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A COMPARISON ON PERFORMANCE EVALUATION OF VARIOUS IMAGE FUSION TECHNIQUES

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ABSTRACT

Image Fusion is a technique used in various application areas. Image Fusion is a process of combining the relevant information from a set of images into a single image, where the resultant fused image will be more informative and complete than any of the input images. The images obtained from different medical imaging techniques such as Computer Tomography (CT) and Magnetic Resonance (MR) images are fused into a new image to improve the information content for diagnosis. In this paper, various algorithms for fusing two different modality medical images and results are analyzed using different quantitative measures such as, Peak Signal to Noise Ratio (PSNR), Edge Strength(Q), Mutual Information (MI), Spatial Frequency (SF), and Entropy (EN). Comparison of all the techniques concludes the better approach for future research.

General Terms

Fusion, Transform, CT, MRI, Performance Measures.

Keywords

Wavelet, Curvelet, Haar, Contourlet, Laplacian, aDWT, DTCWT, ALM, PSNR, Q, MI, SF, EN

1. INTRODUCTION

In today's advanced world, medical field have grown a tremendous growth. Many new inventions are implemented in order to diagnosis the patient's disease in very fast and accurate manner. One such advanced technique is Image Fusion. It is a process of combining different medical images. The objective of image fusion is to merge the quality and useful information from different medical images into one fused image which results in more accurate and clear information, it combines the relevant information from a set of images of the same scene into a single image, resultant fused image will be more complete and informative thanthat of input images. A fusion of multimodal images can be very useful for clinical applications such as diagnosis and treatment planning. The input images taken for Fusion process are at different resolutions and intensity values. This different technique helps physicians to extract the features that may not be normally visible in a single image by different modalities. There are different types of medical images. Some of the examples of medical images are CT, MRI, PET and SPECT images. A CT image is a type of X- ray technology used for broken bones, blood clots, tumors, blockages and heart disease. CT image provides better information about denser tissue and structure of tissue bone is better visualized by CT image. MRI image is a type of medical diagnostic imaging used to look at the blood vessels, brain, heart, spinal cord and other internal organs. MRI image provides better information on soft tissue and normal and pathological soft tissues are better visualized. The information provided by Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) is complementary. The composite image not only provides salient information from both images but also reveals the position of soft tissue with respect to the bone structure[1].

One of the important pre-processing steps for the fusion process is image registration. Image registration is the process of transforming different sets of data into one coordinate system. In this paper, it is assumed that the input images are registered. The Paper is organized as follows: Section II presents the Literature Survey of existing methods, Section III describes various Fusion methods and Transforms, Section IV explains various Performance Measures used in our study, Section V analyze and compares the performance of some recent fusion and transform methods and finally Section VI gives the conclusion.

2. LITERATURE REVIEW

Rajiv Singh and Ashish Khare has analyzed a multiscale fusion of multimodal medical images in **wavelet** domain. Fusion of medical images has been performed at multiple scales varying from minimum to maximum level using maximum selection rule which provides more flexibility and choice to select the relevant fused images. The higher the scale is the more the detailed information is captured from source images to fused image. Since medical images are of poor contrast, more detailed and relevant information should be preserved. Thus, by varying scale, we have flexibility to select appropriate fused image for further operations. [6]

Deepika.L and Mary Sindhuja.N.M has presented a novel approach for the fusion of CT and MRI medical images based on **HAAR Wavelet** Transform. The Haar transform is one of the simplest Wavelet Transforms. The special features of the Haar transform is fast for implementation. Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. The image fusion methods used to fuse two different modality medical images are Simple Average, Select Minimum, Select Maximum, PCA and Laplacian Pyramid. [8]

