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Image Fusion Techniques and Quality Assessment Parameters for Clinical Diagnosis: A Review

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ABSTRACT**: Image fusion is a tool that serves to combine multi sensors images by using advanced image processing techniques. Particularly it serves best in medical diagnosis i.e. computed tomography (CT), magnetic resonance image (MRI), scan provides different types of information, by fusing them we can get accurate information for better clinical diagnosis. Transform domain image fusion methods such as wavelet transform, curvelet transform have its specific advantages while going for multi-sensors image fusion. Analysis is done to determine the image fusion algorithm which is more suitable for clinical diagnosis. Analysis is also done on image quality assessment parameters of image fusion. This paper presents a literature review on image fusion techniques and image quality assessment parameters such as Structural similarity index measure, laplacian mean squared error, mean squared error, Peak signal to noise ratio, entropy, structural content, Normalized cross correlation, Maximum difference, normalized absolute error. Comparison and effective use of all the techniques in image quality assessment is also determined.**

Keywords: Image fusion, discrete wavelet transform, curvelet transform, image quality assessment parameter

I. INTRODUCTION

The need for better diagnosis and clear interpretation of the obtained images give rise to image fusion. The term fusion means to combine the information acquired in several domains. Image fusion has become a popular technique used within medical diagnosis and treatment. Image fusion is the process of integrating information from two or more images of an object into a single image. The integrated image is more informative for explanation and analysis. It is possible that several images of same object provide different information based on different resolution and viewing angle, to merge the different information and obtain a new and improved image we have a fusion technique. Fused images can be created by combining information from multiple modalities [2] such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET) and single positron emission computed tomography (SPECT).

In medical imaging we have a CT scan and MRI from the brain of the same patient. The CT scan images are used more often to diagnose tissue density while MRI images are more often used to diagnose brain tumors. The first is functional image displaying the brain activity whereas the second provides anatomical information without functional activity, By combining CT scan image and MRI image we get the anatomical information displaying the brain activity.

Image fusion methods can be broadly classified into two that is spatial domain fusion and transform domain fusion. Averaging, Brovery method, principal Component analysis and IHS based methods are spatial domain methods. The main problem with spatial domain methods is that their peak signal to noise ratio (PSNR) ratio is less and they produce spatial distortion. Such distortion in images creates further problem in processing of images and also the quality of the fused image are degraded [1].

Fusion consists of two basic stages: image registration, which brings the input images to spatial alignment, and combining the image functions (intensities, colors, etc) in the area of frame overlap. Image registration works usually in four steps.

- Feature detection. Attention is paid on the effect of fusion on corners, line intersections, edges, contours, closed boundary, regions, etc. whether there are clearly detected. For further processing, these features can be represented by their point representatives (distinctive points, line endings, centers of gravity), called in the literature control points.

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- Feature matching. Features detected in the fused image are compared with those detected in the reference image. Various feature descriptors and similarity measures along with spatial relationships among the features are used for that purpose.
- Transform model estimation. The type and parameters of the so-called mapping functions, aligning the sensed image with the reference image, are estimated. The parameters of the mapping functions are computed by means of the established feature correspondence.
- Image resampling and transformation. The sensed image is transformed by means of the mapping functions. Image values in non-integer coordinates are estimated by an appropriate interpolation technique.

The problem faced in spatial domain methods can be very well handled by Transform domain image fusion methods. The fusion methods such as discrete wavelet transform, complex wavelet transform, curvelet transform and laplacian pyramid based methods.

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II. WAVELET TRANSFORM BASED FUSION METHOD

Wavelet transforms have been successfully used in many fusion schemes. A common wavelet transform technique used for fusion is the DWT. It has been found to have some advantages over pyramid schemes such as: increased directional information; no blocking artifacts that often occur in pyramid-fused images; better signal to noise ratios than pyramid based fusion, improved perception over pyramid based fused images, compared using human analysis.

As a powerful analytical tool, wavelet based methods have been developed for signal and image processing. The principle of wavelet image fusion is to get the best resolution without altering the spectral contents of the image. More clearly this principle is based on multiresolution analysis provided by wavelet Transform.

