule. By this rule the coefficient yielding the highest energy is directly transferred to the fused decomposed representation. Hence, for each decomposition level j , orientation band p and location n, the fused, detail images y j
F are defined as

$$y_F^j[\mathbf{n}, p] = \begin{cases} y_A^j[\mathbf{n}, p] & \text{if } \left|y_A^j[\mathbf{n}, p]\right| > \left|y_B^j[\mathbf{n}, p]\right| \\ y_B^j[\mathbf{n}, p] & \text{otherwise} \end{cases}. \quad \text{.........(2)}$$

This choice is motivated by the fact that salient features, such as edges, lines or other discontinuities, result in large magnitude coefficients, and thus can be captured using this combination scheme. However, the simple CM fusion rule does not take into account that, by construction, each coefficient within a multiscale decomposition is related to a set of coefficients in other orientation bands and decomposition levels. Hence, in order to conserve a given feature from one of the source images, all the coefficients corresponding to it have to be transferred to the composite multiscale representation as well. One way to improve the fusion results is therefore the use of intrascale grouping in combination with the CM fusion scheme of Eq. (2) (CM-IS)

$$y_F^j[\mathbf{n}, p] = \begin{cases} y_A^j[\mathbf{n}, p] & \text{if } \sum_{q=1}^{Q} \left|y_A^j[\mathbf{n}, q]\right| > \sum_{q=1}^{Q} \left|y_B^j[\mathbf{n}, q]\right| \\ y_B^j[\mathbf{n}, p] & \text{otherwise} \end{cases}$$

……… *(3)*

where the fusion decision at each decomposition level is taken jointly for all orientation bands. Since the combination schemes of Eqs. (2) and (3) suffer from a relative low tolerance against noise which may lead to a "salt and pepper" appearance of the selection maps, robustness can be added to the fusion process using an area based selection criteria. For this purpose we expand the CM-IS combination scheme of Eq. (2) by defining the following fusion rule (CM-A): Calculate the activity a jk of each coefficient as the energy within a 3× 3 window W centered at the current coefficient position n

$$a_k^j[\mathbf{n}, p] = \sum_{\Delta\mathbf{n} \in \mathcal{W}} \left|y_k^j[\mathbf{n} + \Delta\mathbf{n}, p]\right|^2$$

……………..*(4)*

and select the coefficient which yields the highest activity, again, by considering the intra-scale dependencies between coefficients from different orientation bands The fusion rules discussed so far work well under the condition that only one of the source images provides the most useful information. However, this assumption is not always valid and a fusion rule which uses a weighted combination of the transform coefficients may give better results. Following this reasoning we implement as the fourth fusion rule, a modified version of the one given by Burt and Kolczynski in (CM-AM). In their approach a match measure m jAB is calculated which is used to determine the similarity between the transformed source images.

$$y_F^j[\mathbf{n}, p] = \begin{cases} y_A^j[\mathbf{n}, p] & \text{if } \sum_{q=1}^{Q} a_A^j[\mathbf{n}, q] > \sum_{q=1}^{Q} a_B^j[\mathbf{n}, q] \\ y_B^j[\mathbf{n}, p] & \text{otherwise} \end{cases}$$

………(5)

where W is a 3×3 window centered at n and a jk is the activity measure.The fused coefficients y j F are given by the weighted average.

y jF[n, p] = wjA[n, p]y jA[n, p] + wjB[n, p]y jB[n, p]

……….(6)

The low-pass approximation images will be treated differently by our combination schemes. Unlike the case of the detail images, high magnitudes in the approximation images do not necessarily correspond to important features within the source images. Thus, for all previously introduced combination schemes, the fused approximation coefficients xJF are obtained by a simple averaging operation

xJF[n] = xJA[n] + xJB[n]2 … ….(7)

3.1.1 Entropy

Entropy measures the information quantity contained in an image. Higher entropy value of the fused image indicates presence of more information and improvement in fused image. If L is the total of grey levels and p= {p0, p1,…..,pL-1} is the probability distribution of each level, Entropy is defined

$$\sum_{i,j=0}^{N-1} P_{i,j} \left(-\ln P_{i,j}\right)$$

…………(8)

3.1.2 Performance measure QPAB/F :

Having QAF(n,m) and QBF(n,m) for N*M size images, a normalised weighted performance metric QPAB/F of a given fusion process P that operates on images A and B, and produces F is obtained as follows:

$$Q_P^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M} Q^{AF}(n,m)w^A(n,m) + Q^{BF}(n,m)w^B(n,m)}{\sum_{i=1}^{N}\sum_{j=1}^{M} (w^A(i,j) + w^B(i,j))}$$

………(9)

Notice that the edge preservation values, QAF(n,m) and QBF(n,m), are weighted by wA(n,m) and wB(n,m) respectively. In general edge preservation values which correspond to pixels with high edge strength, should influence QPAB/F more than those of relatively low edge strength. Thus, wA(n,m)=[gA(n,m)]L and wB(n,m)=[gB(n,m)]L where L is a constant. Also note that 0 ≤ QPAB/F(n,m) ≤ 1.

