

Medical Image Fusion using Fast Discrete Wavelet Transform and Quality Assessment of Fused Images

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Abstract— Our aim is to obtain accurate information in fused medical images. Multi-sensored image fusion is the process of combining information from two or more images into a result image. The resulting image contains more information as compared to individual images. So, in this paper, we present image fusion on Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) images and improve the quality of fused image by the process of denoising and dilation operation in fast wavelet transformation levels and fusion levels. Each level of sub band images of Fast wavelet transformation are denoised and dilated. For appropriate diagnosis, we need quality image with good-look and feel of resultant image for real world medical applications and finally improving the quality by applying laplacian sharpener to fused image. Not just good-look and feel of image, we also measure performance metrics like Entropy, Standard Deviation, Mean, Peak signal Noise Ratio (PSNR) and Correlation coefficient.

Keywords— PET, MRI, DWT, PSNR.

I. INTRODUCTION

Image fusion is the process of combining multimodality of input images into single resultant image which has more information gathered from individual images compared to individual image. Image fusion takes place at three varieties i.e. pixel level, feature level and decision level.

- Pixel level- A Pixel-based fusion is performed on a pixel-by-pixel basis. So generated fused image in which information associated with each pixel is determined from a set of pixels in source images to improve the performance of image processing tasks such as segmentation.
- Feature level- Feature-based fusion at feature level requires an extraction of objects recognized in the various data sources. It requires the take out of salient features which are depending on their environment such as pixel intensities, edges or textures. In our paper implemented using pixel level image fusion.
- Decision level- Decision-level fusion consists of merging data at a higher level of abstraction, integrates the results from multiple algorithms

to yield a final fused decision. Source images are processed individually for data extraction. The obtained data is then combined by applying decision rules.

Magnetic Resonance Imaging (MRI) provides pathological soft tissue information. MRI scans can be used to study and observe the brain, spinal cord, bones, joints, breasts, the heart and blood vessels. It can also be used to look at other internal organs. MRI scans can be helped to find blood clots as well. An MRI scan can be used as an extremely accurate method of disease detection throughout the body. Neurosurgeon doctors use an MRI scan not only in defining brain anatomy but in evaluating the integrity of the spinal cord after an injury. An MRI scan can estimate the structure of the heart. Even small amount of noise can change the image classification [2] and Positron Emission Tomography (PET) delivers high-resolution molecular imaging which allows us to observe the brain's molecular changes using the specific reporter genes and probes [1].

Denoising method improves quality of image. So we use four denoising filters. They are Average Filter, Median Filter, Reduce Noise Filter.

Mean filter or average filter is a simplest linear filter which is used to smoothing image applications. Image pixel variation from one pixel to another where Average filter is used to reduce the noise and intensity [2]. Median filtering is a nonlinear operation, used to remove the noise from given Images. It is widely used as effective noise removing and preserving the edges. Medical images are typically included by salt and pepper noise. Median filter was achieved by simply applying 3x3 window method over the image [3, 4]. Reduce Noise Filter is used for effective noise

removal which is library filter developed by jhlab. Despecklefilter reduces littlenoise in image. Basically, it tries to convert each pixel closer in value to its neighbours[6].

In the year of 1988,Mallat generated a fast wavelet decomposition and reconstruction[Mall89] .The Mallat algorithm for discrete wavelet transform (DWT) is, in the signal processing community known as two channel subband coder using conjugate quadrature filters or conjugate mirror filters. Fast Wavelet transform decomposes image into four sub bands at wavelet level1 and wavelet level2 and also inverse wavelet transform yields blended resultant images. The basic operation for calculating steps in the DWT is convolving the input samples with the low-pass and high-pass filters of the wavelet and down sampling the output.These methods can be found in many surveyed papers[4][5][7].We also applied dilation to denoised resize images of high subbands(LH,HL,HH) at level1 and level2.Finally applying Laplacian Sharphner to fused images to enhance image.

We compute performance Metrics like Entrophy,Mean,Standard Deviation,PSNR,,Correlation to test fused resultant images and input images.

II. DENOISING MECHANISM

MRI and PET images are need to be denoised in wavelet transformation because each level images are degraded by noise. At every level of transformation, fusion and rescaling, image looses its quality.

A.Salt and Pepper Noise

Medical images loses quality by salt-and-pepper noise (ON or OFF pixels), modeled as only two possible values . Salt and pepper noise may occur in white (salt) and black (pepper) pixels. The typical intensity value for pepper noise of an 8 bit/pixel image is close to zero and for salt noise is situated value closely to 256. The noise density term usually determine the qantity of the number of salt and pepper noise in a picture. A complete noise density of ND in an M x N image means ND x M x N pixels contain noise . The whole noise density is given as follows[2].

$$ND = ND1 + ND2 \text{----- (1)}$$

Where ND1 and ND2 are salt and pepper noise densities respectively.Fig. 1. Shows Denoising mechanism to filter noisy image.This mechanism uses four filre Average Filter,Medaian Filter,ReduceNoise Filter,Despeckle Filter.