The wavelets-based approach is appropriate for performing fusion tasks for the following reasons:

(1) It is a multiscale (multiresolution) approach well suited to manage the different image resolutions. In recent years, some researchers have studied multiscale representation (pyramid decomposition) of a signal and have established that multiscale information can be useful in a number of image processing applications including the image fusion.

(2) The wavelets transform (WT) allows the image decomposition in different kinds of coefficients preserving the image information.

(3) Such coefficients coming from different images can be appropriately combined to obtain new coefficients, so that the information in the original images is collected appropriately.

(4) Once the coefficients are merged, the final fused image is achieved through the inverse wavelet transform (IWT), where the information in the merged coefficients is also preserved

A. *Discrete wavelet transform*

Discrete wavelet transform with Haar based fusion scheme is discussed herewith**.** The Haar wavelet is the first known wavelet. The Haar wavelet ψ(t) can be described as and its scaling function φ(t) can be described as Ψ(t) =

$$\begin{cases} 1 & 0 \le t \le 1/2 \\ -1 & 1/2 \le t \le 1 \\ 0 & Otherwise \end{cases} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots..(1)$$

The 2x2 Haar matrix is associated with

$$H_2 = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$$

The filters, thus, considered here would be

F1 = $[* \; 0.5 * 0.5 \; *]$

F2 = $[* \; 0.5 * 0.5 \; *]$

The couple of filters, when applied on the input images matrices, would produce 4 resultant matrices. The fourth matrix, which would consist of all the high frequencies, would act as the input matrix for the next level of decomposition. The other three matrices, consisting of the low frequencies, are used to produce 3 pyramids at each level. The pyramids are produced as in pyramidal method. The re-composition process is performed with the help of the three pyramids formed at each level of decomposition.

B *Orthogonal wavelet decomposition based image fusion*

The orthogonal wavelet decomposition (OWD) is a popular method used for fusing multisensor images. The OWD allows the decomposition of an image with a wavelet basis according to a pyramid scheme. The resolution is reduced by one-half at each level by sub sampling data by two. The complete decomposition produces the same number of pixels as the original image. Four plans are produced at each resolution level corresponding to one approximation image (low resolution content) and three detail images (horizontal, vertical and diagonal detail images).

The use of the OWD for image fusion allows improving the quality of the fused image compared to the Laplacian pyramid [9]. However, some limitations can be evoked:

- The OWD is implemented for discrete images with sizes that are powers of two because the resolution is reduced by two at each level. From this fact, it is not possible to fuse images of any sizes.
- The analysis pixel by pixel is not possible since data are reduced at each resolution; it is then not possible to follow the evolution of a dominant feature through levels.

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• The OWD does not permit to distinguish easily the dominant features of the image. Finally, there is presently no satisfactory rule allowing good quality of the fusion with an orthogonal decomposition.

Redundant wavelet decomposition

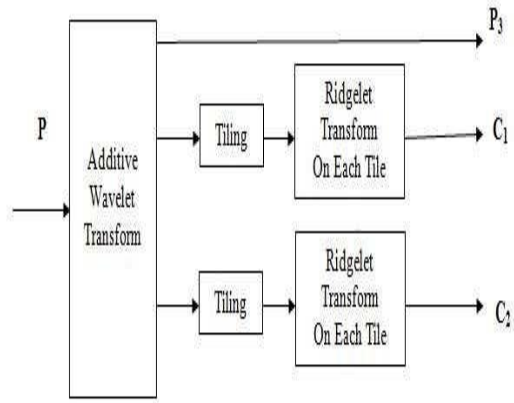
Redundancy of information is always helpful when one is concerned with an analysis problem. This fact remains true for fusion applications since any fusion rule essentially reduces to a problem of analyzing the images to fuse and then select the features that are important in a particular sense. An algorithm to compute such a redundant decomposition requires more calculations than the usual OWD. A redundant representation, which avoids image decimation, has the same number of wavelet coefficients at all levels. This fundamental Property allows the development of a fusion procedure based on the following intuitive idea: When a dominant or significant feature appears at a given level, it should appear at successive levels. In contrast, a non-significant feature as the noise does not appear in next levels. It thus appears

