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IMAGE FUSION TECHNIQUE FOR ACQUISITION OF SAR AND OPTICAL IMAGES USING NSCT

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ABSTRACT

Multi Sensor Imaging Fusion that is designed to enhance perception by combining data captured from various image sensors. Image fusion is a popular choice for a number of image enhancement applications like two image product overlays, refinement of alignment image resolutions and image combinations for functional extraction and target recognition. In this paper a fresh image fusion algorithm based on the non-sampled contourlet transformation (NSCT) should be developed to confuse the Synthetic Aperture Radar (SAR) images and Optical images. The two images are first co-registered by the registration technique before the image fusion. Synthetic Aperture Radar (SAR) and Optical images will be merged and contrasted with current technologies by means of quantitative and qualitative measures, using the suggested methods. Quantitative measures such as Entropy (EN) and the Structural Similarity Index (SSIM) will be used to validate the algorithms.

1. INTRODUCTION

Noise is undesired information that contaminates an image. Noise appears in image from various sources. The digital image acquisition process converts an optical image into a continuous electrical signal. This electrical signal sampled, is primary process by which noise appears in digital image. There are several ways through which noise can be introduced into an image, depending on how the image is created. This is the main problem in remote sensing applications. Satellite image, containing the noise signals and lead to a distorted image and not being able to understand. So to study it properly, requires the use of appropriate filters to limit or reduce much of the noise. It helps the possibility of better interpretation of the content of the image.

Multi sensor fusion can occur at the signal, image, feature, or symbol level of representation. Signal-level fusion refers to the direct combination of several signals in order to provide a signal that has the same general format as the source signals. Image-level fusion (also called pixel-level fusion) generates a fused image in which each pixel is determined from a set of pixels in each source image. Clearly, image-level fusion, or image fusion, is closely related to signal-level fusion since an image can be considered a two-dimensional (2D) signal. A simple diagram of a system using pixel-level image fusion is shown in the block diagram in Figure 1.1. For simplicity, only two imaging sensors survey the environment, producing two different representations of the same scene. The representations of the environment are, again, in the form of image signals which are corrupted by noise arising from the atmospheric conditions, sensor design, quantization, etc.

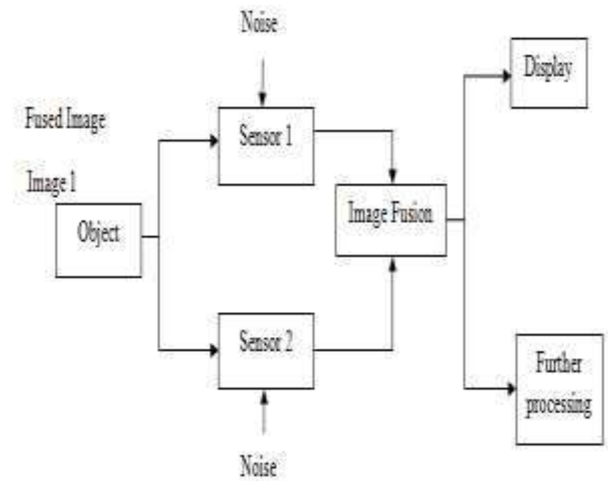


Figure 1.1 Basic structure of Image fusion

2. IMAGE FUSION USING NSCT

Image fusion is the process of combining relevant information from two or more images into a single image. In medical field fusion is needed when one modality image can't provide enough information itself. Doctors need high spatial and spectral information for researches, monitoring, diseases diagnosing and treatment process in a single image. This type of information cannot be obtained by single modality images. For example, computed tomography (CT) image shows bone structures clearly but provides little information about the tissues but a magnetic resonance image (MRI) can show soft tissues. Thus, an individual modality image has their own limitations in providing needed information because each image is taken with different radiation power. To solve this, complementary information from different modality image is taken and fusion is the technique used to combine these images in different modalities such as computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), Optical images and SAR images.