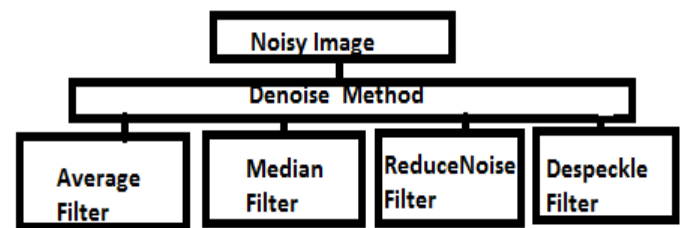


Fig. 1.Denoising Mechanism

Average Filter

The Average filter is a simple sliding-window spatial filter that replaces the center value in the window with the average (mean) of values of square window pixels. The window is usually square but can be any shape. An example of mean filtering of a single window 3x3 size of values is shown below Fig 2 and 3.

unfiltered values		
6	4	7
3	2	10
9	5	8

Fig. 2.Unaltered Values

mean filtered		
*	*	*
*	6	*
*	*	*

Fig. 3.Mean Filtered Values

$$6 + 4 + 7 + 3 + 2 + 10 + 9 + 5 + 8 = 54 \text{ and } 54 / 9 = 6$$

Center value (previously 2) is replaced by the mean of all nine values (6)

MedianFilter

Median filter for noise reduction.This filter replaces each pixel by the median of the input pixel and its eight neighbours in square window. Each pixel of the RGB channels is considered separately. The median filter is also a sliding-window filter, but it replaces the center value with the median of all the pixel values in the square window. As concerned mean filter, the window which is usually square but

approach to calculate 2D dyadic DWT is shown in Fig. 6 and dyadic representation of the DWT is shown in Fig.7 . The wavelet coefficients are of smaller spatial resolution as they go from finer scale to coarser scale. The wavelet coefficients are called the approximation (A), horizontal detail (H), vertical detail (V) and diagonal detail (D) coefficient.

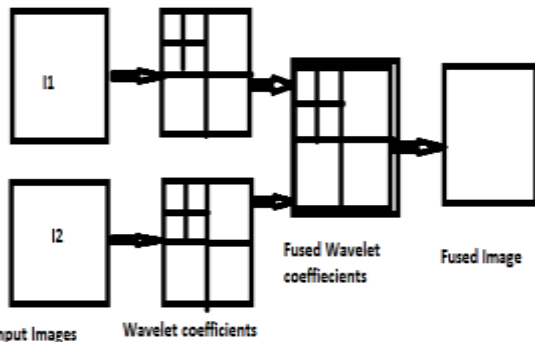


Fig. 6. Wavelet multi-dimensional fusion

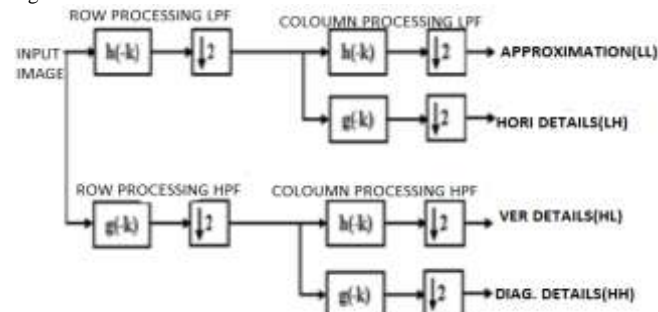


Fig. 7. Two-dimensional orthogonal wavelet decomposition

IV. PROPOSED WORK

Algorithm Steps

- 1) Read two images MRI and PET images
- 2) Both images resize to 256×256 if input images dimensions (Width and Height) are < 256×256
- 3) Apply Fast Wavelet Transform to both images up to wavelet level 2.
- 4) Generate High Subbands (LH, HL, HH) and Resize to 256×256 then apply denoise method to all subbands.

5) Use Blending method to fuse high subband images up to wavelet level 2 and apply denoise method to each fusion step.

6) Finally Apply Laplacian Sharpener to fused images at wavelet level 1 and wavelet level 2 for sharpen image to quality enhance.

7) Calculate Entropy, Mean, Standard Deviation, Peak Signal Noise Ratio (PSNR), Correlation Coefficient of Output images.

V. Fused Image Evaluation

Medical images from different sensors provide complementary information. Some applications require integration of such information. Doctors get anatomical knowledge from Magnetic Resonance Imaging (MRI) whereas physiological/functional knowledge from Photon Emission Tomography (PET). Image fusion can form a single composite image from different modality images of the same subject and provide complete information for further analysis and diagnosis. But it is necessary to align two images accurately before they are fused. Before fusing images we should preserve all features in the images and should not introduce any artifacts or inconsistency which would distract the observer. Wavelet based fusion satisfies the requirement due to lots of advantages.

