Biomedical Image Fusion &Segmentation using GLCM

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ABSTRACT

In this paper we present a new fusion technique to increase the information content of the fused image. We propose information fusion by maximizing the wavelet entropy using windowing technique. It helps to diagnose the diseases like tumor, cancer …etc effectively. The images are decomposed by wavelet transform and using maximum selection rule the low frequency and high frequency bands are fused. After fusion The entropy is maximized using windowing technique. Using IDWT the fused image is resulted. The affective area in fused image is isolated and analyzed using GLCM based segmentation. GLCM based segmentation preserves the discontinuity and edge information better than other segmentation techniques.

Keywords

Image fusion ,Wavelet Transform, MS rule, GLCM

1. INTRODUCTION

For last several years research are going on different method of bio-medical image fusion as it plays an important role in clinical applications and provide accurate information to diagnose diseases.The medical images are taken from different sensors at different time and at different view point .Before the images to be fused should be properly aligned and should have equal size which can be achieved from image registration techniques. Multimodal medical images provide complementary information like the structural image with higher spatial resolution provides more anatomy information while the functional image contains functional information of tissues. So when they are fused better image with greater accuracy is resulted Ex: CT scan of brain contains bony information while PET or MRI scan provides the soft tissue information. Thus resulted fused image contains both the information, The quality metric of several approaches such as pixel-based fusion, Laplacian Pyramid based fusion[7], DWT based fusion[2],[3],[4],[5] are evaluated and compared with the proposed method[1]. After fusion to properly analyze, segmentation algorithm is adopted to separate out the affected area. Here gray-level transition frequency and edge information is calculated from GLCM[9],[10] which is needed to compute the threshold value. Fuzzy boundaries between the objects and background can be determined accurately. The GLCM based segmentation is compared with region growing method for segmentation and shows better results.

Here in this paper bio-medical images like CT, MRI , PET[12],[13],[14] are used to diagnose brain tumor and cancer. This scheme can also be applied to any fracture in bones, ulcer and stones in the body.

2. IMAGE FUSION

2.1 Based On Wavelet Decomposition

Wavelet transforms are useful to extract local details from "non-stationary" signals. DWT is based on sub-band coding and normally used for multi-resolution analysis. In DWT [2],[3],[4],[5] the time is not discrete but the translation and the scale steps are discrete. The CWT (continuous wavelet transform) is defined as:

$$W_{\psi_{a,b}} f(a,b) = |a|^{-1/2} \int f(t)\psi\left(\frac{t-b}{a}\right)dt \qquad (1.1)$$

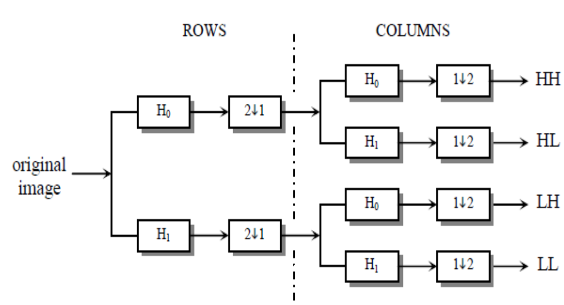
The functions $\psi_{a,b}$ are called wavelets. Note that the function ψ is called as the mother wavelet The discrete wavelet transform (DWT) can be derived from Eq. (1.1) by restricting 'a' and 'b' to have only discrete values : $a = a_0^m$ & $b = nb_0 a_0^m$ with m,n $\in$ Z . Note that both a & b are positive and $a_0 > 1$ & $b_0 > 0$. Thus, the DWT is defined as:

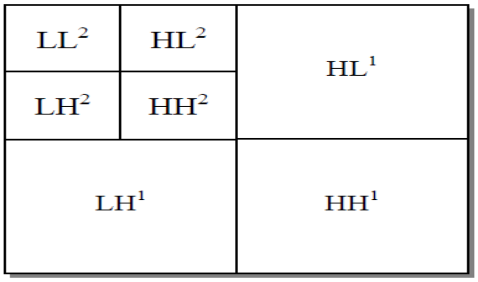
$$W_{\psi_{m,n}} f = a_0^{\frac{-m}{2}} \int f(t)\psi(a_0^{-m}t - nb_0)dt \qquad (1.2)$$

The corresponding discretely labeled wavelets are given by:

$$\psi_{m,n}(x) = a_0^{\frac{-m}{2}}\ \psi(a_0^{-m}x - nb_0) \qquad (1.3)$$

Proper choice of a^0, b^0 and $\psi_{a,b}$ constitute an orthonormal basis set for different signal and image processing applications. Here HH,HL,LH are the horizontal , vertical and diagonal detail coefficients and LL is the approximate coefficient .





