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MEDICAL IMAGE FUSION USING GAUSSIAN FILTER, WAVELET TRANSFORM AND CURVELET TRANSFORM FILTERING

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Abstract

Image fusion is a process of blending the complementary as well as the common features of a set of images, to generate a resultant image with superior information content in terms of subjective as well as objective analysis point of view. The objective of this research work is to develop some novel image fusion algorithms and their applications in various fields such as crack detection, multi spectra sensor image fusion, medical image fusion and edge detection of multi-focus images etc. Image Fusion is still a challenging problem for researchers. There have been several published algorithms and each approach has its assumptions, advantages, and limitations The search for efficient image fusion methods still is a valid challenge, at the crossing of functional analysis and statistics. In spite of the sophistication of the recently proposed methods, most algorithms have not yet attained a desirable level of applicability. All show an outstanding performance when the image model corresponds to the algorithm assumptions, but fail in general and create artefacts or remove image structures. The main focus of this paper is first to define a hybrid Transform Domain algorithm and based on that two medical images (CT and MRI images) are fused. This algorithm provides better MSE, PSNR, Entropy and Standard Deviation than other classic algorithms (The Wavelet Transform Method and The Curvelet Transform Method) which will be clearly shown in result section.

Index Terms*: Wavelet Transform, HAAR, MFHWT, CT & MRI, MSE, PSNR etc.*

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1. 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. Several approaches to image fusion can be distinguished, depending on whether the images are fused. The purpose of image fusion is to combine information from several different source images to one image, which becomes reliable and much easier to be comprehended by people [16]. Image fusion can be broadly defined as the process of combing multiple input images or some of their features into a single image without the introduction of distortion or loss of information. The objective of image fusion is to combine complementary as well as redundant information from multiple images to create a fused image output. Therefore, the new image generated should contain a more accurate description of the scene than any of the individual source image and is more suitable for human visual and machine perception or further image processing and analysis task. The fusion process should be shift and rotational invariant; it means that the fusion result should not depend on the location and orientation of an object the input image. The main principles of image fusion are the redundancy, the complementary, the time-limit and low cost [6].

1.1 Basic Levels of Image Fusion

Image fusion can be divided into three levels:
1.1.1 Pixel-level fusion
1.1.2 Feature-level fusion
1.1.3 Decision-level fusion.

1.1.1 Pixel Level Fusion

Pixel level fusion generates a fused image in which information content associated with each pixel is determined from a set of pixels in source images. Fusion at this level can be performed either in spatial or in frequency domain. However, pixel level fusion may conduct to contrast reduction. [4]

1.1.2 Feature Level Fusion

Feature level fusion requires the extraction of salient features which are depending on their environment such as pixel intensities, edges or textures. These similar features from the input images are fused. This fusion level can be used as a means of creating additional composite features. The fused image can also be used for classification or detection.[9]

1.1.3 Decision Level Fusion

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Decision level is a higher level of fusion. Input images are processed individually for information extraction. The obtained information is then combined applying decision rules to reinforce common interpretation.[1]

1.2 Conventional Methods of Image Fusion

1.2.1 Spatial Domain Methods

The term spatial domain refers to the image plane itself and approaches in this category are based on direct manipulation of pixels in an image. Spatial domain processes can be denoted by the expression as given by equation

$$g(x, y) = T[f(x,y)] \quad \ldots(1.1)$$

where f (x, y) is the input image, g (x, y) is the processed image and T is an operator on f, defined over some neighborhood of (x, y). One of the principle approaches in this formulation is based on the use of so-called masks (also referred to as kernels, templates, windows or filters). A mask is a small 2-D array in which the values of the mask coefficients determine the nature of the process, such as image sharpening.

The various spatial domain techniques are illustrated below:

1.2.1.1 Average Method

The simplest way of image fusion is to take the average of the two images pixel by pixel. Averaging work well when the images to be fused are from the same type of sensor and contain additive noise [8].

1.2.1.2 Brovey Transform

Brovey transform (BT), also known as color normalized fusion, is based on the chromaticity transform and the concept of intensity modulation. It is a simple method to merge data from different sensors, which can preserve the relative spectral contributions of each pixel but replace its overall brightness with the high spatial resolution image. As applied to three MS bands, each of the three spectral components (as RGB components) is multiplied by the ratio of a high-resolution co-registered image to the intensity component I of the MS data.