Yufeng Zheng, Edward A. Essock and Bruce C. Hansen developed an advanced image fusion algorithm, **aDWT** (**Advanced Wavelet Transform**) that incorporates Principal Component Analysis (PCA) and morphological processing into a regular DWT fusion algorithm. This method is compared with the pyramid methods such as Laplacian Pyramid, Ratio of Low-pass Pyramid, Contrast Pyramid, Gradient Pyramid and Morphological Pyramid and DWT methods. In aDWT, at each scale of the wavelet transformed images, a principle vector was derived from two input images and then applied to two of the images' approximation coefficients. They were fused by using the principal eigenvector. For the detail coefficients, the larger absolute values were chosen and subjected to a neighborhood morphological processing procedure which served to verify the selected pixels by using a “filling” and “cleaning” operation. This operation filled or removed isolated pixels in a 3-by-3 local region. [3]

Rajiv Singh, Richa Srivastava, Om Praksh and Ashish Khare proposed a method for multimodal medical image fusion based on **Dual Tree Complex Wavelet Transform (DTCWT)**.The major disadvantages of DWT are shift sensitivity, poor directionality and lack of phase information. The drawbacks of DWT are removed with the use of Dual Tree Complex Wavelet Transform (DTCWT). In this method, initially source images are decomposed into low pass and high pass wavelet coefficients using DTCWT and better fusion process is provided through merging of wavelet coefficients. High valued wavelet coefficients carry salient information about images. Hence combination of wavelet coefficients plays an important role in case of image fusion. Two kind of fusion rule: i. Max-Max Rule ii. Avg-Max Rule is used. [4]

T.S.Anand, K.Narasimhan and P.Saravanan has implemented an algorithm for fusing two different modality medical images based on the Multi-Wavelet Transform (MWT) and **Curvelet Transform** using different fusion techniques such as Select Maximum, Select Minimum, Simple Average, Principal Component Analysis(PCA) and Laplacian Pyramid. The major limitation of the singular wavelet functions is their time-frequency localization property. Multi-wavelets have two or more scaling and wavelet functions. The multi-wavelet has several remarkable properties like orthogonality, short support, symmetry, and high degree of vanishing moments.The Curvelet Transform is suited for objects which are smooth away from discontinuities across curves. Wavelet transform handles point discontinuities well and doesn't handle curve discontinuities well. Curvelet Transform handles curve discontinuities well as they are designed to handle curves using only a small number of coefficients. It is observed that, in Select Minimum, PCA and Laplacian Pyramid fusion methodology based on the Curvelet Transform has given curved visual details better than those given by the Multi-Wavelet fusion algorithm. [7]

The algorithm for fusing images using the Curvelet transform is explained as follows: 1. The two input images are initially registered. 2. Each input image is then analyzed and a set of Curvelet coefficients are generated. 3. The maximum frequency fusion rule or any other rule (Minimum, Average, PCA and Laplacian pyramid) is used for the fusion of the Curvelet coefficients. 4. Finally the Inverse Curvelet transform (ICVT) step is performed to obtain the fused image. [7, 14]

Sudeb Das and Malay Kumar Kundu found a novel multimodality **M**edical **I**mage **F**usion (MIF) method, based on a novel combined **A**ctivity **L**evel **M**easurement (ALM) and **Contourlet Transform** (CNT) for medical images. Now a days several Multi-scale Geometric Analysis (MGA) tools like Ridgelet, Curvelet, Contourlet and Ripplet etc. are used. These MGA tools do not suffer from the problems of wavelet and also improve the fusion result. However, the importance of each source images in the fused image is unequal, thus how to measure it and combine the corresponding coefficients have become the most important problem in MIF methods based on MGA-tools. To handle this inequality regarding the importance of each of the source images in the fused image, different Activity Level Measurements (ALMs) have been applied in the Image Fusion methods. [5]

3. FUSION METHODS AND TRANSFORMS

Medical Image Fusion is the process of combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce redundancy in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems.

Image Transforms can be simple arithmetic operations on images or complex mathematical operations which convert images from one representation to another.

3.1 Fusion Methods

Image fusion methods can be broadly classified into two groups

- Spatial domain fusion.
- Transform domain fusion.