(Image Decomposition)

The fusion process is performed by combining the detail and approximate coefficient as follows :

$$D_f(m,n) = K1_A(m,n) * D_A(m,n) + K2_B(m,n) * D_B(m,n)$$

(1.4)

The coeeficients can also be fused by using maximum selection rule

$$D_f(m,n) = \begin{cases} D_A(m,n), & |D_A(m.n)| \geq |D_B(m,n)| \\ D_B(m,n), & \text{otherwise} \end{cases} \quad (1.5)$$

Where $D_f(m,n)$, $D_A(m,n)$, $D_B(m,n)$ are the detail and approximate coefficient of the fused and input images.

2.2 Proposed Method :

In proposed method[1] using 'db' wavelet and DWT function the detailed and approximate coefficient of the two source images are determined.

Low Frequency Band Fusion:

For low frequency band fusion the activity level is determined by using eq(1.5). After maximum selection a window based verification is performed. A small window is taken whose center is located at the current position and if the entropy of the fused image with in the window is greater than the entropies of the 3x3 source images then the pixels of the fused image will not change , but if the entropy of the source image1is highest then all 9 pixels will replaced with the pixels of image1 and if the entropy of the source image2 is higher then all the pixels are replaced by the pixels of image2.. The window moves one position from left to right and verifies all the columns and then shifts one position from top to bottom and verifies all the rows. In this way it covers the whole image. 5x5 or 7x7 window can also be taken.

High Frequency Band Fusion:

The detailed part is considered as High frequency components . The fusion performance will be better if the resulted fused image preserves the details like edges , textures of the input images . The detailed information of image is normally contained in the high frequency components.The mean and variance of the images are calculated and the coefficients are selected using maximal variance scheme .

Mean and variance can be calculated using following equation .

$$m(x,y) = \frac{1}{(M \times N)} \left[\sum_{p=-N/2}^{N/2} \sum_{q=-M/2}^{M/2} D(x+p, y+q) \right]$$

$$\sigma(x,y) = \frac{1}{(M \times N)} \left[\sum_{p=-N/2}^{N/2} \sum_{q=-M/2}^{M/2} \left(D(x+p, y+q) - m(x,y)\right)^2 \right]$$

$$D_{f,l}(m.n) = \begin{cases} D_{A,l}(m,n), & \sigma_A(x,y) \geq \sigma_B(x,y) \\ D_{B,l}(m,n), & \text{otherwise} \end{cases}$$

Where MxN is the size of the window , m(x,y) and σ(x,y) are the mean and variance .

After selection of maximum values the fused image is resulted by taking the inverse wavelet transform of the detailed and approximate component of the fused image.

3. EXPERIMENTAL RESULTS ANDANALYSIS OF FUSION

To verify the effectiveness of image fusion schemes explained some evaluation criteria is needed **.**

Information Entropy(H) :

Information entropy of an image is defined as:

$$H = \sum_{i=0}^{L-1} P_i \ln P_i \quad (1.6)$$

Where L is number of gray level

P_i is the ratio between the number of pixels whose gray Value is i(0≤i≤L-1) and total pixel contained in the image .

As it measures the richness of information in an image, so more entropy indicates better result.

Cross Entropy(CE):

It measures the difference between the source image and fused image. Small value indicates better results .It is mathematically defined as :

$$CE = \sum_{i=0}^{L-1} P_i \ln\left(\frac{P_i}{q_i}\right) \quad (1.7)$$

where q_i is the gray level distribution of the fused image .

Cross entropy due two image1 and image2 with respect to the fused image is determined **.**

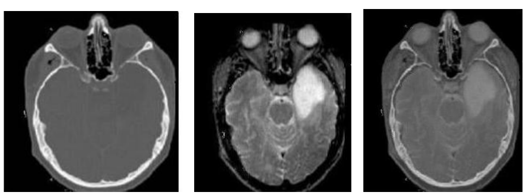
Average Gradient (G):

It deals with the clarity of the image and measures the spatial resolution of the fused image . More the average gradient indicates higher resolution .It detects the meaningful discontinuities in intensity values.

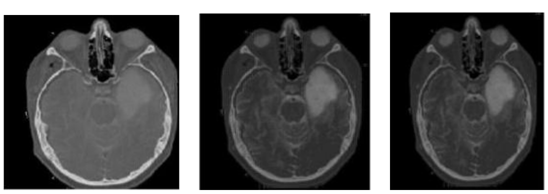
The average gradient with image size P x q is defined as

$$Avg = \sum_{y=1}^{q-1}\sum_{x=1}^{p-1}\sqrt{\left[\left(\frac{df(x,y)}{dx}\right)^2+\left(\frac{df(x,y)}{dy}\right)^2\right]\Big/2} \bullet \frac{1}{(p-1)(q-1)} \quad (1.8)$$

