

**A Comparative Analysis of Different Multi-focus Image Fusion Techniques**Devang Bhatt¹, Dixesh Patel², Dhara Patel³, Prof. Kalpesh R. Jadav⁴¹ Department of Electronics & Communication Engineering , Parul Institute of Engineering & Technology , Vadodara, Gujarat-391760, India,² Department of Electronics & Communication Engineering , Parul Institute of Engineering & Technology , Vadodara, Gujarat-391760, India,³ Department of Electronics & Communication Engineering , Parul Institute of Engineering & Technology , Vadodara, Gujarat-391760, India,⁴ Department of Electronics & Communication Engineering , Parul Institute of Engineering & Technology , Vadodara, Gujarat-391760, India,

Abstract — This paper presents a review on the different multi focus image fusion techniques. The main application of image fusion in multi-focus cameras to combine information from multiple images of the same scene in order to deliver only the multi focused image. The discrete cosine transforms (DCT) based methods of image fusion are more suitable and time-saving in real-time systems using DCT based standards of still image or video. In this paper an efficient approach for fusion of multi-focus images based on variance calculated in DCT domain is presented. Also effect of varying block size from 8x8, 16x16, 32x32 and so on is analyzed in this paper. The aim is to find the gaps in existing literature and suggesting a suitable method to reduce the gaps of existing techniques.

Keywords- Fusion, DCT, Cross check, Blocks, Variance, Cross check

I. INTRODUCTION

Image fusion is the process of to combine relevant information from two or more images into a single image [1]. The resulting image will contain all the important information as compare to input images. The new image will extracts all the information from source images. Image fusion is a useful technique for merging single sensor and multi-sensor images to enhance the information. The objective of image fusion is to combine information from multiple images in order to produce an image that deliver only the useful information. The discrete cosine transformation (DCT) based methods of image fusion are more suitable and time-saving in real-time systems. In this paper an efficient approach for fusion of multi-focus images is presented which is based on variance calculated in DCT domain.

Image fusion takes place at three different levels i.e. pixel, feature and decision. Pixel level is a low level of fusion which is used to analyze and combine data from different sources before original information is estimated and recognized. Feature level is a middle level of fusion which extract important features from an image like shape, length, edges, segments and direction. Decision level is a high level of fusion which points to actual target. Its methods can be broadly classified into two that is special domain fusion and transform domain fusion. Averaging, Brovery method, Principal Component Analysis (PCA), based methods are special domain methods. But special domain methods produce special distortion in the fused image .This problem can be solved by transform domain approach. The DCT based method will be more efficient for fusion.

The discrete wavelet transform has become a very useful tool for fusion. The images used in image fusion should already be registered. Pixel level fusion technique is used to increase the special resolution of the multi-spectral image. Image fusion is a concept of combining multiple images into composite products, through which more information than that of individual input images can be revealed.

II. LITERATURE SURVEY

There are many methods for image fusion. But we are focusing on the multi-focus image fusion. So far, many researches have concentrated on image fusion performed on the images in the spatial domain [2]-[3]. The algorithms based on multi-scale decompositions are more popular. The basic idea is to perform a multi-scale transform on each source image, and then integrate all these decompositions to produce a composite representation. The fused image is finally reconstructed by performing the inverse multi-scale transform. Examples of this approach include the Laplacian, gradient, or morphological pyramids, and the superior ones, discrete wavelet transform (DWT) [4] and shift invariant discrete wavelet transform (SIDWT) [5] which are treated in literature as standard methods. There is a very good survey found in [6] and [7]. Tang [8] has proposed two image fusion techniques in DCT domain, namely, DCT + Average and DCT + Contrast. Tang has implemented his proposed methods on 8x8 DCT blocks defined in JPEG standard. In DCT + Average, Averaging leads to undesirable side effects including blurring. In DCT + Contrast This algorithm is also