1.2.1.3 Intensity Hue Saturation (IHS)

It is most popular fusion methods used in remote sensing. The fusion is based on the RGB-IHS conversion model, whose various mathematical representations have been developed. No matter which conversion model is chosen, the principle of the IHS transformation to merge images attributes to the fact that the IHS color space is catered to cognitive system of human beings and that the transformation owns the ability to separate the spectral information of an RGB composition in its two components H and S, while isolating most of the spatial information in the I component. In this method three MS bands R, G and B of low resolution Image are first transformed into the IHS color coordinates, and then the histogram - matched high spatial resolution image substitutes the intensity image which describes the total color brightness and exhibits as the dominant component a strong similarity to the image with higher spatial resolution. Finally, an inverse transformation from IHS space back to the original RGB space yields the fused RGB image, with spatial details of the high resolution image incorporated into it. The intensity I define the total colour brightness and exhibits as the dominant component. After resolution using the high resolution data, the merge result is converted back into the RGB After applying an IHS transformation on the low spatial resolution images, we replace the Intensity component by the high spatial resolution image. The fused images are obtained by applying a reverse IHS transformation on the new set of components

1.2.1.4 Principle Component analysis (PCA)

This technique, also known as the Karhunen-Loeve transform, is extensively used in image encoding, image data compression, image enhancement and image fusion for various mapping and information extraction. The PCA method is similar to the IHS method, with the main advantage that an arbitrary number of bands can be used [12].

1.2.2 Transform Domain Method

Transform domain processing techniques are based on modifying the Fourier transform of image.

1.2.2.1 Pyramid Method

Image pyramids have been initially developed for multiresolution image analysis and as a model for the binocular fusion in human vision. A generic image pyramid is a sequence of images where each image is constructed by low pass filtering and sub sampling from its predecessor. Due to sampling, the image size is halved in both spatial directions at each level of the decomposition process, thus it leads to an multiresolution signal representation. The difference between the input image and the filtered image is so much necessary to allow an exact reconstruction from the pyramidal representation. The image pyramid approach thus leads to a signal representation with two pyramids: The smoothing pyramid containing the averaged pixel values, and the difference pyramid containing the pixel differences which is edges. So we can say that the difference pyramid can be viewed as a multiresolution edge representation of the input image. The basic idea is to construct the pyramid transform of the fused image from the pyramid transforms of the source images, and then the fused image is obtained by taking inverse pyramid transform.

1.2.2.2 Wavelet Transform

More recently with the development of wavelet theory, people began to apply wavelet decomposition to take the place of pyramid decomposition. It retains most of the advantages for image fusion as compare to other fusion methods. Wavelet Transform - The most common form of transform image fusion is wavelet transform fusion. In common with all transform domain fusion techniques the transformed images are combined in the transform domain using a defined fusion rule then transformed back to the spatial domain to give the resulting fused image. Wavelet transform fusion is more formally defined by considering the wavelet transforms ω of the two registered input images I1(x,y) and I2(x ,y) together with the fusion rule φ. Then, the inverse wavelet transform ω-1 is computed, and the fused image I (x ,y) is reconstructed .

1.2.2.3 Multiwavelet transform

Multi-wavelets is an expansion of traditional wavelet and has more advantages. It is most important that a multiwavelets system can simultaneously have these characteristics that are preserving length (orthogonality), good performance at the boundaries because of linear-phase symmetry, and a high order of approximation also named vanishing moments. Thus, multi-wavelets transform offers the possibility of superior performance for image fusion, compared with traditional scalar wavelets [13]. Multiwavelet is an extension from scalar wavelet. It not only maintains the good time-domain and frequency domain localization properties which scalar wavelet possess, but also overcomes the shortcomings of the scalar wavelet

1.2.2.4 Curvelet Transform

The curvelet transform has evolved as a tool for the representation of curved shapes in graphical applications. Then, it was extended to the fields of edge detection, image denoising and image fusion [5]. When the curvelet transform (CT) is introduced to image fusion, the fused image will take more characteristics of original images and more information for fusion is maintained [11]. The aim of curvelet transform is to generate an image of better quality in terms of reduced noise than the original image. Conventional methods have very erratic decision making capabilities when compared with curvelet method. Curvelet Transform is a new multi-scale representation most suitable for objects with curves. Curvelet Transformation is an enhancement technique to reduce image noise and to increase the contrast of structures of interest in image. Compared to other techniques, this method can manage the vagueness and ambiguity in many image reconstruction applications efficiently [11].

2. HYBRID TRANSFORM DOMAIN ALGORITHM

When an image is captured with some media, some artefacts are introduced in the image, which need to be averaged or denoised. Thus a multi enhancement technique is required as we don't know which type of noise may come in the image. So, we are presenting here the hybrid transform algorithm to enhance the images [7] and then fuse the enhanced images.

