FUSION OF MULTI FOCUSED IMAGES USING HDWT FOR MACHINE VISION

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Abstract

During image acquisition in machine vision, due to limited depth of field of lens, it is possible to take clear image of the objects in the scene which are in focus only. The remaining objects in the scene will be out of focus. A possible solution to bring clear images of all objects in the scene is image fusion. Image fusion is a process of combining multiple images to form the composite image with extended information content. This paper uses three band expansive higher density discrete wavelet transform to fuse two numbers of images focusing different objects in the same scene and also proposes three methods for image fusion. Experimental results on multi focused image fusion are presented in terms of root mean square, peak signal to noise ratio and quality index to illustrate the proposed fusion methods.

Keywords**:** Higher Density Discrete Wavelet Transform (HDWT), Image Fusion, Root Mean Square Error (RMSE), Peak Signal to Noise Ratio (PSNR) and Quality Index (QI).

1. Introduction

The driving forces in manufacturing environments are quality improvement, cost reduction, increased volume of production and shorter cycle times of manufacturing. The quality of many raw materials, parts, and products can be measured by electrical or mechanical means or by visual inspection. For high speed and real time applications, manual inspection is not possible. Therefore, more and more manufacturers look for fast, accurate, reliable, and consistent machine vision system for automated visual inspection of their products. Machine Vision involves acquisition of the image of an object of interest followed by processing and interpretation of this image using computer for useful applications like inspection of quality of raw materials, parts and products in industries. The first step in machine vision is to acquire the image of objects in the scene, which requires an imaging system. An imaging system consists of lens, imaging sensor and frame grabber through which the imaging sensor is connected to computer for processing and analysis. Due to limited depth of field of lens, it is possible to take clear image of the objects in the scene which are in focus only. The remaining objects in the scene will be out of focus. A possible solution to bring clear images of all the objects in the scene is to combine several pictures taken by the camera with different focus points into a composite image. The resulting composite image, called as fused image, will contain clear images of all relevant objects in the scene. This is known as multi-focused image fusion. There are two approaches to image fusion, namely Spatial Fusion and Transform fusion. In Spatial fusion, the pixel values from the source images are summed up and taken average to form the pixel of the fused image at that location. Transform fusion uses pyramid or wavelet transform for representing the source image at multi scale [1, 2]. The most commonly used wavelet transform is critically sampled Discrete Wavelet Transform (DWT) which can be implemented using perfectly reconstructed Finite Impulse Response filter banks. But, critically sampled DWT suffers from four shortcomings namely Oscillations, Shift variance, poor directionality and aliasing. Shift variance in critically sampled discrete wavelet transform exists due to down sampling during analysis and up sampling during synthesis [3].

Improved performance can be found using an over complete or redundant wavelet transform in variety of signal and image processing applications. For example, the Undecimated Discrete Wavelet Transform (UDWT), which is expansive by the factor 3J+1, when J scales are implemented, shows improved results due to its shift invariant property. Complex Wavelet Transform (CWT) is also an alternate and complex valued extension to DWT with limited redundancy. CWT uses complex valued filtering that decomposes the real or complex signal into real and imaginary parts in transform domain. It is approximately shift invariant and directionally selective in higher dimensions. It achieves this with a redundancy factor of only 2^d for *d*-

dimensional signals, which is lower than the UDWT. The double-density discrete wavelet transform (DDWT) which provides a compromise between the UDWT and the critically-sampled DWT is two-times expansive, regardless of the number of scales implemented. Even so, the DDWT is approximately shift-invariant. Like the CWT, the DDWT is redundant by a factor of 4 for two dimensions, independent of the number of levels. These above said expansive transform do not increase the sampling with respect to frequency or scale. An expansive dyadic wavelet transform, namely High Density Discrete Wavelet Transform (HDWT) over samples both space and frequency by a factor two [4]. This paper uses HDWT and also proposes three methods to fuse two numbers of images focusing different objects in the same scene for image fusion and the performance of HDWT for the fusion of multifocused images are evaluated using RMSE, PSNR and QI [6].

2. Lens Model of Imaging System in Machine Vision

Machine vision is defined as the process of acquisition of image of objects of interest followed by processing and interpretation of this image using computer for some useful applications like inspection and feature extraction. The image of a scene formed by an optical system used in machine vision contains information about the distance of objects in the scene. Objects at a particular distance are focused whereas other objects are defocused or blurred by different degrees depending on their distance. This is shown in fig 1.