complex in calculating the contrast measure for each coefficient. Furthermore, it suffers from side effects including blocking artifacts. In DCT + Variance technique variance is used as a activity measure. The DCT + Variance + Consistency verification technique used in [9] gives better result than DCT + Variance method. In order to reduce the complication for the real-time applications and also enhance the quality of the output image, an image fusion technique in DCT domain. Here, the variance of 8x8 blocks calculated from DCT coefficients is used as a contrast criterion for the activity measure. Then, a consistency verification (CV) stage increases the quality of output image. Simulation results and comparisons show the considerable improvement in the quality of the output image and reduction of computation complexity.

Discrete cosine transform (DCT) is an important transform extensively used in digital image processing. Large DCT coefficients are concentrated in the low frequency region; hence, it is known to have excellent energy compactness properties . The 2D discrete cosine transform $X(k_1, k_2)$ of an image or 2D signal $x(n_1, n_2)$ of size $N_1 \times N_2$ is defined as:

$$X(k_1, k_2) = \alpha(k_1)\alpha(k_2) \sum_{n_1=0}^{N_1-1} \sum_{n_2=0}^{N_2-1} x(n_1, n_2) \cos\left(\frac{\pi(2n_1+1)k_1}{2N_1}\right) \cos\left(\frac{\pi(2n_2+1)k_2}{2N_2}\right), \quad \begin{matrix} 0 \leq k_1 \leq N_1-1 \\ 0 \leq k_2 \leq N_2-1 \end{matrix} \quad (1)$$

$$\text{Where } \alpha(k_1) = \begin{cases} \frac{1}{\sqrt{N_1}}, & k_1 = 0 \\ \sqrt{\frac{2}{N_1}}, & 1 \leq k_1 \leq N_1-1 \end{cases} \quad \text{and} \quad \alpha(k_2) = \begin{cases} \frac{1}{\sqrt{N_2}}, & k_2 = 0 \\ \sqrt{\frac{2}{N_2}}, & 1 \leq k_2 \leq N_2-1 \end{cases}$$

k_1 and k_2 discrete frequency variables (n_1, n_2) pixel index Similarly, the 2D inverse discrete cosine transform is defined as:

2.1 DCT Based Multi-focus Image fusion methods[1]

Image to be fused are divided into non-overlapping blocks of size $N \times N$ as shown in Fig-2. DCT coefficients are computed for each block and fusion rules are applied to get fused DCT coefficients. IDCT is then applied on the fused coefficients to produce the fused image/block. The procedure is repeated for each block.

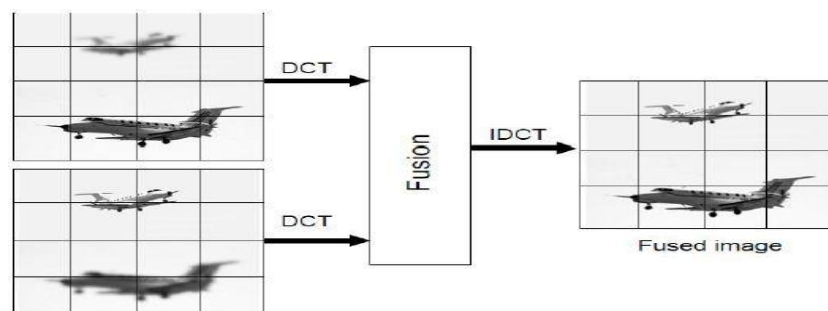


Figure 1 DCT Based Fusion Process

Six different types of image fusion algorithms based on discrete cosine transform (DCT) were developed and their performance was evaluated. Fusion performance is not good while using the algorithms with block size less than 8x8 and also the block size equivalent to the image size itself. These algorithms are very simple and might be suitable for real time applications.

In similar line, contrast based image fusion algorithm in DCT domain has been presented to fuse the out of focus images. Local contrast is measured by 8x8 blocks. However, there is no discussion on the fusion performance by choosing different block sizes. This paper presents six different DCT based image fusion techniques and studies their performance.