$f(x, y)$ is the pixel value of the fused image at (x,y) position .



a)(CT image) b) (MR image) c) (Pixel Method)

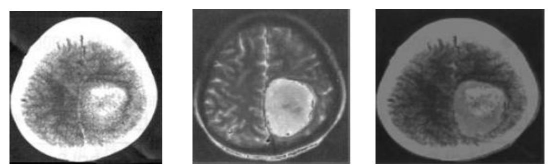


d) (Laplace) e)(DWT Method) f)(Proposed)

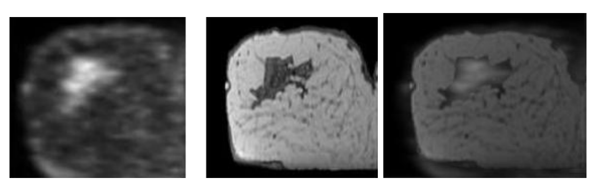
	Pixel Based	Laplacian Pyramid	DWT	Proposed Method
H	5.3275	5.3063	5.3817	5.4098
CE	1.6932, -0.0342	-1.6205, -0.0363	-3.9660, -3.6091	-4.0056, -3.7191
G	0.1243	0.1235	0.0497	0.0550

(1.1Performance Evaluation result of fusion)

Some Fused Images Based on Proposed Method:



(CT Image) (MR Image) (Fused Image)



(PET Image) (MR Image) (Fused Image)

4. GLCM BASED SEGMENTATION

In global threshold technique the threshold value is constant, thus for non- uniform illumination, noisy image and complex background the threshold value should vary over the entire image which can be achieved by GLCM based segmentation[9],[10].

Choosing Threshold using Co-occurrence Matrix:

Let I be an image whose pixel grey levels are in the range 0,…., L-1. Let take an integer valued displacement vector $\bar{d} = (p, q)$, specifies the relative position of the pixels at coordinates (x,y) and (x+p,y+q). A GLCM is a L X L matrix whose (i,j) element is the number of pairs of pixels of I in relative position $\bar{d}$ such that the first pixel has gray level i and the second pixel has gray level j. So the GLCM matrix M involves counts of pairs of neighboring pixels. Then M is form for each of four quantized directions 0, 45, 90, and 135. So GLCM matrix can be represented as M(p,q) or $\mathrm{M}(\bar{d},\theta)$, where $\bar{d}$ refers to displacement distance and θ refers to particular angle. There are simple relationships exist among certain pairs of the estimated GLCM $\mathrm{M}(\bar{d},\theta)$. Let $\mathrm{M}^T(\bar{d},\theta)$ denote the transpose of matrix $\mathrm{M}(\bar{d},\theta)$.

$$\mathrm{M}(\bar{d},0^0)=\mathrm{M}^T(\bar{d},180^0)$$
$$\mathrm{M}(\bar{d},45^0)=\mathrm{M}^T(\bar{d},225^0)$$
$$\mathrm{M}(\bar{d},90^0)=\mathrm{M}^T(\bar{d},270^0)$$

$$\mathrm{M}(\bar{d},135^0)=\mathrm{M}^T(\bar{d},315^0)$$

If 't' is the threshold value it divides the image into 4 blocks .Region-1 (shown as A) for which m≤ T and n≤ T . Region-2 (shown as D) for which m>T and n>T . Border region of region-1(shown as B) for which m ≤ T and n>T, the border region of region-2 (shown as C) for which m >T and n ≤ T.

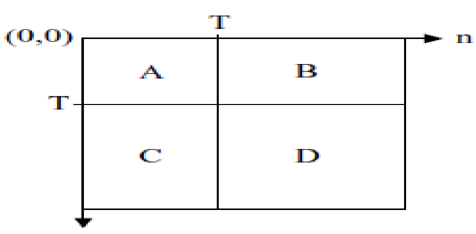
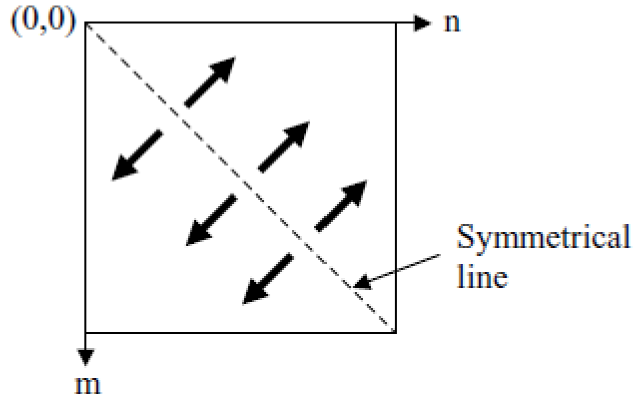


Fig1.1(Partition of a GLCM with respect to threshold)

