IMAGE FUSION USING NSCT: DENOISING AND TARGET EXTRACTION FOR VISUAL SURVEILLANCE

Anjana Jayachandran[1], R.Gayathri[2]

[1]*Student, Applied electronics, Anna University, Paavai College of Engineering, Namakkal, TN, India*
[2]*Professor, in Anna University, Paavai College of Engineering, Namakkal, TN, India*

Abstract

Image fusion is a method of combining information from multiple images of same scene to get a composite image that is more suitable for human visual perception or further image processing task. In this paper we propose a fusion framework based on Non-Subsampled Contourlet Transform of infrared and visible images. The fused result contains the details of target present in the infrared image. For the identification and extraction of the target from the IR image the threshold and watershed algorithm is used so that only the relevant information from the IR image is introduced into the fused result so that the result becomes more accurate. A NLM filter is then used to denoise the fused image.

Keywords*— Denoising; Image fusion; Image Segmentation; Non Subsampled Contourlet Transform*

--***--

1. INTRODUCTION

With the development in the sensor field many surveillance systems have been developed in the recent year. Infrared sensors are employed in the field of military surveillance, medical imaging and machine vision. Infrared sensors have the ability to capture information under poor lightning conditions than the visible cameras. The sensor differs in modalities so image data acquired using different sensors exhibit different modalities like thermal and viaual characteristics. A surveillance system can perform better if data acquired from different sensors are combined together. This is known as image fusion. Image fusion is defined as the process of combining information from two or more sensors to get a single image, which is more precise and is suitable for humal viaual perception for further image processing tasks.

In this study, we focus on fusion process of visible and infrared images that has high resolution and contains more textural information. The infrared images are obtained in the low light conditions, which is captured by the heat emitting from the object. Thus combination of visible images and infrared information in the IR image is obtained as a single image. Many more fusion methods are developed [1], [2], [3], [4], [5] during the past two decades. The fusion algorithm can be of three types pixel, feature and decision levels[13]. In pixel image fusion, the visual information in the source images are combined based on the original pixel information [14]. The pixel level fusion algorithm can be categorized into sapatial domain fusion and trandform domain fusion. The spatial domain technique uses local spatial frequency and local standard derivation for source image fusion. For transform domain methods, the source images are projected onto localized bases, which are designed to represent the sharpness and edges of the image [3]. So the transformed coefficients are used in detecting features of the source images to construct the fused image. So far, many multi resolution image fusion techniquehave been proposed and used with the development of different bases; pyramidal decomposition such as laplacian pyramid, gradient pyramid, contrast pyramid [4], [5] fail to introduce spatial oriented selectivity in decomposition process and results in blocking effects. Another family of of multi resolution fusion technique is wavelet-based method [6]. The problem with WT [8] is that, it can provide better spatial and spectral localization of image information but fails to provide spatial characteristics. The advantage of DWT compared to pyramid fused image is that it provide better SNR , but it lacks shift-invariant properties and does not show singular curves. The curvelet transform (CVT) and contourlet transform (CT) [10] overcomes the problem of Wavelet Transform. The CT overcomes the lack of geometrical structure in WT, but the CT is not shift-invariant.

In this paper, we propose an improved contourlet transform the Non Subsampled Contourlet Transform (NSCT). The NSCT is fully shift invariant, multi scale and multi direction expansion that has better directionality frequency localization and a fast implementation. The filter design problem of NSCT is much less constrained than that of CTs because of its redundancy. This enables us to design filters with better frequency selectivity thereby achieving a better subband decomposition.
The structure of this paper is as follows: section 2 introduces the target extraction algorithm section 3 discusses the fusion framework and section 4 discusses the results. Finally, the conclusion is given in section 5.

2. TARGET EXTRACTION ALGORITHM

There are number of image segmentation technique eg [13], [14], [15] and [18]. Most of the methods first employ multi scale transform to the source images and extract regions from the transform coefficients. The final fusion performance depends on the quality of segmentation process. In case of IR-visible image fusion, proper segmentation map for all input images is different nature of imaging sensors.