The detailed algorithm for the proposed Hybrid Transform Domain Algorithm is given as follows:

1. Take the two medical images.
2. Load the image first and then load the second image.
3. Apply Hybrid Filter on both medial images:
    i. Apply Gaussian Filter to Input Images to produce Output Image 1.
    ii. Apply Wavelet Transform to this Output Image 1 to produce Output Image 2.
    iii. Apply Curvelet Transform to this Output Image 2 to produce Final Enhanced Output Image.
4. By applying this Hybrid Filter on both the input images we will get two enhanced images as Enhanced Image 1 from Input Image 1 and Enhanced Image 2 from Input Image 2.
5. The Enhanced images are then fused using Modified Fast Haar Wavelet Transform to produce Final Fused Image.

3. EXPERIMENTS AND DISCUSSION

The proposed technique is compared with the existing Image Fusion Methods: wavelet transform and Curvelet transform. To check the performance of the proposed fusion method as well as the existing fusion method, the performance-measures: MSE and PSNR are evaluated for all cases. Here, three MRI and CT images are taken as test images. Table clearly shows that our proposed fusion method gives improved MSE and PSNR.

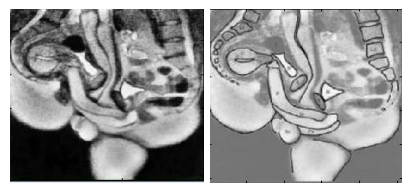

Fig 1: Medical Image Input Set 1

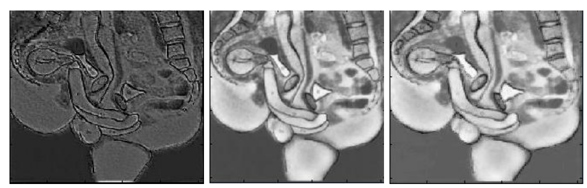

Fig 2: Fused Images by Wavelet Transform (left), Curvelet Transform (center) and The Proposed Technique (right)

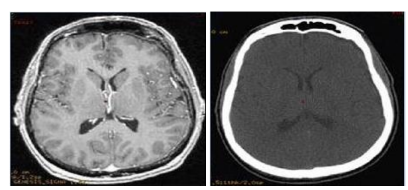

Fig 3: Medical Image Input Set 2

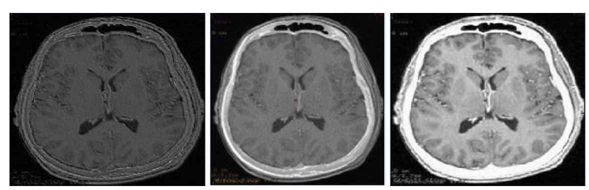

Fig 4: Fused Images by Wavelet Transform (left), Curvelet Transform (center) and The Proposed Technique (right)

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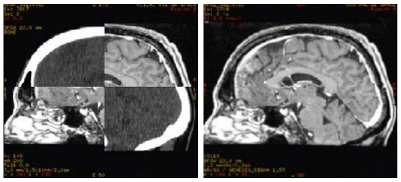

Fig 5: Medical Image Input Set 3

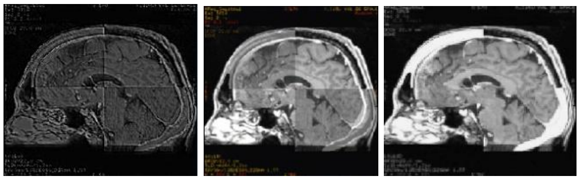

Fig 6: Fused Images by Wavelet Transform (left), Curvelet Transform (center) and The Proposed Technique (right)

4. QUANTITATIVE ANALYSIS

In order to compare the Wavelet based image fusion, curvelet based Image Fusion and The proposed Technique, we have selected two parameters: Entropy and Standard Deviation

4.1 Mean Square Error (MSE)

$$MSE = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} \left[\hat{f}(i,j) - f(i,j)\right]^2$$

where M is the height of the Image implying the number or pixel rows, N is the width of the image, implying the number of pixel columns, f(i, j)' is the original image and '$\hat{f}$(i, j)' is the reconstructed output image.

Mean square error is one of the most commonly used error projection method where, the error value is the value difference between the actual data and the resultant data. The mean of the square of this error provides the error or the actual difference between the expected/ideal results to the obtained or calculated result. The difference between the pixel density of the perfect image and the fused image is squared and the mean of the same is the considered error. MSE value will be 0 if both the images are identical.