C. Curvelet Transform based Image Fusion

The wavelet fusion technique has also succeeded in both satellite and medical image applications. The basic limitation of wavelet fusion algorithm is in the fusion of curved shapes. Thus, there is a need for another technique that can handle curved shapes efficiently. So, the applications of the curvelet transform result in better fusion efficiency. A few attempts of curvelet fusion have been made in the fusion of satellite images but no attempts have been made in the fusion of medical images. The main objective of medical imaging is to obtain a high resolution image with as much details as possible for the sake of diagnosis. There are several medical imaging techniques such as the MR and the CT techniques. Both techniques give special sophisticated characteristics of the organ the MR and the CT images of the same organ would result in an integrated image of much more details. Researchers have made few attempts for the fusion of the MR and the CT images. Most of this attempt the application of the wavelet transform for this purpose. Due to the limited ability of the wavelet transform to deal with images having curved shapes, the application of the curvelet transform for MR and CT image fusion is presented in this work.

The algorithm of the curvelet transform of an image *P* can be summarized in the following steps:

- The image *P* is split up into three subbands Δ1, Δ2 and *P*3 using the additive wavelet transform.
- Tiling is performed on the subbands Δ1 and Δ2.
- The discrete ridgelet transform is performed on each tile of the subbands Δ1 and Δ2.



Sub band Filtering: The purpose of this step is to decompose the image into additive components; each of which is a sub band of that image. This step isolates the different frequency components of the image into different planes without down sampling as in the traditional wavelet transform.

Tiling: Tiling is the process by which the image is divided into overlapping tiles. These tiles are small in dimensions to transform curved lines into small straight lines in the sub bands Δ1 and Δ2 [11–13]. The tiling improves the ability of the curvelet transform to handle curved edges.

Ridgelet Transform: The ridgelet transform belongs to the family of discrete transforms employing basis functions. To facilitate its mathematical representation, it can be viewed as a wavelet analysis in the Radon domain. The Radon transform itself is a tool of shape detection. So, the ridgelet transform is primarily a tool of ridge detection or shape detection of the objects in Image:

III. . IMAGE QUALITY METRICS

Image Quality is a characteristic of an image that measures the perceived image degradation (typically, compared to an ideal or perfect image). Imaging systems like the fusion algorithm may introduce some amounts of distortion or artefacts in the signal, so the quality assessment is an important problem. Image Quality assessment methods can be broadly classified into two categories: Full Reference Methods (FR) and No Reference Method (NR). In FR, the quality of an image is measure in comparison with a reference image which is assumed to be perfect in quality. NR methods do not employ a reference image. The image qualities metrics considered and implemented here fall in the FR category. In the following subsections, we discuss the SSIM and some other image quality metrics implemented to assess the quality of our fused

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A. *Structural similarity index measure (SSIM)*

The Structural similarity index measures follows that a measure of structural information change can provide a good approximation to perceived image distortion. The SSIM compares local patterns of pixel intensities that have been normalized such as luminance and contrast. It is an improved version of traditional methods like PSNR and MSE. The SSIM index is a decimal value between 0 and 1. A value of 0 would mean zero correlation with the original image, and 1 means the exact same image

- Symmetry: S(x, y) = S(y, x)
- Boundedness: S(x, y) <= 1
- Unique maximum: S(x, y) = 1 if and only if x = y (in discrete representations $x_i = y_i$, for all i = 1, 2,…………,N)

SSIM can be calculated using SSIM Mean $\left(\frac{(2\mu_1\mu_2+C_1)(2\sigma_{12}+C_2)}{(\mu_1^2+\mu_2^2+C_1)(\sigma_1^2+\sigma_2^2+C_1)}\right)$ …………………… (2)

Where $\sigma_1^2 = (A_{ij}^2.G) - \mu_1^2$

$\sigma_2^2 = (A_{ij}^2.G) - \mu_2^2$

$\sigma_{12}^2 = (A_{ij}\, B_{ij}\, G) - \mu_1.\mu_2$

$\mu_1 = A.G$ where G being Gaussian filter window i.e. ('gaussian', 11, 1.5)