Only the infrared image has the detail of the targets so in this methods instead of segmenting both source images only the knowledge of the properties of IR images is used to extract objects of interest for segmenting both infrared or visible images. In this work, a marker controlled watershed transformation is used to extract targets from the IR image. The marker image is computed using the gradient modulus maxima of the undecimated wavelet transform (UWT). The block diagram of the target extraction algorithm is shown in Fig.1. It consists of three parts: marker extraction, image simplification, and watershed transformation.

2.1 Marker Extraction

The direct application of watershed transform leads to over segmentation of the input images. To improve the result, watershed transform is used along with the marker image, which limits the segmentation process to some “marked ” areas. Since the IR images are bounded by transient regions such as edges, we first apply an undecimated wavelet transform based edge detector to the input image [14]. Then three images are obtained at each scale, the modulus of gradient vector, the angle of steepest ascent of the gradient vector and a binary image containing local modulus maxima of the gradient vector. Then the binary modulus maxima images are multiplied

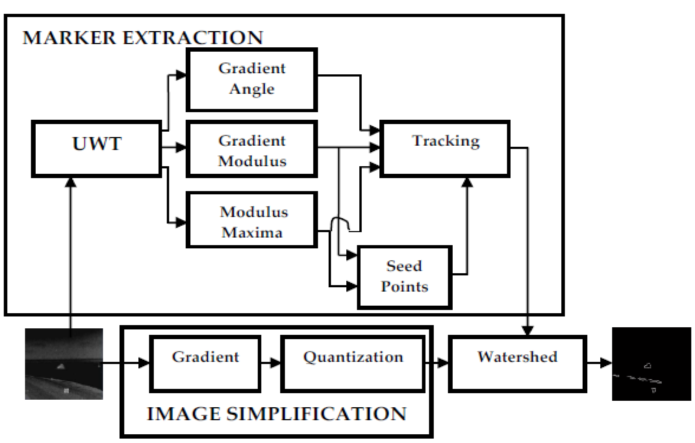


Fig 1: Block diagram of the target extraction approach

with the corresponding gradient modulus images and first threshold is applied. The binary image then contains only those modulus maxima above the chosen threshold. After combining the threshold image of 1st and 2nd decomposition level, first course segmentation is obtained. From this segmentation the starting point for the edge tracking operation is computed. The proposed tracking algorithm takes a seed point from the seed point list and follows target border in the direction perpendicular to the gradient angle. So in order to track a target it is important that a single seed point or starting point is located on target edge. This will minimize introduction of false targets in the segmentation process and allows selection of highest first threshold. At each new point, the tracking algorithm multiplies the 8 connected neighborhood of the tracked pixel with a directional mask and discards those pixels, which does not agree the masks angle. The directional masks with their corresponding directions are given in Fig.3. Form all candidate pixels, tracking algorithm chooses the one with highest gradient modulus and marks it as a tracked. All the 4 connected neighbors and remaining candidate pixels arising from the previously tracked pixels are marked as discarded to avoid the use of those pixels as candidate pixels again. The tracking stops when, the new point is 8 connected to previously tracked point or the averaged gradient modulus of the new point is below a particular threshold value. The fig 2 shows the tracking operation. After tracking operation all the true targets from the input image form the bounded region.

The post processing steps removes all edge segments, which do not form a closed region, thereby cleans tracked image from the wrongly tracked portions. Before performing marker controlled WT, the original has to be simplified [15] by computing morphological gradient of the source images and quantizing it to 100 gray levels. After image simplification, it is combined with the marker image and watershed transformation is applied. The result is shown in the fig 2.