Image quality assessment plays an important role in medical applications. Image quality metrics are used to benchmark different image processing algorithms by comparing the objective metrics. There are two types of metrics that are subjective and objective used to evaluate image quality.

1) subjective metric: In this metric users rate the images based on the effect of degradation and it varies from user to user

2) objective metrics: This metric quantifies the difference in the image due to processing.

Assessment of image fusion performance can be first divided into two types: one with and one without reference images. In reference image-based assessment, a fused image is evaluated with the reference image which serves as a ground truth. Furthermore, fusion assessment can be classified as either qualitative or quantitative in type. In practical and real world applications, however, neither qualitative nor quantitative assessment of fusion performance alone will satisfy the needs completely. Given the nature of complexity of specific applications, a new assessment paradigm combining both qualitative and quantitative assessment will be most appropriate in order to achieve the best assessment result.

Assessment without Reference Images

In non reference image-based assessment, the fused images are evaluated with the original source images for similarity.

Quality Metrics:

1) *Entropy:*

Entropy is defined as amount of information contained in a signal. The entropy is used to quantify the information which was first introduced by Shannon. The entropy of the image can be estimated as

$$H = -\sum_{i=1}^Q P(i) \log_2 P(g_i) \text{-----(4)}$$

Where Q is the number of possible gray levels, P(g_i) is probability of occurrence of a particular gray level g_i.

Entropy can directly reflect the average information content of an image. The higher value of entropy can be produced when each gray level of the whole range has the same frequency. If the value of entropy of fused image is greater than parent image then it indicates that the fused image contains more information.

2) *Standard Deviation:*

This performance metric is more efficient in the absence of noise and quantifies the contrast in the fused image. An image with greater contrast would have a high standard deviation..

$$\sigma = \sqrt{\sum_{i=0}^L (i - i^-)^2 h_{i_f}(i) \dots i^- = \sum_{i=0}^L i h_{i_f}} \text{-----(5)}$$

Where $h_{i_f}(i)$ is the normalized histogram of the fused image $I_f(x,y)$ and L is number of frequency bins in histogram.

Assessment With Reference Image

In reference image-based assessment, a fused image is evaluated with the reference image which serves as a ground truth.

1) *Corelation coefficient*

The correlation coefficient measures the closeness or similarity in small size structures between the original and the fused images. It can vary between -1 and +1. Values close to +1 indicate that they are highly similar while the values close to -1 indicate that they are highly dissimilar. The ideal value of corelation coefficient is one when the fused and reference are exactly alike and it will be less than one when the dissimilarity increases.

$$CORR = \frac{2C_{rf}}{C_r + C_f} \text{-----(6)}$$

Where

$$C_r = \sum_{i=1}^M \sum_{j=1}^N I_r(i,j)^2$$

$$C_f = \sum_{i=1}^M \sum_{j=1}^N I_f(i,j)^2$$

$$C_{rf} = \sum_{i=1}^M \sum_{j=1}^N I_r(i,j) I_f(i,j)$$

2) *Peak Signal Noise Ratio*

The quality of the pre-processed, noisy, and fused images are analyzed using Peak Signal to Noise Ratio (PSNR). It is defined as the ratio between the utmost possible powers of an image to the power of corrupting noise measure of the peak error. Peak signal-to-noise ratio is measured in decibels among two images. To evaluate PSNR using following equation

$$PSNR = 10 \log_{10} \left(\frac{R^2}{mse} \right) \text{-----(7)}$$

$$MSE = \sum_{M,N} [I1_{(m,n)} - I2_{(m,n)}]^2$$

Where I1 (m,n) denotes original image, I2 (m,n) denotes denoised image and M and N are the number of rows and columns in the input images. Logically, if the PSNR is higher it gives the better quality of the reconstructed image.

VI.RESULTS AND DISCUSSIONS

We have sample images MRI and PET shown in Fig.8 and Fig.9 and applied denoising mechanism to denoise noisy images using four filters at wavelet decomposition levels , fusion wavelet levels and after resizing images.Below Fig.10 to Fig.14 shows the effect of filters to denoise the images and also Table 1 gives performance of filtered images by calculating PSNR values.