$\mu_2 = B.G$

$C_1 = (K_1 * L)^2$

$C_2 = (K_2 * L)^2$ where L =255 and value of k varies from K = [0.01 0.03],

B. *Laplacian Mean Squared Error*

Laplacian mean square error, error is calculated based on the laplacian value of the expected and obtained data is given by. LMSE is given by

$$\text{LMSE} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(\nabla^2 A - \nabla^2 B)^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(\nabla^2 A)^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Laplacian operator is defined by the following expression.

$$\nabla^2 u = \left(\delta^2 u + \frac{\delta^2 u}{\delta^2 x\, \delta^2 y}\right)$$

Where u be defined as a function of (x, y).

Here each image pixel is subtracted from the average of the neighbouring pixels on the right, bottom, left and the top. This is considered the laplacian value of the particular pixel. The laplacian operator is denoted as,

$$\nabla^2 u = \frac{(u_{i,j+1} + u_{i,j-1} + u_{i+1,j} + u_{i-1,j}) - u\, ij}{4}$$

. For an ideal situation, the fused and perfect image being identical, the LMSE value is supposed to be 0. The error value which would exist otherwise would range from 0 to 1.

C. *Mean Squared Error*

Mean square error is a measure of image quality index. The large value of mean square means that image is a poor quality. Mean square error between the reference image and the fused image is

$$\text{MSE} = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} - B_{ij})^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Where $A_{i,j}$ and $B_{i,j}$ are the image pixel value of reference image.

D. *Peak signal to Noise Ratio*

The ratio between maximum possible power of the signal to the power of the corrupting noise that creates distortion of image. The peak signal to noise ratio can be represented as

$$\text{PSNR (db)} = 20\log\frac{255\sqrt{3mn}}{\sqrt{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij} - B_{ij})^2}} \quad \ldots\ldots\ldots\ldots (5)$$

Where A- fused image, B – perfect image, i – pixel pow index, j – pixel column index, M, N – Number of rows and columns respectively.

E. *Entropy*

Entropy is used to evaluate the information quantity contained in an image. The higher value of entropy implies that the fused image is better than the reference image. Entropy is defined as

$$E = -\sum_{i=0}^{L-1} pi\, log_2 p_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6)$$

Where L = total of grey labels,

P = {p_0, p_1, …….….. p_{L-1}} is the probability distribution of each labels

F. *Structural Content*

The structural content measure used to compare two images in a number of small image patches the images have in common. The patches to be compared are chosen using 2D continuous wavelet which acts as a low level corner detector. The large value of structural content SC means that image is poor quality

$$SC = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}(B_{ij})^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (7)$$

G. *Normalized Cross Correlation*

Normalized cross correlation is a measure of similarity of two waveforms as a function of the time lag applied to one of them. The cross correlation is similar in nature to the convolution of two functions.

$$NCC = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{(A_{ij} * B_{ij})}{A_{ij}^2} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

H .*Maximum Difference*

Difference between any two pixels such that the larger pixel appears after the smallest pixel. The large value of maximum difference means that image is poor in quality.

$$MD = Max(|A_{ij} - B_{ij}|), \quad i = 1,2,\ldots.m; \; j = 1,2,\ldots\ldots n \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (9)$$

I. *Normalized Absolute Error*

The large value of normalized absolute error means that image is poor quality. NAE is defined as follows

$$NAE = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(|A_{ij} - B_{ij}|)}{\sum_{i=1}^{m}\sum_{j=1}^{n}(A_{ij})} \quad \ldots\ldots\ldots\ldots\ldots\ldots (10)$$

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IV. CONCLUSION

Selection of proper fusion technique depends on the specific application. Spatial domain provides high spatial resolution But in spatial domain spectral distortion is the main drawback therefore transform domain image fusion is done. Based on the analysis done on various transform domain techniques such as, wavelet transform, discrete wavelet transform, curvelet transform. It has been concluded that each technique it meant for specific application and one technique has an edge over the other in terms of particular application.

Finally the image quality assessment parameters have been reviewed and determine the role of individual image quality assessment parameter to determine the quality of the fused image.

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