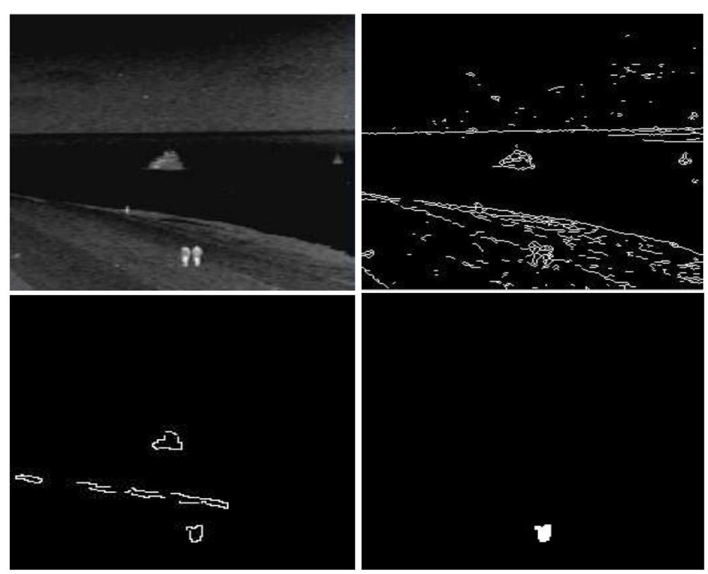
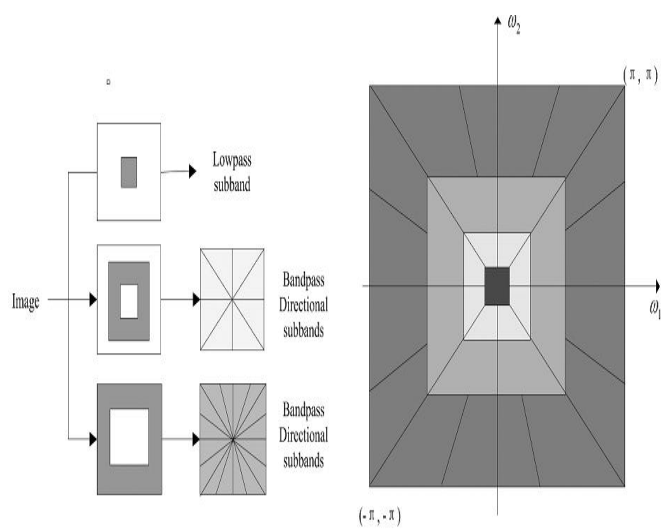


Fig 2: Results of the target extraction: (Top-Left) Original image, (Top-Right) Seed points. (Bottom left) Result of the tracking operation. (Bottom-Right) Final result after application of the watershed transformation

3. FUSION FRAMEWORK

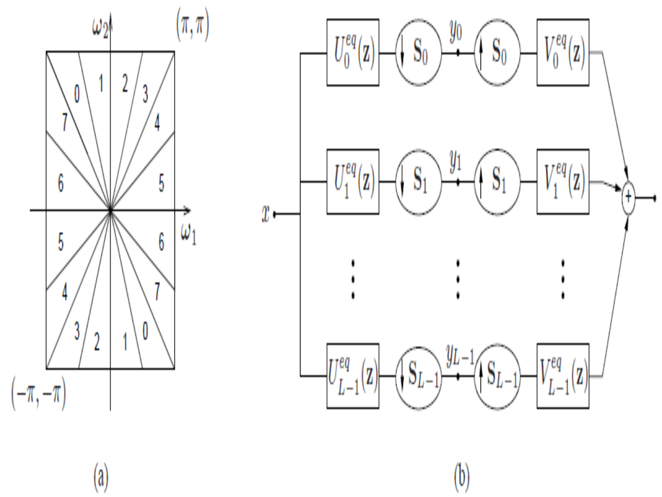
In this work an improved contourlet transform is used in the fusion framework of infrared and visible images, the Non Subsampled Contourlet Transform. NSCT is a multiscale and multidirection fusion framework of the discrete images [16]. Fig 3(a) displays a high-level view of the NSCT. The structure consists in a bank of filters that splin the 2-D frequency plane in a bank of filters that splits the 2-D frequency plane in the subbands illustrated in Fig 3(b). The transform is divided into two parts that are both shift invariant; a non subsampled pyramid structure that ensures multiscale property and a directional filter bank structure that gives directionality. The multi scale property of the NSCT is obtained from a shift-invariant filtering structure that achieves subband decomposition similar to that of the Laplacian pyramid. This is achieved by using two-channel non-subsampled 2-D filter banks. At each NSP decomposition level one low frequency image and one high frequency image is obtained. The subsequent NSP decomposition are carried out to decompose the low frequency component iteratively to capture the singularities in the image. As a result NSP results in K+1 sub images, it consists of one low frequency and k high frequency images having the same size as the source image where k denotes the no.of decomposition levels. Fig 3(a) shows NSP decomposition with k=3 levels. The NSDFB is a two-channel non subsampled filter bank and are constructed by combining the directional decompositions with l stages in high frequency images from NSP at each scale and produces 2^l directional sub images with same size as source images. A



