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Comparative Analysis of Various Image Fusion Techniques For Biomedical Images: A Review

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ABSTRACT-
Image Fusion is a process of combining the relevant information from a set of images, into a single image, wherein the resultant fused image will be more informative and complete than any of the input images. This paper discusses implementation of DWT technique on different images to make a fused image having more information content. As DWT is the latest technique for image fusion as compared to simple image fusion and pyramid based image fusion, so we are going to implement DWT as the image fusion technique in our paper. Other methods such as Principal Component Analysis (PCA) based fusion, Intensity hue Saturation (IHS) Transform based fusion and high pass filtering methods are also discussed. A new algorithm is proposed using Discrete Wavelet transform and different fusion techniques including pixel averaging, min-max and max-min methods for medical image fusion.
KEYWORDS: Principal Component Analysis, Image Fusion, Approximation and Detail Coefficients, Multiresolutional Analysis, Pixel Averaging

I. INTRODUCTION

Image fusion is the process by which two or more images are combined into a single image retaining the important features from each of the original images. The fusion of images is often required for images acquired from different instrument modalities or capture techniques of the same scene or objects [1]. Fusion techniques include the simplest method of pixel averaging to more complicated methods such as principal component analysis and wavelet transform fusion. Several approaches to image fusion can be distinguished, depending on whether the images are fused in the spatial domain or they are transformed into another domain, and their transforms fused [2]. The successful fusion of images acquired from different modalities or instruments is of great importance in many applications such as medical imaging, microscopic imaging, remote sensing computer vision and robotics. Many methods exist to perform image fusion [3]. The very basic one is the high pass filtering technique. Later techniques are based on Discrete Wavelet Transform, uniform rational filter bank, and Laplacian pyramid. Image fusion can be defined as the process by which several images or some of their features are combined together to form a single image fusion can be performed at different levels of the information representation. Four different levels can be distinguished i.e. signal pixel feature and symbolic levels [4]. To date the results of image fusion in areas such as remote sensing and medical imaging are primarily intended for presentation to a human observer for easier and enhanced interpretation [5]. Therefore the perception of the fused image is of paramount importance when evaluating different fusion schemes. Some generic requirements can be imposed on the fusion result [6].

a) The fused image should preserve as closely as possible all relevant information contained in the input images.
b) The fusion process should not introduce any artifacts or inconsistencies which can distract or mislead the human observer or any subsequent image processing steps.
c) In the fused image relevant features and noise should be suppressed to a maximum extent.
d) Spatial distortion can be very well handled by frequency domain approaches on image fusion. The multi resolution analysis has become a very useful tool for analyzing remote sensing images. The discrete wavelet transform has become a very useful tool for fusion. Some other fusion methods are also there such as Laplacian- pyramid based, Curvelet transform based etc. These methods show a better performance in spatial and spectral quality of the fused image compared to other spatial methods of fusion.

II. NEED FOR IMAGE FUSION

Multisensor data fusion has become a discipline which demands more general formal solutions to a number of application cases. Several situations in image processing require both high spatial and high spectral information in a single image [7]. This is important in remote sensing. However, the instruments are not capable of providing such information either by design or because of observational constraints [8]. One possible solution for this is data fusion. The fusion of CT scan , MR and SPECT images can make medical diagnosis much easier and accurate. Multi-modal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images [9]. There is a growing interest and application of the imaging technologies in the areas of medical diagnostics, analysis and historical documentation. Since computer aided imaging techniques enable a quantitative assessment of the images under evaluation, it helps to improve the efficacy of the medical practitioners in arriving at an unbiased and objective decision in a short span of time. In addition, the use of multi-sensor [10] and multi-source image fusion methods offer a greater diversity of the features used for the medical analysis applications; this often leads to robust information processing that can reveal information that is otherwise invisible to human eye. There exist several medical imaging modalities that can be used as primary inputs to the medical
image fusion studies. The selection of the imaging modality for a targeted clinical study requires medical insights specific to organs under study. It is practically impossible to capture all the details from one imaging modality that would ensure clinical accuracy and robustness of the analysis and resulting diagnosis and. The obvious approach is to look at images from multiple modalities to make a more reliable and accurate assessment. This often requires expert readers and is often targeted at assessing details that complement the individual modalities eg. Computer Tomography such as angiography (CTA), Quantitative Computed Tomography (QCT), Dual-energy X-ray absorptiometry (DXA) such as for Bone Mineral Density (BMD) and Hip Structural Analysis (HSA), Magnetic resonance imaging such as for Angiography (MRA) etc. The aim of this review is to provide a collective view of the applicability and progress of information fusion techniques in medical imaging useful for clinical studies [11].