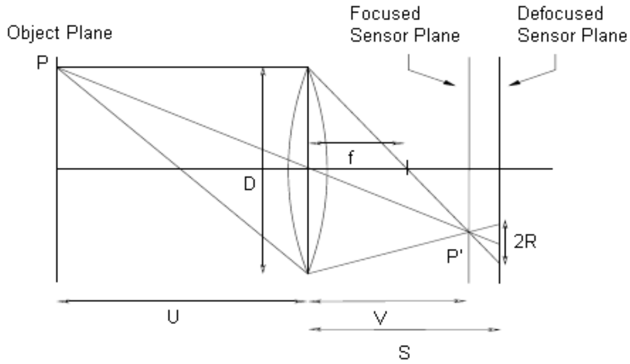

Figure 1: Model of Lens System

The point P on the object plane is clearly focused and perfectly imaged as point P’ on the image plane. For a camera with a lens of focal length 'f', the relation between the position of a point close to the optical axis in the scene and the position of its focused image is given by the well known lens formula

$$\frac{1}{f} = \frac{1}{U} + \frac{1}{V} \tag{1}$$

where U is the distance of the object, and V is the distance of the image. Therefore, in the image formed by a camera, only objects at a certain distance are in focus; other objects are blurred by varying degrees depending on their distance. Further, each lens must have a finite aperture of diameter D, which can be used to estimate radius of the blur circle induced as

$$\frac{D}{V} = \frac{2R}{S - V} \tag{2}$$

where S is sensor plane and the lens. Then the depth of field of a lens system can be given as,

$$DOF = U_{far} - U_{near} \tag{3}$$

$$U_{far} = \frac{Uf(1 - 2\frac{R}{D})}{f - 2\frac{R}{D}U} \tag{4}$$

$$U_{near} = \frac{Uf(1 + 2\frac{R}{D})}{f + 2\frac{R}{D}U} \tag{5}$$

where U_{near} and U_{far} are the distances to the nearest and farthest object planes. Due to limited depth of field of lens, it is possible to take clear image of the objects which are in between U_{near} and U_{far} only. The remaining objects in the scene will be out of focus. A possible solution to bring clear images of all the objects in the scene is to combine several pictures taken by the camera with different focus points into a composite image. The resulting fused image will contain clear images of all relevant objects in the scene.

3. Higher Density DWT

The higher density DWT is an expansive dyadic wavelet transform that over samples both space and frequency by a factor of two. Like DDWT, at each scale of HDWT, there are twice as many coefficients as the critically sampled DWT. However, HDWT also has intermediate scales; it has one scale between each pair of scales of the critically-sampled DWT. The 'over complete' wavelet basis associated with this expansive transform has two generators, $\psi_i(t)$, i = 1, 2. The spectrum of the first wavelet $\psi_1(\omega)$ is concentrated between the spectrum of the second wavelet $\psi_2(\omega)$ and the spectrum of its dilated version $\psi_2(2\omega)$ In addition, the second wavelet is translated by integer multiples of one half, rather than whole integers. The transform can be implemented with digital filter banks like the conventional DWT as shown in the following figure 2. Similar to DDWT, it uses three filters, one scaling and two wavelet filters. However, one of the wavelet filters is band pass instead of high-pass filters. And also the high pass filter is not down sampled and up sampled during analysis and synthesis. The analysis filter bank structure of HDWT is shown in fig 2. Therefore, the 2-D form of the HDWT is 5-times expansive.

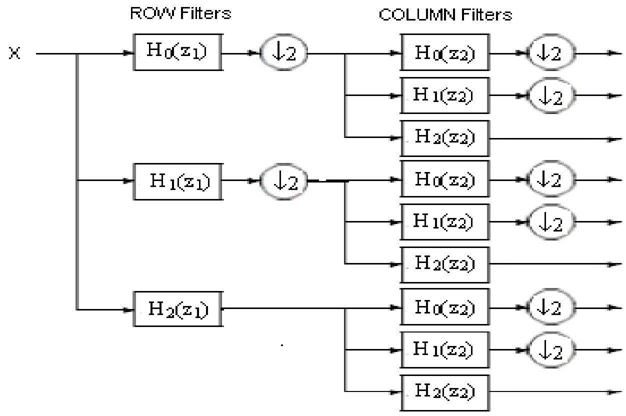

Figure 2: 2D Higher Density Discrete Wavelet Transform

4. Higher Density DWT based Image Fusion

The HDWT based image fusion is taking the following common steps. HDWT is first performed on each source images, and then a fusion decision map is generated based on a set of fusion rules. There will be nine subbands at each stage after HDWT was taken namely LL ,LB, LH, BL, BB, BH, HL, HB, HH, where L stands for 'lowpass', H stands for 'highpass', and B stands for 'bandpass'. The fused wavelet coefficient map can be constructed from the wavelet coefficients of the source images according to the fusion decision map. Finally the fused image is obtained by performing the inverse HDWT.