3. PROPOSED METHOD

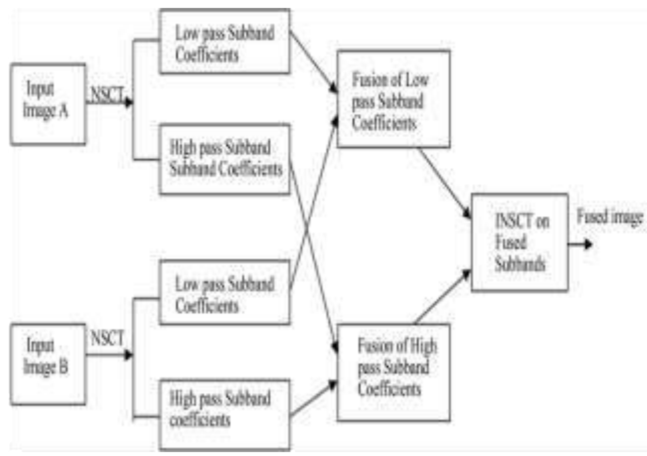


Fig. 3.1 frame work model for based fusion

In the proposed method image fusion is done based on non sub-sampled counter let transform (NSCT). It is an efficient transform that takes the essence of a given signal or a group of signals with few basic functions. The transform is fully shift-invariant with multi scale and multidirectional property. In this model the registered source images are first transformed by . The transform will split the images into low frequency and high frequency components. Combining of low and high frequency of the two images will takes place based on two fusion rules. The low frequency bands are fused by considering phase congruency. Directive contrast is adopted as the fusion measurement for high- frequency bands. Then inverse is applied to get the fused image.

Features of the model:

- The use of two different fusion rule will preserve more information in the fused image with improved quality.
- Phase congruency is a feature that is unvarying to different pixel intensity mappings and illumination changes.
- The most important texture and edge information are selected from high-frequency coefficients of the two images and combined using directive contrast.
- The fusion relies on which is shift-invariant and has multi scale, multidirectional properties.

By examining Figure 3.1, in first step transformation is take place for the two registered medical images in two different modes. For example a optical images and SAR images. can be divided into two stages including non sub-sampled pyramid (NSP) and non sub-sampled directional filter bank (NSDFB). Non Sub-sampled Pyramid (NSP) uses two-channel non sub-sampled filter bank to decompose image into one low frequency and high frequency component.

4. PERFORMANCE EVALUATION

4.1 Entropy:

Syntax:

E = entropy(I)

Description:

E = entropy(I) returns E, a scalar value representing the entropy of grayscale image I. Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. Entropy is defined as

-sum(p.*log2(p))

where p contains the histogram counts returned from imhist. By default, entropy uses two bins for logical arrays and 256 bins for uint8, uint16, or double arrays.

I can be a multidimensional image. If I has more than two dimensions, the entropy function treats it as a multidimensional grayscale image and not as an RGB image.

Class Support:

I can be logical, uint8, uint16, or double and must be real, nonempty, and non-sparse. E is double.

Notes: entropy converts any class other than logical to uint8 for the histogram count calculation so that the pixel values are discrete and directly correspond to a bin value.

Examples

I = imread('circuit.tif'); J = entropy(I)

4.2 Structure Similarity INDEX (SSIM):

It is a perpetual metric that quantifies image quality degradation caused by the processing such as data compression or by losses in data transmission. It is a full reference metric that requires two images from the same image capture – a reference image and a processed image. SSIM is best known in the video industry, but has strong applications for still photography.

It actually measures the perpetual difference between two similar images. It cannot judge which of the two is better.

This is an implementation of the algorithm for calculating the structural similarity (SSIM) index between two images.

Input :

(1) img1: the first image being compared

(2) img2: the second image being compared

(3) K: constants in the SSIM index formula [[mssim, ssim_map] = ssim(img1, img2, K, window, L)] (. default value: K = [0.01 0.03]

(4) window: local window for statistics. Default window is Gaussian given by
window = fspecial('gaussian', 11, 1.5);

(5) L: dynamic range of the images. default: L = 255

Output:

(1) mssim: the mean SSIM index value between 2 images. If one of the images being compared is regarded as perfect quality, then mssim can be considered as the quality measure of the other image. If img1 = img2, then mssim = 1".