(a) (b)

Fig 3 The nonsubsampled contourlet transform. (a) Nonsubsampled filter bank structure that implements the NSCT. (b) The idealized frequency partitioning obtained with the proposed structure.

four channel NSDFB is constructed with two channel fan filter banks. The result is a tree structured filter bank that splits the frequency plane in the directional wedges as shown in Fig 4 (a).



(a) (b)

Fig 4: Directional filter Bank (a) Ideal partitioning of the 2-D frequency plane into 23 = 8 wedges. (b) Equivalent multichannel filter bank struture.

The NSDFB offers multidirection property and give more precise directional details information. The proposed system is based on these two methods the fusion of infrared image and visible image using the NSCT transformation and extracting the target from the IR images using the marker ex traction and watershed algorithm. The block diagram of the proposed system is shown in figure 5.

The proposed system is based on these two methods the fusion of infrared image and visible image using the NSCT transformation .

The step in the proposed system is as follows:
It should be noted that all the images should be registered before doing the fusion process so that the pixels match.

Step 1: The source images for the image fusion is an Infrared image and the visible image

Step 2: The source images are prepossessed using Guassian filter to remove the noise present in the images.

Step 3: The marker extraction and watershed algorithm are applied to the Infrared image.

Step 4: To decompose the coefficients NSCT is applied to the two source images.

Step 5: The lower coefficients of the source images are fused using low frequency fusion rules and higher coefficients are fused using high frequency fusion rules to get a fused low frequency image and fused high frequency image.

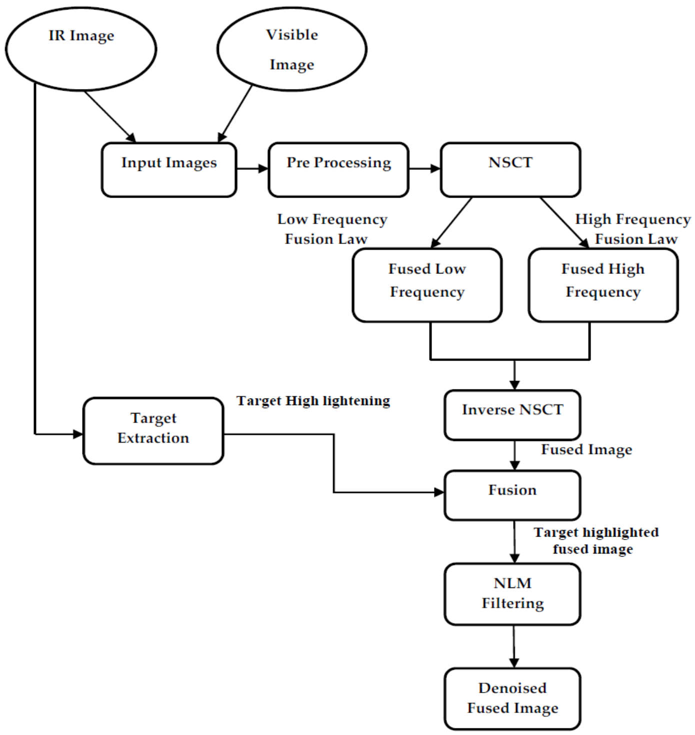
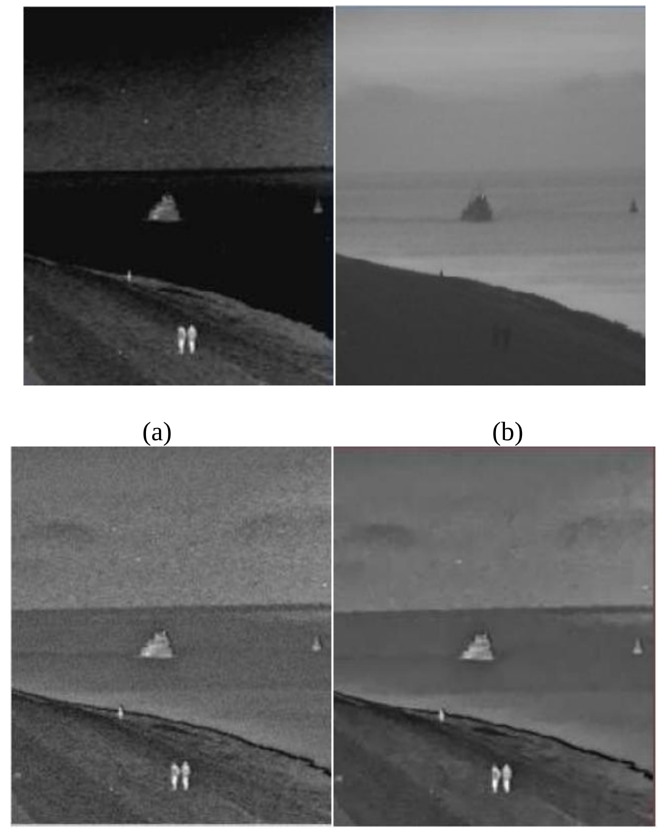