3.1.1 Spatial Domain Fusion

Spatial domain fusion method directly deal with pixels of input images. The fusion methods such as

- Simple Maximum
- Simple Minimum
- Averaging
- Principal Component Analysis (PCA)
- IHS based methods

fall under spatial domain approaches. [9]

3.1.1.1 Simple Maximum Method

In this method, the resultant fused image is obtained by selecting the maximum intensity of corresponding pixels from both the input image.

$$F(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} MaxA(i,j)B(i,j)$$

A(i,j), B(i,j) are input images and F(i,j) is fused image. [10,12]

3.1.1.2 Simple Minimum Method

In this method, the resultant fused image is obtained by selecting the minimum intensity of corresponding pixels from both the input image

$$F(i,j) = \sum_{i=0}^{m} \sum_{j=0}^{n} MinA(i,j)B(i,j)$$

A(i,j), B(i,j) are input images and F(i,j) is fused image. [10,12]

3.1.1.3 Simple Average Method

In this method the resultant fused image is obtained by taking the average intensity of corresponding pixels from both the input image

$$F(i,j) = \frac{A(i,j)+B(i,j)}{2}$$

A(i,j), B(i,j) are input images and F(i,j) is fused image. [10,12]

3.1.1.4 Principal Component Analysis (PCA)

Principal Component Analysis is a subspace method, which reduces the multidimensional data sets into lower dimensions for analysis. This method determines the weights for each source image using the eigen vector corresponding to the largest eigen value of the covariance matrix of each source image. [10,12]

3.1.1.5 IHS

The IHS technique is a standard procedure in image fusion. It was based on the RGB true color space. It offers the advantage that the separate channels outline certain color properties, namely Intensity (I), Hue (H), and Saturation (S). [11]

3.1.2 Transform Domain Fusion

In *Transform Domain* method, image is transformed in to frequency domain. [2] The fusion methods such as

- DWT
- DCT
- Pyramid

fall under transform domain method.

3.1.2.1 Discrete Wavelet Transform (DWT)

Wavelet transforms are multi-resolution image decomposition tool that provide a variety of channels representing the image feature by different frequency sub-bands at multi-scale. When decomposition is performed, the approximation and detail component can be separated 2-D Discrete Wavelet Transformation (DWT) converts the image from the spatial domain to frequency domain. The image is divided by vertical and horizontal lines and represents the first-order of DWT, and the image can be separated with four parts those are LL1, LH1, HL1 and HH1. [10,12]

3.1.2.2 Discrete Cosine Transform (DCT)

The DCT technique is an algorithm that work on the frequency domain. This technique divide the image in fixed size blocks in order to decide which source image should be selected to constitute the final resulting image. DCT is an important transformation used in digital image processing. DCT based image fusion are more suitable and time saving in real time system using DCT based standard of still image or video. [13]

3.1.2.3. Pyramid Method

An image pyramid consists of a set of low pass or band pass copies of an image, each copy representing pattern information of a different scale. The basic idea is to construct the pyramid transform of the fused image from the pyramid transforms of the source images, and then inverse pyramid transform is performed to obtain the fused image. [9, 14]. Various types of Pyramid methods are available in fusion, they are Gaussian Pyramid, Laplacian Pyramid, Ratio Pyramid, Contrast Pyramid, Filter-Subtract-decimate (FSD) Pyramid, Morphological Pyramid, Gradient Pyramid. [9,15]

3.2. Transforms

Transform is used to transform time domain to frequency domain and vise-verse. Some of the commonly used Transforms are

- Wavelet
- Multi wavelet
- Haar
- Curvelet
- Contourlet etc.

3.2.1 Wavelet Transform

Wavelet transforms have emerged as a powerful signal and image processing tool which provides an efficient way of fusion using multi resolution analysis. DWT analysis is capable of providing three spatial orientations, namely, horizontal, diagonal and vertical. The DWT provides an efficient way for performing image fusion at multiple scales with several advantages such as locality, multi resolution analysis, edge detection, de-correlation, energy compaction. [6].