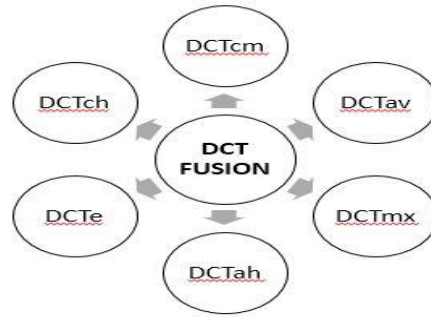


Figure 2 DCT Based Multi-Focus Image Fusion Techniques

DCTav: In this fusion rule, all DCT coefficients from both image blocks are averaged to get fused DCT coefficients. It is very simple and basic image fusion technique in DCT domain.

$$X_f(k_1, k_2) = 0.5 X_1(k_1, k_2) + X_2(k_1, k_2)$$

Where $k_1, k_2 = 0, 1, 2, \dots, N-1$

(2)

DCTma: The DC components from both image blocks are averaged. The largest magnitude AC coefficients are chosen, since the detailed coefficients correspond to sharper brightness changes in the images such as edges and object boundaries etc. These coefficients are fluctuating around zero.

$$X_f(0, 0) = 0.5 X_1(0, 0) + X_2(0, 0)$$

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & |X_1(k_1, k_2)| \geq |X_2(k_1, k_2)| \\ X_2(k_1, k_2) & |X_1(k_1, k_2)| < |X_2(k_1, k_2)| \end{cases}$$

Where $k_1, k_2 = 1, 2, 3, \dots, N-1$

(3)

DCTah: The lowest AC components including DC coefficients are averaged and the remaining AC coefficients are chosen based on largest magnitude.

$$X_f(k_1, k_2) = 0.5 X_1(k_1, k_2) + X_2(k_1, k_2)$$

Where $k_1, k_2 = 0, 1, 2, \dots, 0.5N-1$

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & |X_1(k_1, k_2)| \geq |X_2(k_1, k_2)| \\ X_2(k_1, k_2) & |X_1(k_1, k_2)| < |X_2(k_1, k_2)| \end{cases}$$

Where $k_1, k_2 = 0.5N, 0.5N+1, 0.5N+2, \dots, N-1$

(4)

DCTcm: The DC coefficients are averaged and the AC coefficients are chosen based on largest contrast measure.

$$X_f(0, 0) = 0.5 X_1(0, 0) + X_2(0, 0)$$

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & C_1(k_1, k_2) \geq C_2(k_1, k_2) \\ X_2(k_1, k_2) & C_1(k_1, k_2) < C_2(k_1, k_2) \end{cases}$$

Where $k_1, k_2 = 1, 2, 3, \dots, N-1$

(5)

DCTch: It is very much similar to DCTah. The lowest AC components including DC coefficients are averaged and the remaining AC coefficients are chosen based on largest contrast measure.

$$X_f(k_1, k_2) = 0.5 X_1(k_1, k_2) + X_2(k_1, k_2)$$

Where $k_1, k_2 = 0, 1, 2, \dots, 0.5N-1$

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & C_1(k_1, k_2) \geq C_2(k_1, k_2) \\ X_2(k_1, k_2) & C_1(k_1, k_2) < C_2(k_1, k_2) \end{cases}$$

Where $k_1, k_2 = 0.5N, 0.5N+1, 0.5N+2, \dots, N-1$

(6)

DCTe: It is similar to DCTcm. DC components are averaged together. AC coefficients correspond to the frequency band having largest energy is chosen.

$$X_f(0,0) = 0.5 X_1(0,0) + X_2(0,0)$$

$$X_f(k_1, k_2) = \begin{cases} X_1(k_1, k_2) & E_{j1} \geq E_{j2} \\ X_2(k_1, k_2) & E_{j1} < E_{j2} \end{cases}$$