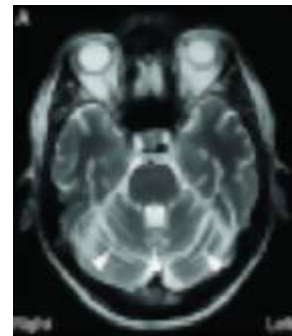


Fig. 14 Despeckle Filter and Final Denoised image

TABLE 1

PERFORMANCE METRICS PSNR OF FILTERS

Filters	PSNR in (db)
Average	19.54512073712573
Median	22.994872780092763
ReduceNoise	44.1783668404957
Despeckle	48.24910583095901

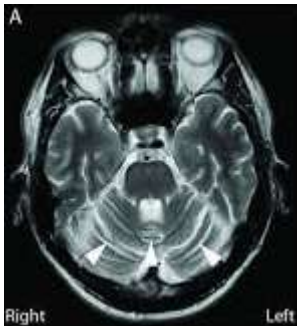


Fig.8 sample MRI image

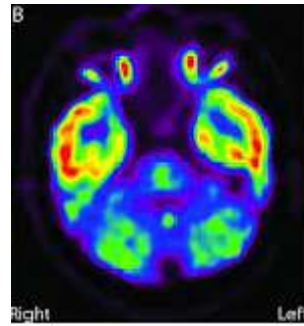


Fig.9 sample PET image

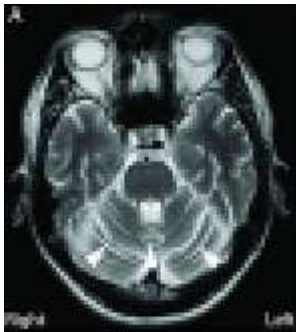


Fig. 10 Noisy Image

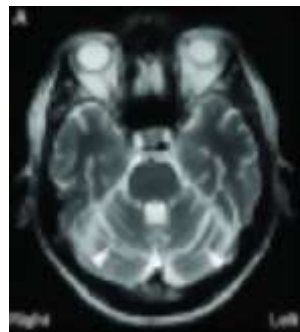


Fig. 11 Average Filtered Image

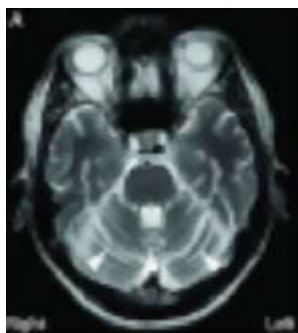


Fig.12 Median Filter

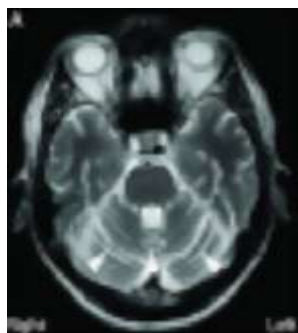


Fig. 13 ReduceNoise Filter

The images are fused at wavelet level 1 and wavelet level 2 as shown below in Fig. 15 and Fig. 16. Table 2 and Table 3 shows the Quality Metrics with and without reference of input images and output fused images.

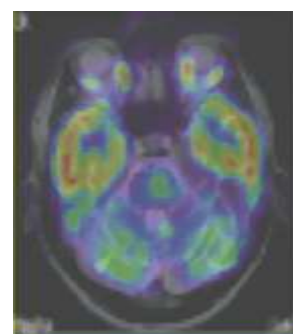


Fig. 15 Fused at Wavelet Level 1

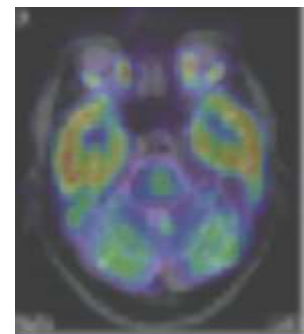


Fig. 16 Fused at Wavelet Level 2

TABLE 2

PERFORMANCE METRICS WITHOUT REFERENCE IMAGES

TABLE 3
PERFORMANCE METRICS WITH REFERENCE IMAGES

Metrics	Wavelet Level 1	Wavelet Level 2
PSNR(Input1 with Wavelet level 1 and 2)	10.9220	10.7235
PSNR(Input2 with Wavelet level 1 and 2)	9.8430	9.7427
Correlation Coefficient (Input 1 with Wavelet level 1 and 2)	0.3993	0.3557
Correlation Coefficient (Input 2 with Wavelet level 1 and 2)	0.2626	0.2343

III.CONCLUSIONS

In this paper we have practically studied and

Metrics	Wavelet Level 1	Wavelet Level 2
Entropy	4.69402	4.81279
Mean	93.57078	91.1454
Standard Deviation	29.1133	31.6672

analysed image fusion techniques specifically Fast Discrete Wavelet Transform method using Entropy, Mean, Standard Deviation, PSNR and Correlation Coefficient Image Metrics. Fast wavelet transform decomposes subband images at wavelet levels. The MRI and PET brain images are

preprocessed by denoising mechanism and dilated. According to computation results, the increased performance metrics indicates the enhancement of information content as presented in TABLE 1 and TABLE 2. Clarity of fused image is increased by applying the technique known as Laplacian Sharpner.

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