3.2.2 Multi-wavelet Transform

The operational procedure for the multi-wavelet based image fusion approach is now summarized as follows: 1. The two input images are registered initially. 2. Each input image is analyzed and a set of multi-wavelet Coefficients are generated. 3. The maximum frequency fusion rule or any other rule (Minimum, Average, PCA and Laplacian pyramid) is used for the fusion of the wavelet coefficients. 4. The inverse multi-wavelet transform step is performed to obtain the fused image. [14]

3.2.3 Haar Transform

The Haar transform is one of the simplest Wavelet Transforms. The attracting features of the Haar transform, including fast for implementation and used in computer engineering applications, such as signal and image compression. Haar wavelet is a sequence of rescaled "square-shaped" functions which together form a wavelet family or basis. Wavelet analysis is similar to Fourier analysis in that it allows a target function over an interval to be represented in terms of an orthonormal function basis. Haar sequence is now recognized as the first known wavelet basis. [8]

3.2.4 Curvelet Transform

A curvelet transform differs from other directional wavelet transforms in that the degree of localization in orientation varies with scale. Curvelets are an appropriate basis for representing images, which are smooth apart from singularities along smooth curves, where the curves have bounded curvature. When the image is of the right type, curvelets provide a representation that is considerably sparser

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than other wavelet transforms. This can be quantified by considering the best approximation of a geometrical test image that can be represented using only n wavelets, and analyzing the approximation error as a function of n.

3.2.5 Contourlet Transform

The major drawback of DWT in two dimensions is their limited ability in capturing directional information. To overcome this, a new transform Contourlet (CNT) is developed which is based on an efficient two-dimensional multi-scale and directional filter bank (DBF). CNT not only possess the main features of DWT, but also offer a high degree of directionality and anisotropy. It allows for different and flexible number of directions at each scale, while achieving nearly critical sampling. In addition, CNT uses iterated filter banks, which makes it computationally efficient. [5]

4. PERFORMANCE MEASURES

The general requirement of an image fusing process is to preserve all valid and useful information from the source images, while at the same time it should not introduce any distortion in resultant fused image. Performance measures are used essential to measure the possible benefits of fusion and also used to compare results obtained with different algorithms. Some of the performance measures considered in this paper are

1. Root Mean Square Error (RMSE)
2. Peak Signal to Noise Ratio (PSNR)
3. Entropy (EN)
4. Spatial Frequency (SF)
5. Edge Strength (Q)
6. Mutual Information (MI)

4.1 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) between the fused image and original image provides error as a percentage of mean intensity of the original error. The RMSE value is calculated as:

$$\mathbf{RMSE}=\sqrt{\frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(R(i,j)-(F(i,j))^2}$$

Where R(i, j) is the reference image and F(i, j) is fused image, and m and n are image dimensions. **Smaller** the value of the RMSE, better the performance of the fusion algorithm.

4.2 Peak Signal to Noise Ratio(PSNR)

The PSNR is used to calculate the similarity between two images. The PSNR between the reference image R and the fused image F is calculated as

$$\mathbf{PSNR = 10 \times \log}\left(\frac{fmax^{2}}{RMSE^{2}}\right)$$

Where fmax is the maximum gray scale value of the pixels in the fused image. **Higher** the value of the PSNR, better the performance of the fusion algorithm.

4.3 Entropy (EN)

Entropy is used to calculate the amount of information. **Higher** value of entropy indicates that the information increases and the fusion performances are improved.

$$\mathbf{EN = -\sum_{l=0}^{L-1} p(\ell) \log_2 p(\ell)}$$

where p(ℓ) is the probability of gray level ℓ

4.4 Spatial Frequency (SF)

Spatial frequency can be used to measure the overall activity and clarity level of an image., **Larger** SF value denotes better fusion result, which is defined as follows.

$$SF=\sqrt{RF^2+CF^2}$$

where RF and CF are row frequency and column frequency respectively.