III. IMAGE FUSION TECHNIQUES

There are various methods that have been developed to perform image fusion. Some well-known image fusion methods are listed below [3]:-

(1) Intensity-hue-saturation (IHS) transform based fusion
(2) Principal component analysis (PCA) based fusion
(3) Multi scale transform based fusion:-
(a) High-pass filtering method
(b) Pyramid method:-
(i) Gaussian pyramid
(ii) Laplacian Pyramid
(iii) Gradient pyramid
(iv) Morphological pyramid
(v) Ratio of low pass pyramid
(c) Wavelet transforms:-
(i) Discrete wavelet transforms (DWT)
(ii) Stationary wavelet transforms
(iii) Multi-wavelet transforms
(d) Curvelet transforms

Some of these techniques are explained below:

IV. Intensity Hue Saturation transform based fusion

IHS fusion technique is mostly applied in remote sensing applications that has been used as a standard procedure in many commercial packages. The intensity (I) band in the IHS space is replaced by a high - resolution Pan image and then transformed back into the original RGB space together with the previous hue (H) band and the saturation (S) band , resulting in an IHS fused image. However, the IHS method can be easily implemented by the procedure which the fused images can be obtained by adding e difference image between Pan and I images to the MS images, respectively. Aside from its fast computing capability for fusing images, this method can extend traditional three-order transformation to an arbitrary order. It can also quickly merge massive volumes of data by requiring only resampled MS data. That is, it is well suited in terms of processing speed for merging high-resolution satellite images.

V. Principal component analysis (PCA) based fusion

PCA is a mathematical tool which transforms a number of correlated variables into a number of uncorrelated variables. The PCA is used extensively in image compression and image classification. The PCA involves a mathematical procedure that transforms a number of correlated variables into a number of uncorrelated variables called principal components. It computes a compact and optimal description of the data set. The first principal component accounts for as much of the variance in the data as possible and each succeeding component accounts for as much of the remaining variance as possible. First principal component is taken to be along the direction with the maximum variance. The second principal component is constrained to lie in the subspace perpendicular of the first. Within this Subspace, this component points the direction of maximum variance. The third principal component is taken in the maximum variance direction in the subspace perpendicular to the first two and so on. The PCA is also called as Karhunen-Loève transform or the Hotelling transform. The PCA does not have a fixed set of basis vectors like FFT, DCT and wavelet etc. and its basis vectors depend on the data set.

VI. DWT based Image Fusion

Over the past two decades, multiscale transforms, such as the pyramid transform and discrete wavelet transform (DWT), have been widely used for pixel-level image fusion. The motivation for transform-based image fusion techniques stems from the fact that transformed data often exhibit certain properties that enable the image fusion task to be performed more efficiently. For instance, multiscale representation of the transformed coefficients, space-frequency localization of the coefficients in a scale, high energy compaction by representing data using a fewer number of significant coefficients, and flexibility in choosing a suitable basis function are important properties of the DWT for the construction of effective image fusion algorithms. Due to these inherent properties of the DWT, the significant features of images such as edges and textures can be represented more efficiently in the DWT domain, and detailed information can be easily extracted from the source images in order to fuse them. In general, the DWT-based fusion methods perform better than any of the pyramid transform-based methods. Other transforms that have been used for image fusion include the complex wavelet, curvelet, contourlet, morphological wavelet, maximal gradient wavelet, and multiwavelet. Although the complex wavelet, contourlet, and curvelet transforms possess shift-invariance property and improved directional selectivity as compared to the DWT and, therefore, are useful for the development of an image fusion algorithm; the increased computational complexity of these transforms cannot be ignored. Hence, the DWT-based fusion techniques are still preferable when massive volumes of image data need to be merged quickly. Apart from its success in developing image fusion algorithms, the DWT has been widely used in performing other key image processing tasks such as image denoising and compression. Thus, the routines for DWT-based image fusion can be seamlessly embedded into the routines of other image processing operations resulting in a fast image processing algorithm. Furthermore, any fusion rule designed in the DWT domain can be easily extended for application in other wavelet-like transform domains.