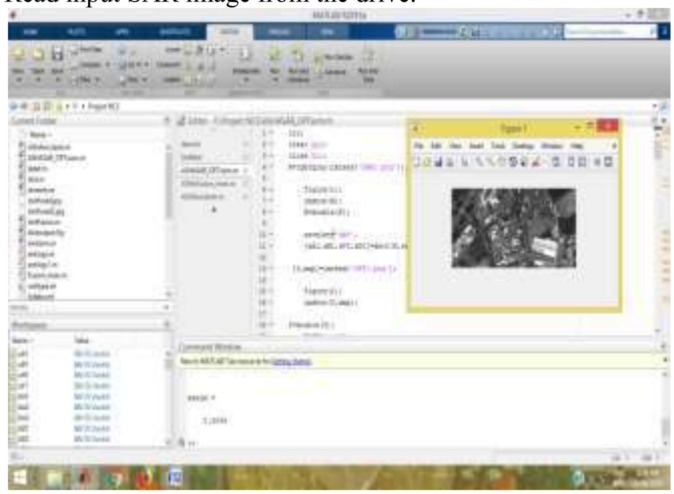
(2) ssim_map: the SSIM index map of the test image. The map has a smaller size than the input images. The actual size depends on the window size and the downsampling factor.

5.RESULTS

5.1 Step Wise Procedure (Running the Code):

Step 1:

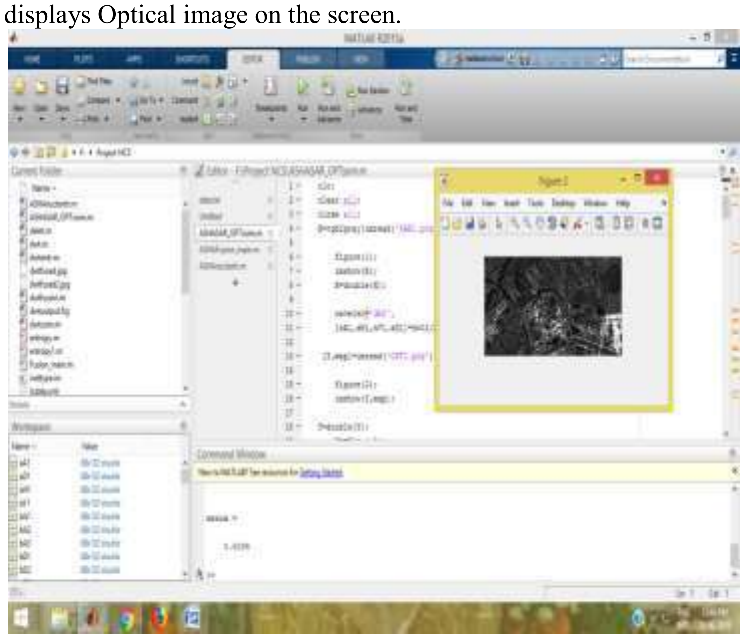
Read input SAR image from the drive.



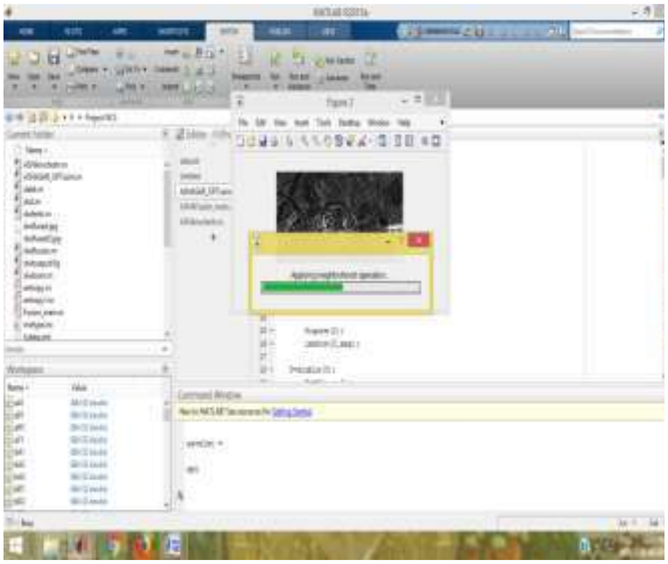
"im read" instruction reads the image from the storage and Showing SAR image using "imshow" instruction.