4.5 Edge Strength (Q)

For two source images A, B and fused image F, the Edge Strength Q is defined as

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

Where $Q^{AF}(n,m)$ and $Q^{BF}(n,m)$ are edge information preservation values. The value of Q ranges in between 0 and 1. Value 0 denotes the complete loss of edge information and 1 indicates fusion with no loss of edge information. Since metric represents the edge information associated with the fused image and visually supported by human visual system. Hence a **higher** value of F ABQ value implies better edge preserved fused image.

4.6 Mutual Information (MI)

It measures the degree of dependence of the two images. A **larger** measure implies better quality. Given two images *xF* and *xR*, MI is defined as

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$$\mathbf{MI = I(x_A;x_F) + I(x_B;x_F)}$$

Where $I(x_R;x_F)$=

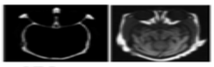
$$\sum_{u=1}^{L}\sum_{v=1}^{L} h_{R,F}\ (u,v) log_2 \frac{h_{R,F}\ (u,v)}{h_R\ (u) h_R\ (v)}$$

where *hR*, *hF* are the normalized gray level histograms of *xR* and *xF*, respectively. *hR,F* is the joint gray level histogram of *xR* and *xF*, and *L* is the number of bins.

5. PERFORMANCE ANALYSIS

The performance result of the fusion of CT and MRI medical images by using various Fusion algorithms and Various Transforms are given in Table 1. Fusion with DWT has been implemented by Singh and Khare [6] and the performance is measured by Q, MI, EN and SF. Deepika.L and Sindhuja.N.M [8] has presented Simple Average, Select Minimum, Select Maximum, PCA and Laplacian Pyramid fusion methods based on **HAAR Wavelet** Transform and the performance is measured by EN, PSNR and RMSE. Zheng et.al [3] developed an advanced image fusion algorithm, **aDWT** (**Advanced Wavelet Transform**) and the performance is measured by EN and SF. Singh et.al [4] proposed a method based on **Dual Tree Complex Wavelet Transform (DTCWT**) and the performance is measured by Q, MI. Anand et.al [7] has implemented an algorithm based on the Multi-Wavelet Transform (MWT) and **Curvelet Transform** using different fusion techniques such as Select Maximum, Select Minimum, Simple Average, Principal Component Analysis(PCA) and Laplacian Pyramid and the performance is measured by EN, PSNR and RMSE. Das and Kundu [5] found a novel multimodality **M**edical **I**mage **F**usion (MIF) method, based on a novel combined **A**ctivity **L**evel **M**easurement (ALM) and **Contourlet Transform** (CNT) and the performance is measured by MI, EN and SF.

Table 1 shows that, DWT is the best Image fusion method comparing to DTCWT based on the performance measure Q. When considering MI, the combined ALM with Contourlet method is better than DTCWT and DWT. According to Entropy(EN) and PSNR, Laplacian Pyramid with Haar Transform is good comparing to combined ALM with Contourlet, Curvelet Transform, ADWT and DWT methods. ADWT performed well and it is proved by the measure SF comparing to the combined ALM with Contourlet and DWT and finally the Root Mean Square error is calculated. So Laplacian Pyramid with Haar Transform is the best method.

INPUT IMAGES 

CT Image MRI image

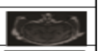
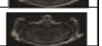
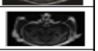
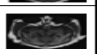
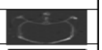
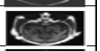
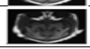
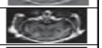
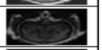
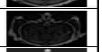
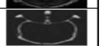
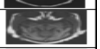
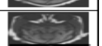
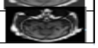
TRANSFORMS	FUSION METHOD	Q	MI	EN	SF	PSNR	RMSE	OUTPUT
DWT	DWT with LEVEL 2	**0.7286**	2.1396	5.9335	9.9138	-	-	
	DWT with LEVEL 3	0.6675	1.6705	6.0177	10.3127	-	-	
	DWT with LEVEL 4	0.6097	1.3475	6.1343	10.4907	-	-	
	DWT with LEVEL 5	0.5844	1.3666	6.1673	10.5698	-	-	
HAAR Wavelet Transform	Simple Average	-	-	8.68	-	28.89	0.04	
	Select Maximum	-	-	10.1291	-	30.81	0.05	
	Select Minimum	-	-	9.3199	-	31.31	0.06	
	PCA	-	-	10.09	-	28.94	0.04	
	Laplacian Pyramid	-	-	**12.66**	-	**57.922**	**0.03**	
ADWT	LP	-	-	6.73	135.53	-	-	
	DWT	-	-	6.2	61.84	-	-	
	ADWT	-	-	6.67	**288.02**	-	-	
DTCWT	DTCWT Max	0.5764	2.2713	-	-	-	-	
	DTCWT Avg-Max	0.5322	1.639	-	-	-	-	
Curvelet Transform	Select Minimum	-	-	3.2565		25.0912	14.19	
	PCA	-	-	6.7125		34.8175	4.6308	
	LAPLACIAN Pyramid	-	-	6.6949		37.412	3.435	
Contourlet	Combined ALM with Contourlet	-	**3.25**	6.76	6.95	-	-	