VII. GENERAL FUSION MODEL USING DWT TECHNIQUE

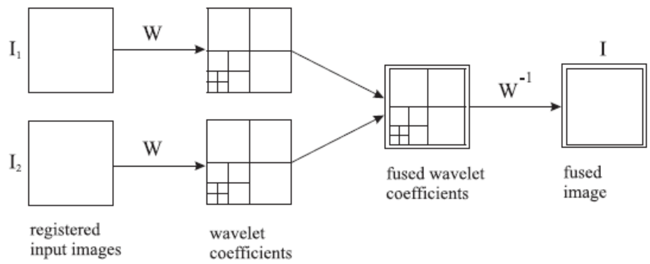


Figure 1: Image Fusion using Discrete wavelet transform

Wavelet based techniques for fusion of 2-D images is described here. In all wavelet based image fusion techniques the wavelet transforms W of the two registered input images I1(x,y) and I2(x,y) are computed and these transforms are combined using some kind of fusion rule Ø as shown in below equation.

I(x,y) = W-1 (Ø (W(I1(x,y)), W(I2(x,y))) (i)

Wavelet analysis represents the next logical step: a windowing technique with variable-sized regions. Wavelet analysis allows the use of long time intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information.

Figure 2: Wavelet Transform on a signal

Wavelet Transform in contrast with the time-based, frequency-based, and STFT views of a signal:

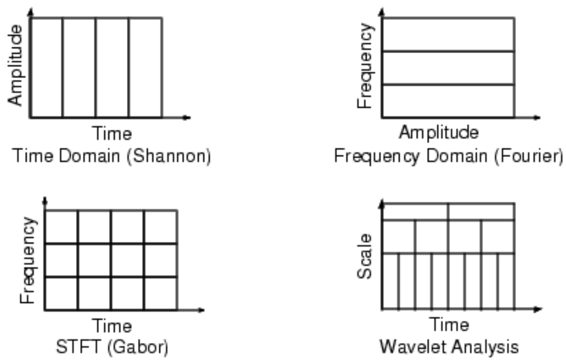


Figure 3: Comparison of Various Transform Techniques

Wavelet analysis does not use a time-frequency region, but rather a time-scale region. Wavelets have scale aspects and time aspects; consequently every application has scale and time aspects. To clarify them we try to untangle the aspects somewhat arbitrarily. For scale aspects, we present one idea around the notion of local regularity. For time aspects, we present a list of domains. When the decomposition is taken as a whole, the de-noising and compression processes are center points.

TYPES OF WAVELETS

i. Haar wavelets

For an input represented by a list of 2^n numbers, the Haar wavelet transform may be considered to simply pair up input values, storing the difference and passing the sum. This process is repeated recursively, pairing up the sums to provide the next scale: finally resulting in $2^n - 1$ differences and one final sum.