Fig 5: Block diagram of the proposed image fusion framework

Step 6: Inverse NSCT is applied to get the fused image with target high lighting.
Step 7: A non local means filtering method is added to denoise and to obtain a fused image.
The Infrared image and visible image is taken as the source images. The source images are denoised using a guassian filter to remove the noises present in the image. The decomposition of the images are done by performing NSCT to get the lower level coefficients and higher level cofficints. The fusion of lower coefficients is done by using lower frequency rule to get a fused low frequency image and the higher coeffients of both images are fused by higher coefficients rules to get fused higf frequency image. Inverse NSCT ia applied to the fused coefficients so that the fused image is obtained. The marker extracted target is then combined with the NSCT fused image so that a target highlighted fused image is obtained. There are certain noise introduced in the images during processing, to remove these noise filtering process is done. In our work a Non Local Mean filter is used for the post processing of the image.

4. RESULTS

Some general requirements for fusion algorithm are: it should be able to extract complimentary features from input images, it must not introduce artifacts or inconsistencies according to Human Visual System and it should be robust and reliable. The fusion result of the proposed method is shown in Fig 6 (c) and (d).



(c) (d)

Fig 6 Source and image fusion results , (a) Infrared image; (b) Visible image; (c) NSCT-based fused image; (d) Filtered image

The performance of the proposed image fusion scheme was compared to the fusion scheme obtained by using Non Subsampled Contourlet Transform (NSCT). It can be seen that, by including target information into the fusion process the result of NSCT can be improved. This is more evident looking at the fusion result shown in fig 7. It can be seen that the proposed work produces fused images that show improved contrast around the target regions. The proposed fusion work is also used to artificially enhance the extracted target within the fused image.

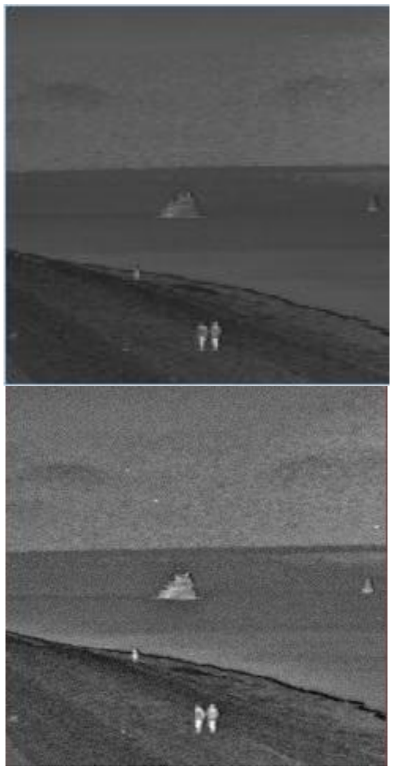


Fig 7 Image fusion results , NSCT-based fused image (left); Proposed image fusion with target extraction (right)