Table 1: Result Comparison of CT and MRI Images on various Fusion and Transform methods

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Fig.1, Fig.2 and Fig.3 shows that the Laplacian Pyramid with Haar Transform performs outstanding than other methods for maximum quantitative measures such as Entropy, PSNR and RMSE respectively.

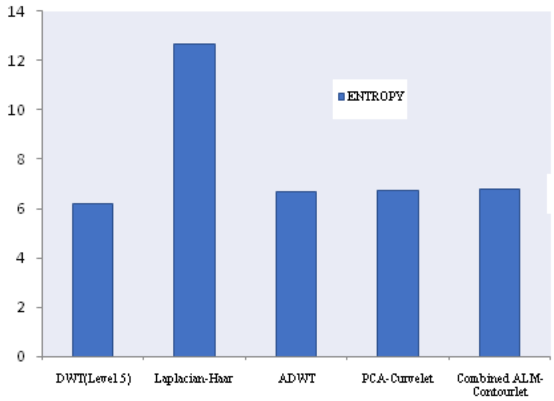

Fig. 1 Performance Analysis in respect to Entropy

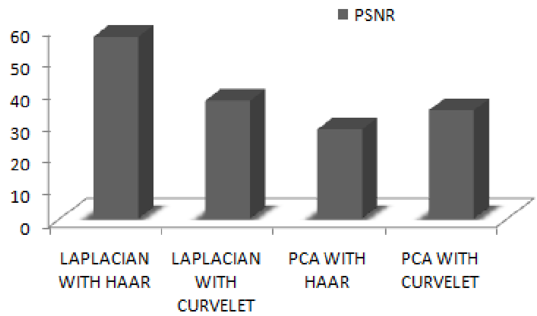

Fig.2 Performance Analysis in respect to PSNR

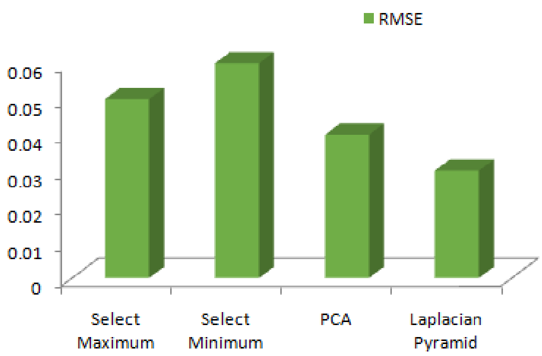

Fig.3 Performance Analysis in respect to RMSE

6. CONCLUSION

In this paper, various algorithms such as DWT, DTCWT, combined ALM with Contourlet, Laplacian Pyramid with Haar Transform, ADWT, Curvelet Transform for fusing two different modality medical images are results are analyzed using different quantitative measures such as, Peak Signal to Noise Ratio (PSNR), Edge Strength(Q), Mutual Information (MI), Spatial Frequency (SF), and Entropy (EN). Comparison of all the techniques concludes the better approach for future research. It is concluded that the Laplacian Pyramid with Haar Transform is the best for image fusion.

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