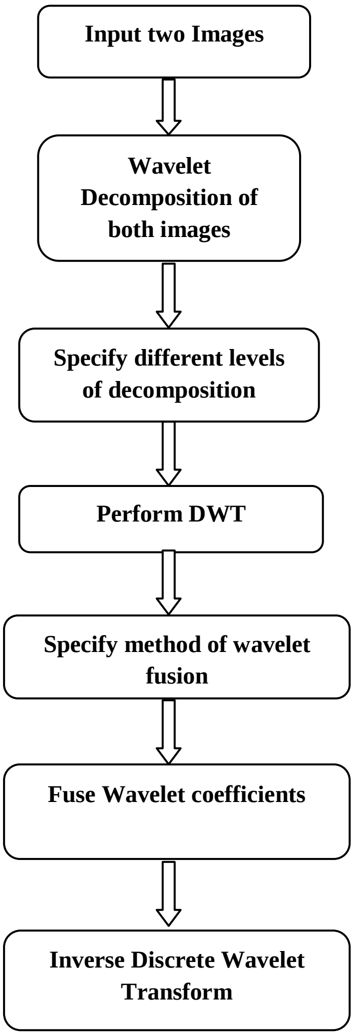
ii. Daubechies wavelets

The most commonly used set of discrete wavelet transforms was formulated by the Belgian mathematician Ingrid Daubechies in 1988. This formulation is based on the use of recurrence relations to generate progressively finer discrete samplings of an implicit mother wavelet function; each resolution is twice that of the previous scale. In her seminal paper, Daubechies derives a family of wavelets, the first of which is the Haar wavelet. Interest in this field has exploded since then, and many variations of Daubechies' original wavelets were developed

iii. The Dual-Tree Complex Wavelet Transform (CWT)

The Dual-Tree Complex Wavelet Transform (CWT) is a relatively recent enhancement to the discrete wavelet transform (DWT), with important additional properties: It is nearly shift invariant and directionally selective in two and higher dimensions. It achieves this with a redundancy factor of only 2^d substantially lower than the undecimated DWT. The multidimensional (M-D) dual-tree CWT is nonseparable but is based on a computationally efficient, separable filter bank (FB).

5. BLOCK DIAGRAM FOR IMAGE FUSION



AVERAGING TECHNIQUE

It is a well documented fact that regions of images that are in focus tend to be of higher pixel intensity. Thus this algorithm is a simple way of obtaining an output image with all regions in focus. The value of the pixel P (i, j) of each image is taken and added. This sum is then divided by 2 to obtain the average. The average value is assigned to the corresponding pixel of the output image which is given in equation (1). This is repeated for all pixel values.

$$K(i, j) = \{X(i, j) + Y(i, j)\}/2 \tag{2}$$

Where X (i , j) and Y (i, j) are two input images

MAXIMUM SELECTION SCHEME

This scheme just picks coefficient in each subband with largest magnitude.

Fused Image = Max.[w(I1(x,y)), w(I2(x,y))]

MINIMUM SELECTION SCHEME

This scheme just picks coefficient in each subband with smallest magnitude.

Fused Image = Min.[w(I1(x,y)), w(I2(x,y))]

6. PERFORMANCE PARAMETERS

The general requirements of an image fusing process are that it should preserve all valid and useful pattern information from the source images, while at the same time it should not introduce artifacts that could interfere with subsequent analyses. The performance measures used in this paper provide some quantitative comparison among different fusion schemes, mainly aiming at measuring the definition of an image.

I. PSNR

PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR measure is given by:-

$$PSNR = 10\log_{10}\left(\frac{R^2}{MSE}\right)$$

R is the maximum fluctuation in the input image data type. For example, if the input image has a double-precision floating-point data type, then *R* is 1. If it has an 8-bit unsigned integer data type, *R* is 255, etc.

II. ENTROPY

Entropy is an index to evaluate the information quantity contained in an image. If the value of entropy becomes higher after fusing, it indicates that the information increases and the fusion performances are improved.
Entropy is defined as:-

$$E = -\sum_{i=0}^{L-1} p_i \log_2 p_i$$

Where L is the total of grey levels, $p = [\, p_0, p_1, \ldots p_{L-1} \}$ is the probability distribution of each level.

III. MEAN SQUARED ERROR (MSE)

The mathematical equation of MSE is giver by the equation

$$MSE = \frac{\sum_{M,N}[I_1(m,n) - I_2(m,n)]^2}{M * N}$$

Where, I_1 - the perfect image, I_2 - the fused image to be assessed, i – pixel row index, j – pixel column index, m, n- No. of row and column

IV. NORMALIZED CROSS CORRELATION (NCC)

Normalized cross correlation are used to find out similarities between fused image and registered image is given by the following equation

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

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