5. CONCLUSIONS

A novel image fusion framework is proposed for multisensor images, which are based on Non Subsampled Contourlet Transform along with a target extraction algorithm using watershed transform to get good results. The infrared target in the natural scene can be clearly distinguished in the resulting fused image. The infrared targets are highlighted using marker extraction.This technique is very useful for visual surveillance.

ACKNOWLEDGMENTS

The authors wish to thank all those who helped in accomplishing this task.

REFERENCES

[1] A.A. Goshtasby, S. Nikolov,Image fusion: advances in the state of the art, Information Fusion 8 (2) (2007) 114–118.

[2] V.S. Petrovic, C.S. Xydeas, Gradient-based multiresolution image fusion, IEEE Transactions on Image Processing 13 (2) (2004) 228–237

[3] N. Mitianoudis, T. Stathaki, Pixel-based and region-based image fusion schemes using ICA bases, Information Fusion 8 (2) (2007) 131–142.

[4] A. Toet, Image fusion by a ratio of low-pass pyramid, Pattern Recognition Letters 9 (4) (1989)

[5] Z. Liu, K. Tsukada, K. Hanasaki, Y.K. Ho, Y.P. Dai, Image fusion by using steerable pyramid, Pattern Recognition Letters 22 (9) (2001) 929–939.

[6] H. Li,B. Manjunath,S. Mitra, Multisensor image fusion using the wavelet transform,Graphical Models and Image Processing 57(3)(1995) 235–245.

[7] Z. Zhang, R.S. Blum, A categorization of multiscale-decomposition-based image fusion schemes with a performance study for a digital camera application, Proceedings of the IEEE 87 (8) (1999) 1315–1326.

[8] G.Pajares, J.Cruz, A wavelet-based image fusion tutorial,Pattern Recognition 37(9)(2004) 1855–1872.

[9] G. Piella,"A general framework for multiresolution image fusion: from pixels to regions", Information Fusion 4 (4) (2003) 259–280.

[10] F. Nencini, A. Garzelli, S. Baronti, L. Alparone, "Remote sensing image fusion using the curvelet transform", Information Fusion 8(2)(2007)143–156.

[11] S. Daneshvar, H. Ghassemian, MRI and PET image fusion by combining IHS and retina-inspired models, Information Fusion 11 (2) (2010) 114–123.

[12] M. Zribi, "Non-parametric and region-based image fusion with Bootstrap sampling", Information Fusion 11 (2) (2010) 85–94

[13] J.J. Lewis, R.J. O'Callaghan, S.G. Nikolov, D.R. Bull, and N. Canagarajah, "Pixel- and region-based image fusion with complex wavelets," Information Fusion, vol. 8, no. 2, pp. 119–130, April 2007.

[14] Z. Zhang and R.S. Blum, "Region-based image fusion scheme for concealed weapon detection," in Proceedings of the 31st Annual Conference on Information Sciences and Systems, March 1997, pp. 168–173.

[15] T. Wan, N. Canagarajah, and A. Achim, "Segmentation-driven image fusion based on alpha-stable modeling of wavelet coefficients," IEEE Transactions on Multimedia, vol. 11, no. 4, pp. 624–633, June 2009.

[16] A. Ellmauthaler, E.A.B. da Silva, and C.L.Pagliari, "Multiscale Image Fusion Using the Undecimated Wavelet Transform With Spectral Factorization and Non-Orthogonal Filter Banks,"

[17] C.S. Xydeas and V. Petrovic, "Objective image fusion performance measure," Electronics Letters, vol. 36, no. 4, pp. 308–309, February 2000.

[18] G. Piella, Adaptive Wavelets and their Applications to Image Fusion And Compression, Ph.D. thesis, University of Amsterdam, 2003.