Edge magnitude which is nothing but the gray value difference of the pixel pair can be computed from the GLCM. It increases diagonally in the GLCM



(Fig1.2: Edge magnitude)

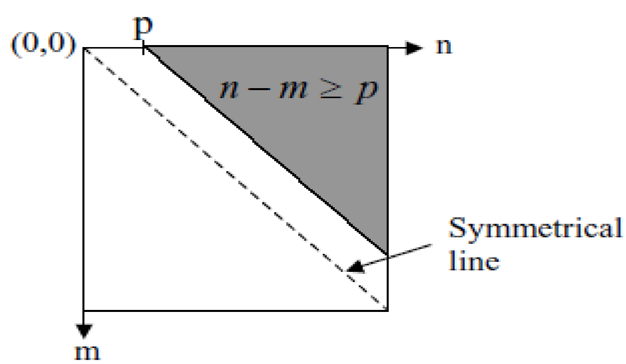
As shown in figure the edge magnitude is zero along the symmetrical line of GLCM where m = n. The maximum of the edge magnitude is located at the M(l,0) and M(0,l) where l= L-1. As contrast computation carries the information of the edge magnitude, it can measure coarseness of an image. Here the edge information is calculated by considering the current pixel pair and the mean pixel value.

Among four regions shown in figure region A represent the gray-level transition in the object (dark area), Region D represents the gray-level transition in the background i.e the bright area. The gray-level transition between the object and background or along the edge of the object is represented by Region B and Region C.

Here in our program the GLCM at 0,45,90,135 degrees and at a distance d are calculated using graycomatrix function. Then the final GLCM is calculated by taking their average.

$$GLCM=\frac{[M(d,0)+M(d,45)+M(d,90)+M(d,135)]}{4} \quad (1.9)$$

After evaluation of GLCM, the threshold value is calculated.



(Fig1.3:Threshold computation area)

Threshold value is computed as :

$$T1 = \frac{1}{\eta} \sum_{m=0}^{l-p} \sum_{n=m+p}^{l} \left(\frac{m+n}{2} \right) GLCM(m,n) \qquad \textbf{(1.10)}$$

$$T = \text{round}(V*T1) \qquad (1.11)$$

V is a scalar quantity chosen by inspection and this value is different for different images.

$$\eta = \sum_{m=0}^{l=p} \sum_{n=m+p}^{l} GLCM(m,n) \qquad (1.12)$$

This summation range forces the equation to compute the threshold value in the specific area in GLCM which is restricted by n-m≥p. Thus the pixel pair whose edge magnitude are greater than or equal to p are involved in computation. As shown in figure the computation occurs only in the upper triangle of the GLCM even the edge magnitude greater than p also exits in lower triangle. Because the areas at the upper and lower triangle have similar values due to symmetrical features of GLCM and computation will be reduced. ŋ is defined as the total number of pixel pairs within the GLCM with edge magnitude higher than or equal to p.

The sensitivity in the edge definition in the thresholding process can be changed by changing the d (relative distance between the pixel pair) and p (edge magnitude). For greater fuzziness of the edges higher values of d and p is needed. For different images threshold value will be different and to accurate result can be obtained by calibrating the values of d &p

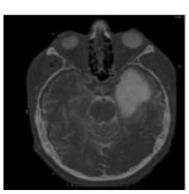
Thresholding:

After calculation of threshold value, thresholding is carried out using window based technique. A 3X3window is moved along the image With in range m≤T and n≤T and, in order to cover the object . Then the central pixel is compared with the neighboring pixels at distance d. If within that window they posses values (m,n)

then the values are assigned to zero . Then to identify the background , take the same window within range m>T and n>T. Then the central pixel will be compared with the neighboring pixels and if their values are equal to (m ,n) then assign them 255.

In this way the object can be isolated from the background, by assigning the pixels of the objects to zero and pixels of the background to 255**.**

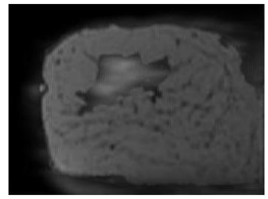
4. EXPERIMENTAL RESULTS AND ANALYSIS OF SEGMENTATION



(Fused Image)

(Region Growing)

(GLCM Based segmentation)



(Fused Image)

(GLCM based seg)

From the human visual perception it is clear that the boundaries between object and background can be well handled by GLCM based method than other.

6. CONCLUSION

Based on the evaluation criterions it is proved that proposed method is effective one .In this method the clarity, information content, texture properties of the fused image is comparatively better than other three methods. From above resulted images it is clear that GLCM based method for segmentation provides better results than the other method provides flexibility over edge definition. The proposed technique is tested on the biomedical images in order to identify the area of defect. It handles better boundaries between objects and background.

7. REFERENCES

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