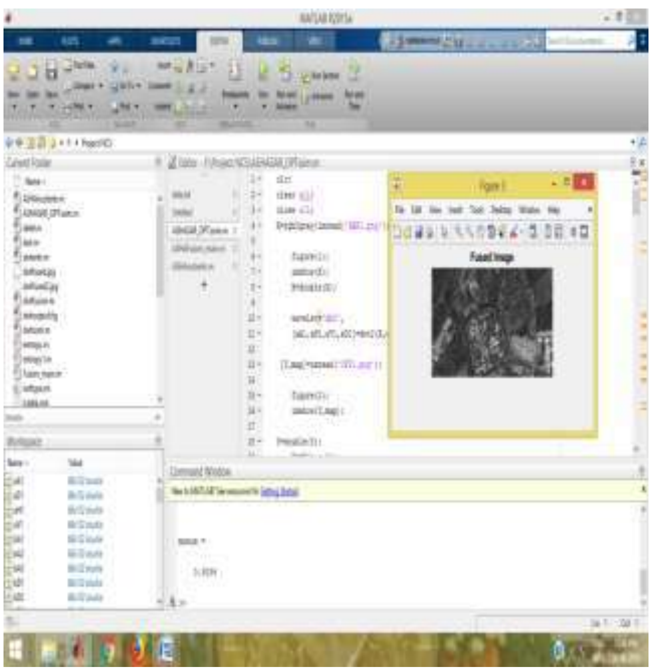
Step 2:

Read second input, optical image from the storage and displays Optical image on the screen.

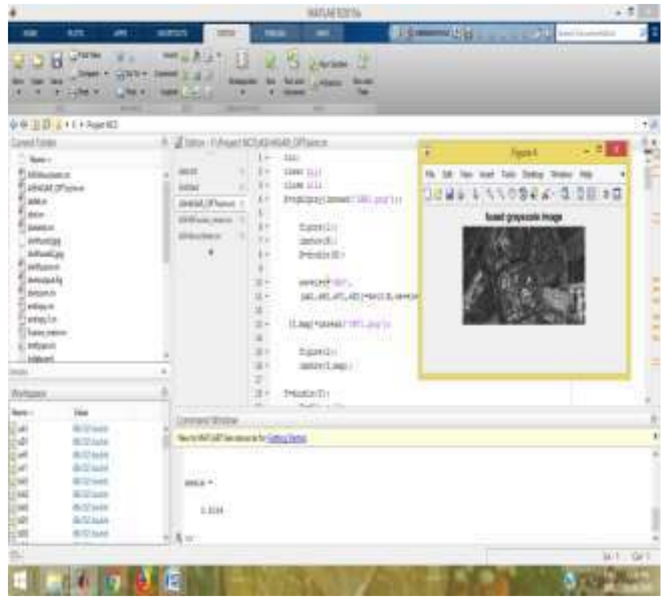


Step 3:
Fusion of approximation is applied at this stage. The fused image using is displayed here

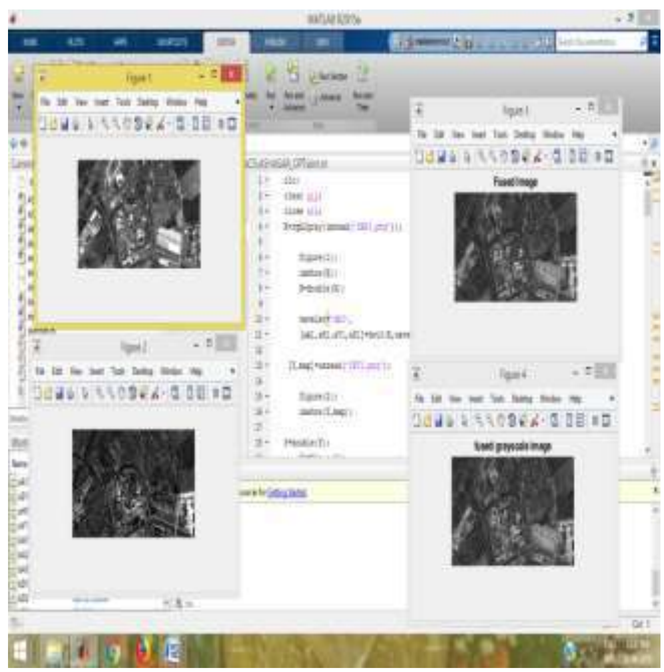




Step 4:

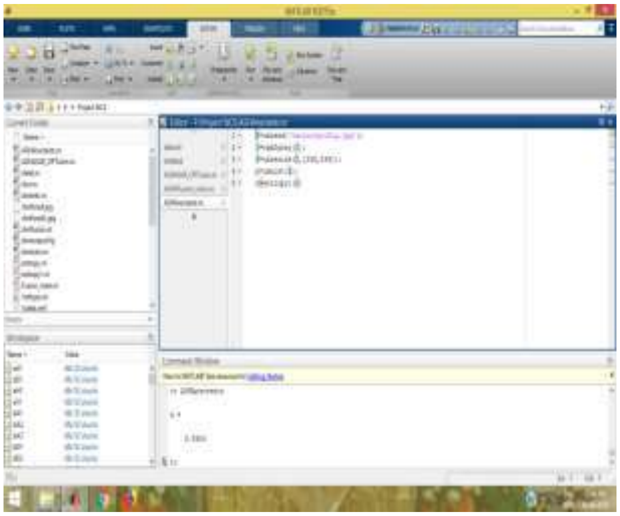


We get fused image in gray scale as it is difficult to apply to color image, since color image consists of red, blue, green components. It is difficult to apply for 3 variable parameters. So we apply NSC transform to gray scale form which has only intensity information (only one parameter).



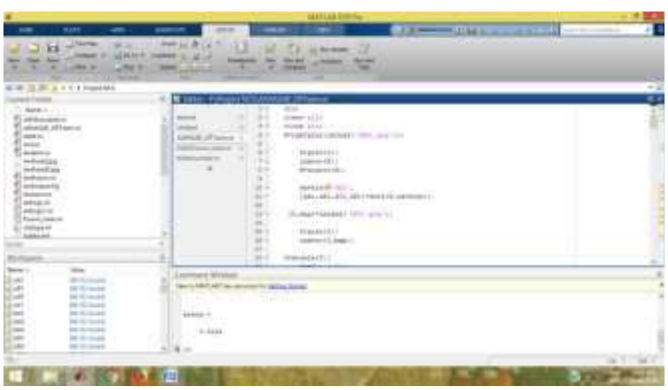
5.2 Discussions:

We have performed internal evaluation by calculating parameters like Entropy and SSIM of both output images and structure similarity index of two output images with reference input SAR image.



As per the results we have obtained the values of entropy like, for a dwt fused image, entropy (h) = 3.857 and for fused image entropy = 3.93. As entropy defines the 'business' of the image , low entropy images have little contrast but run on large pixels(poor quality with large size) and high entropy images have a high contrast and are easy/better to distinguish the color differences of structures. So due to high entropy of fused image, It helps doctors for clear vision for better identification of tissues for diagnosis as compared to dwt fused image.

In the same way, we have calculated structure similarity index of both the and dwt based fusion output images with reference input optical image.



Mean SSIM for dwt fused image is 0.7948 and for fused image is 0.0365, originally the value of SSIM must lies between -1 to +1, so we have obtained valid values for both methods, but more the value of SSIM indicates less image quality degradation after image processing. But in case, lower value of Structure similarity with SAR image may indicate better fusion between SAR and Optical images.

CONCLUSION

In this paper, a novel image fusion framework is proposed for multi-modal SAR images, which is based on non-sub-sampled contourlet transform and directive contrast. For fusion, two different rules are used by which more information can be preserved in the fused image with improved quality. The low-frequency bands are fused by considering phase congruency whereas directive contrast is adopted as the fusion measurement for high-frequency bands. In our experiment, two SAR and Optical images are fused using conventional fusion algorithms and the proposed frame-work. The visual and statistical comparisons like calculating the entropy, structure similarity index (SSIM) demonstrate that the proposed algorithm can enhance the details of the fused image, and can improve the visual effect with much less information distortion than its competitors (several existing methods like principal component analysis (PCA), wavelet transform and others). These statistical assessment findings agree with the visual assessment.

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