3.1.3 Mutual Information

Mutual information is a quantity that measures a relationship between two Images that are sampled simultaneously. In particular, it measures how much information is on average

The formal definition of the mutual information of two Images X and Y , whose joint distribution is defined by P(X, Y) is given by

$$I(X;Y) = \sum_{x\in\mathcal{X}} \sum_{y\in\mathcal{Y}} P(x,y) \log \frac{P(x,y)}{P(x)P(y)}. \quad \ldots\ldots\ldots\ldots\ldots(10)$$

4. Results

Here we have used db1/HAR wavelate transform for fusion of the different images its based on choose max rule of fusion as shown in fig 4.

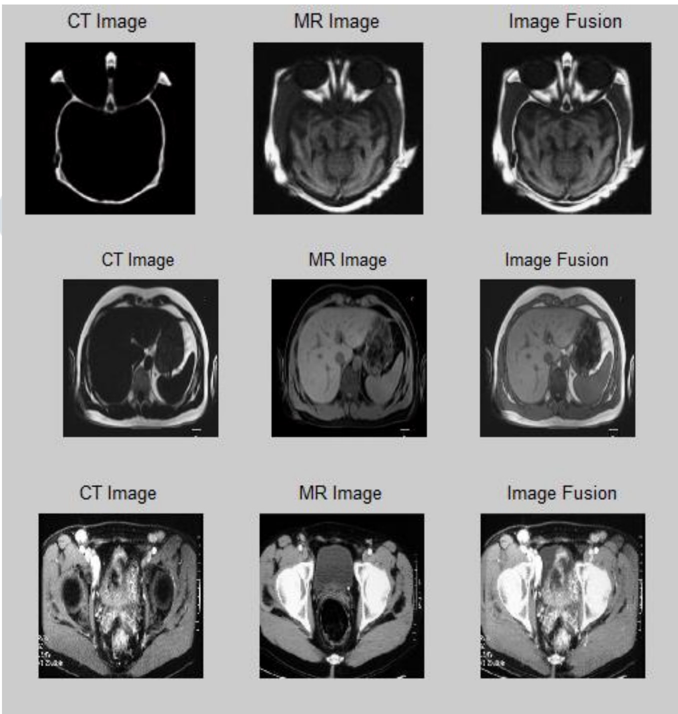


Fig.4: Using HAR Wavelet Transform Image Fusion

4.1 Performance Parameter Analysis

4.1.1 Using Choose Max Rule(CM):

Table 4.1.1: Fusion Rule – choose Max Rule(CM)

Wavelet Type	Mutual Information	Entropy of Fused Image	Q ab/f
db1/haar	4.7782	6.8496	0.7581
db2	5.2738	6.8867	**0.8022**
Coiflets 1	**5.3327**	6.8414	0.7774
Symlets 2	5.2738	6.8867	**0.8022**
Bi-orthogonal 1	4.7782	6.8496	0.7581
Discrete Meyer	5.2059	6.9621	0.7914

Where in above result shows if we use above fusion method with db2 or Symlets1 will get fused image with good edge associated

4.1.2 Using Choose Max With Intra Scaling:

Table 4.1.2: Fusion Rule – CMIS

Wavelet Type	Mutual Information	Entropy of Fused Image	Q ab/f
db1/haar	5.1352	6.8443	0.7850
db2	5.3543	6.9016	0.8032
Coiflets 1	**5.4113**	6.8457	0.7880
Symlets 2	5.3543	6.9016	0.8032
Bi-orthogonal 1	5.1352	6.8443	0.7850
Discrete Meyer	5.2244	**6.9587**	0.7836

Above Result shows that for fusion method CM-IS the Coiflets 1 wavelet gives good output in the form of mutual information.

4.1.3 Using Choose CM-IS with window based activity measures:

Table 4.1.3: Fusion Rule – CM-IS with window based activity measures

Wavelet Type	Mutual Information	Entropy of Fused I	Q ab/f
db1/haar	4.9876	6.8197	0.7597
db2	5.2504	6.8820	0.7874
Coiflets 1	5.2888	6.8439	0.7790
Symlets 2	5.2504	6.8820	0.7874
Bi-orthogonal 1	4.9876	6.8197	0.7597
Discrete Meyer	5.0931	**6.9428**	**0.7904**

Above Result shows that for fusion method CM-IS with window based activity with the Discrete Meyer wavelet gives good output in the form of Entropy and Qab/f but not good as fusion method choose max absolute Measure.

5.1.4 Using Choose max absolute Measure:

Table 4.1.4: Fusion Rule – choose max absolute Measure

Wavelet Type	Mutual Information	Entropy of Fused Image	Q ab/f
db1/haar	4.9705	6.8203	0.7590
db2	5.2501	6.8827	0.7874
Coiflets 1	5.2810	6.8451	0.7785
Symlets 2	**5.2501**	6.8827	0.7874
Bi-orthogonal 1	4.9705	6.8203	0.7590
Discrete Meyer	5.0928	**6.9438**	**0.7904**

Above Result shows that for fusion method Choose max absolute Measure with Discrete Meyer wavelet gives good output in the form Entropy and Qab/f which give good result among all fusion method.

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