4.1. *Proposed Methods:*

Method 1: This method uses pixel level activity measure. It takes the average of approximation and diagonal details of source image to form the LL, LB, LH and HL, HB, HH sub band and uses absolute maximum criterion to form the BL, BB and BH sub bands of fused image.
Method 2: This method combines the activity measure at pixel and area level. The approximation sub band of the fused image F is simply acquired by averaging the approximation sub band wavelet coefficients of source images A&B. The detail sub band of the fused image is formed by the detail sub band wavelet coefficients of source images whose gradient value is higher.
Method 3: In this method, the pyramid image using a wavelet transform is created, and then canny edge detector is applied to the lowest resolution approximation sub band of the image. After the edge detection, region segmentation is performed based on the edge information using region labeling algorithm. In the labeled image, zero corresponds to the edges and other different value represents different regions in the image. The activity level of region k in source image 'n', $Al_n(k)$ is given by

$$Al_n(k) = \frac{1}{N_K} \sum_{1 \le j \le N_k} Pj \tag{6}$$

where N_k is the total number of pixels in region k, P_j is the activity intensity of pixel j in region k, which is the absolute value of pixel j in that region. The approximation sub band of the fused image F is taken from the approximation sub band wavelet coefficients of source images whose activity measure in the particular region is high. The detail sub band of the fused image is formed by the detail sub band wavelet coefficients of source images whose gradient value is higher.

5. Experimental Work and Results

The methods proposed for implementing fusion of multi focused images using HDWT take the following form in general. A pair of source images namely Pepsi is taken for study and are assumed to be registered spatially. The images are transformed into wavelet domain by taking HDWT transform. MATLAB codes are written to take the HDWT of the two images. In each sub-band, activity measure of the two images is compared based on the above proposed fusion methods at that particular scale and space. A fused wavelet transform is created by taking pixels from that wavelet transform that shows greater activity at the pixel locations. The inverse HDWT is the fused image with clear focus on the whole image. The performance of HDWT is measured in terms of RMSE, PSNR & QI and the results are tabulated in table I. The results of image fusion using HDWT are shown in figure 3. From the table, it is inferred that the proposed methods for HDWT based image fusion out performs the existing methods due to its directionality and approximate shift invariant.

Table 1. Results of Image Fusion

Measures	Proposed Methods		
	Method1	Method2	Method3
RMSE	3.2859	3.0783	**2.8982**
PSNR	35.3577	35.8774	**36.4166**
QI	0.9974	0.9977	**0.998**

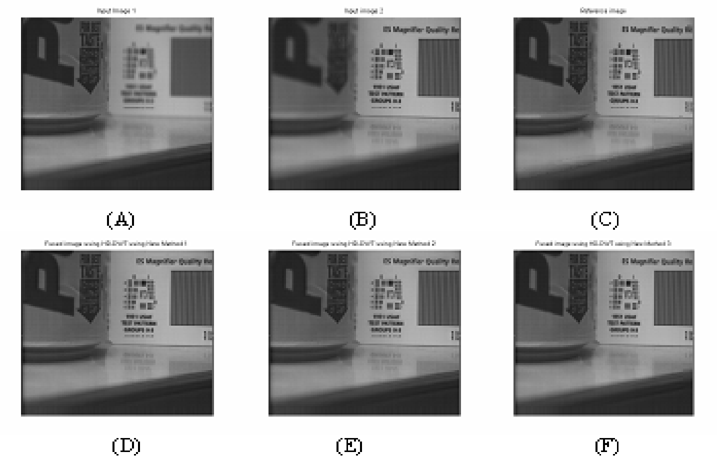

Figure 3: Results of Image Fusion

A, B- Input Images C. Reference Image D,E,F – Fused images using Proposed Methods 1,2,3

6. Conclusions

This paper presents three new methods for fusion of multi focused images using HDWT and their performance is compared in terms of various performance measures like RMSE, PSNR and QI. HDWT provides very good results both quantitatively & qualitatively for fusion of multi focused images due to its improved directionality and preserves geometric structures more faithfully. Hence using these fusion methods, one can enhance the image with high geometric resolution and better visual quality.

References

[1] Burt, P. J. and Kolczynski, R. J, (1993), "Enhanced image capture through image fusion", proceedings
[2] of the 4th International Conference on Computer Vision, pp. 173-182.
[3] Li, H., Manjunath, B.S. and Mitra, S.K., (1995), "Multi-sensor image fusion using the wavelet transform",
[4] Proceedings of the conference on 'Graphical Models and Image Processing', pp. 235–245.
[5] Mallat, S., (1998),Wavelet Tour of Signal Processing, New York, Academic Press.
[6] Selesnick,W.,(2006), " A higher-density discrete wavelet transform", IEEE Trans. on Signal Processing,
[7] 54(8):3039-3048.
[8] Zhang. Z. , and Blum, R., (1999), "A categorization of Multiscale decomposition based image fusion
[9] schemes with a performance study for a digital camera application", proc. of the IEEE, pages 1315-1328,
[10] Zhou Wang and Alan C. Bovik, (2002), "A Universal Image Quality Index", IEEE Signal Processing
[11] Letters, Vol. 9, No.3, pp. 81-84.