4.2 Peak Signal-to-Noise Ratio(PSNR)

PSNR is considered to be the least complex metric, as it defines the image quality degradation as a plain pixel by pixel error power estimate. The Peak Signal-to-Noise Ratio (PSNR) is most commonly used as a measure of quality of reconstruction in image compression, image denoising and image fusion etc. It is measured in decibels (db). It is measured as given by Eq.

$$PSNR = 10 \log_{10} \left[\frac{255 \times 255}{MSE}\right]$$

where the Mean Square Error (MSE) is defined as given by the above equation.

The MSE and PSNR for three Image sets are tabulated in Table 1.

Table 1. MSE and PSNR

Image set	Technique Applied	MSE	PSNR
Image Set 1	Wavelet Based Image Fusion	8704.8379	20.1089
	Curvelet Based Image Fusion	3250.2393	29.9604
	The proposed Technique	1243.982	39.5645
Image Set 2	Wavelet Based Image Fusion	3833.0595	28.3111
	Curvelet Based Image Fusion	5222.7581	25.2175
	The proposed Technique	2945.5952	30.9446
Image Set 3	Wavelet Based Image Fusion	4718.5551	26.2327
	Curvelet Based Image Fusion	2393.5864	33.0198
	The proposed Technique	1747.0307	36.1685

The above table shows the comparison of Wavelet Transform Method, Curvelet Transform Method and The Proposed Method in terms of MSE and PSNR. It is very clear from the plot that there is decrease in MSE and increase in PSNR value of image with the use of proposed method over other methods. This represents improvement in the objective quality of the image.

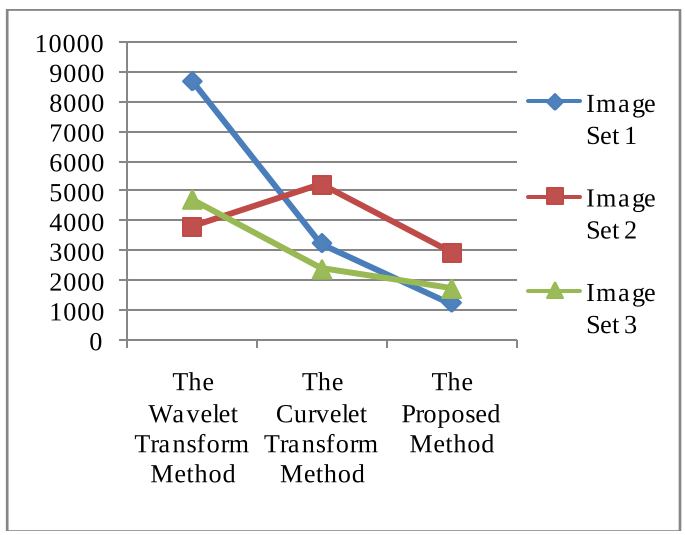

Fig 7: Comparison of Wavelet Transform Method, Curvelet Transform Method and The Proposed Method in terms of MSE for Image Set 1 to Image Set 3

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The above figure shows the comparison of Wavelet Transform Method, Curvelet Transform Method and The Proposed Method in terms of MSE. It is very clear from the plot that there is decrease in MSE value of image with the use of proposed method over other methods. This decrease represents improvement in the objective quality of the image.

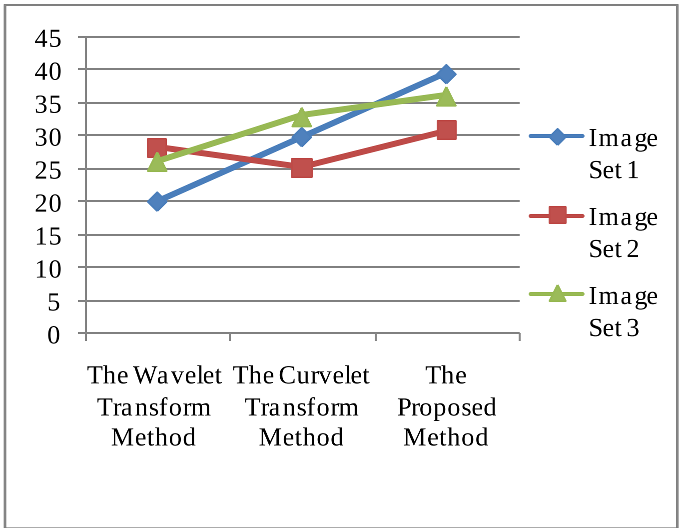

Figure 4.17 Comparison of Wavelet Transform Method, Curvelet Transform Method and The Proposed Method in terms of PSNR for Image Set 1 to Image Set 3

The above figure shows the comparison of Wavelet Transform Method, Curvelet Transform Method and The Proposed Method in terms of PSNR. It is very clear from the plot that there is increase in PSNR value of image with the use of proposed method over other methods. This increase represents improvement in the objective quality of the image.

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