Where $k_1, k_2 = 1, 2, 3, \dots, N-1$ and $j = k_1 + k_2$

(7)

2.2 Variance Based Image Fusion in DCT Domain[9]

In multi-focus images, the focused area is more informative. This information is behind the details of that region which is corresponding to the high variance. Variance value is usually assumed as a contrast criterion in image processing applications. It is shown that the calculation of variance in DCT domain is very easy. Therefore, we can use the variance value as the activity level of the 8×8 blocks of the source images. Fig. 4 illustrates the general framework of a JPEG encoder combining with image fusion for VSN. Here, for simplicity, we consider the processing of just two source images A and B, but the algorithm can be extended straightforwardly for more than two source images. Moreover, it is assumed that the source images were registered. As Fig. 4 shows, after dividing the source images into 8×8 blocks and calculating the DCT coefficients for each block, the fusion algorithm is performed. Here the variances of the corresponding blocks from source images are calculated by equation as the activity measures. Then, the block with high activity level is selected as the appropriate one for the fused image. Finally, the DCT presentation of the fused image is made up of blocks with the larger variances that are from source image either A or B.

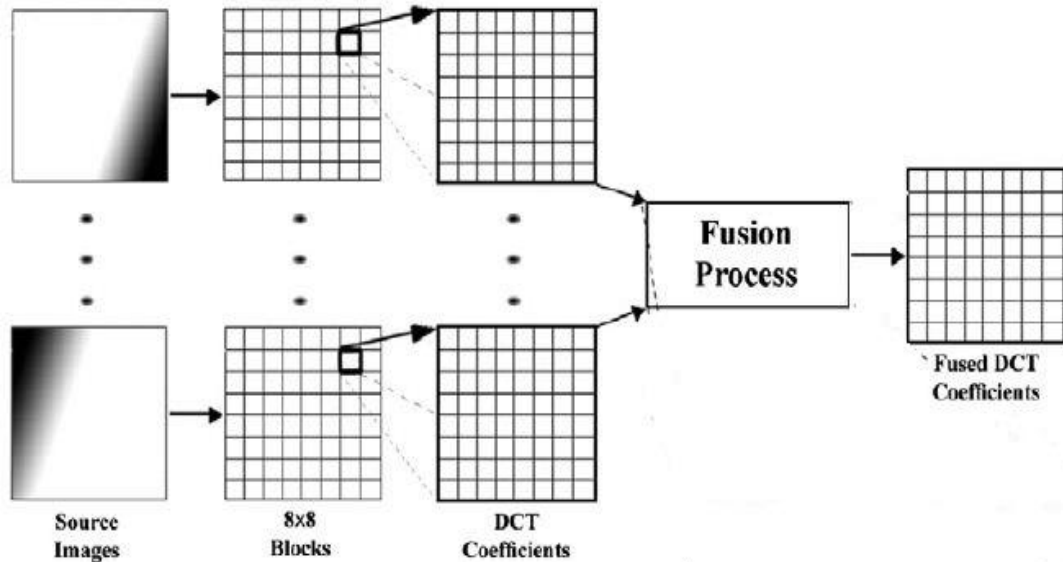


Figure 3 DCT Variance

Two-dimensional DCT transform of an $N \times N$ block of an image $x(m,n)$ is defined as:

$$d(k,l) = \frac{2\alpha(k)\alpha(l)}{N} \times \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} x(m,n) \times \cos\left[\frac{(2m+1)\pi k}{2N}\right] \times \cos\left[\frac{(2n+1)\pi l}{2N}\right]$$

where $k, l = 0, 1, \dots, N-1$ and

$$\alpha(k) = \begin{cases} \frac{1}{\sqrt{2}} & , \text{ if } k = 0 \\ 1 & , \text{ otherwise} \end{cases}$$

The inverse DCT (IDCT) is also defined as:

(8)

$$x(m,n) = \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} \frac{2\alpha(k)\alpha(l)}{N} \times d(k,l) \times \cos\left[\frac{(2m+1)\pi k}{2N}\right] \times \cos\left[\frac{(2n+1)\pi l}{2N}\right]$$

where $m,n=0,1,\dots,N-1$. (9)

$d(0,0)$ is the DC coefficient and the other $d(k,l)$ s are the AC coefficients of the block. The normalized transform coefficients $\hat{d}(k,l)$ s are defined as below:

$$\hat{d}(k,l) = \frac{d(k,l)}{N} \quad (10)$$

Mean value, μ , and variance, σ^2 , of an $N \times N$ block in the spatial domain are calculated as:

$$\mu = \frac{1}{N^2} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} x(m,n)$$

$$\sigma^2 = \frac{1}{N^2} \sum_{m=0}^{N-1} \sum_{n=0}^{N-1} x^2(m,n) - \mu^2 \quad (11)$$

The variance of an $N \times N$ block of pixels can be exactly calculated from its DCT coefficients by sum of the squared normalized AC coefficient of the DCT block as:

$$\sigma^2 = \sum_{k=0}^{N-1} \sum_{l=0}^{N-1} \frac{d^2(k,l)}{N^2} - \hat{d}^2(0,0) \quad (12)$$

2.3 Consistency Verification Method[9]

Assume a region in the scene including several blocks that is only in the depth of focus of image A. Following the above mentioned process, all the blocks in this region must be chosen from image A. However, there may be some errors that can lead to erroneous selection of some blocks from image B. This defect can be solved with a consistency verification procedure. The defective decision map is demonstrated in Fig. 3 introduced a majority filter that can be used for consistency verification. If the center block comes from source image B while the majority of the surrounding blocks come from source image A, the center sample is switched to source image A. The fused image is finally obtained based on the modified decision map. Here, consistency verification is applied in a 3×3 neighborhood window. If the window size increases, the quality of the output image obviously will raise at the expense of complexity increase. But instead of using a 5×5 window and considering 24 items, using a 3×3 window for two consequential times and considering a total of 16 items, will be more efficient in both quality and complexity.

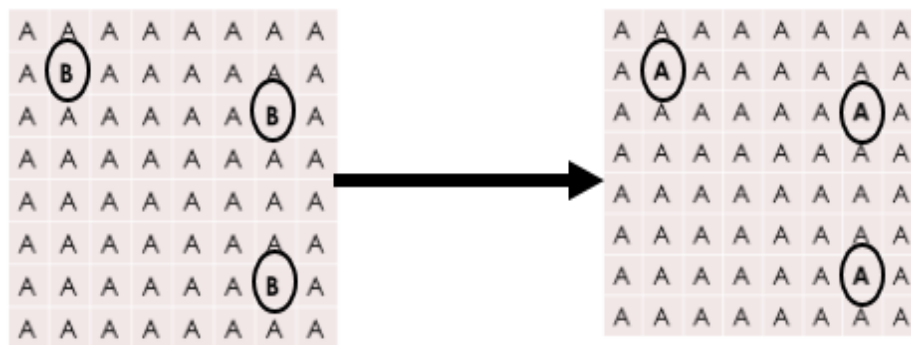


Figure 4 Consistency verification

III. RESULT ANALYSIS

Table 1 PSNR Comparison of different Fusion methods

Fusion Method	Block size		
	8x8	16x16	32x32
DCTav	25.4546	25.4546	25.4546
DCTah	25.4723	25.2325	25.1824
DCTch	25.6567	25.4832	25.4232
DCTmx	27.3428	28.3287	29.4543
DCTe	27.7465	28.6489	29.7765
DCTcm	28.4023	28.6745	29.8971
DCT + Variance	32.5453	32.6453	32.7521
DCT + Variance + CV	34.3865	34.4523	34.7865

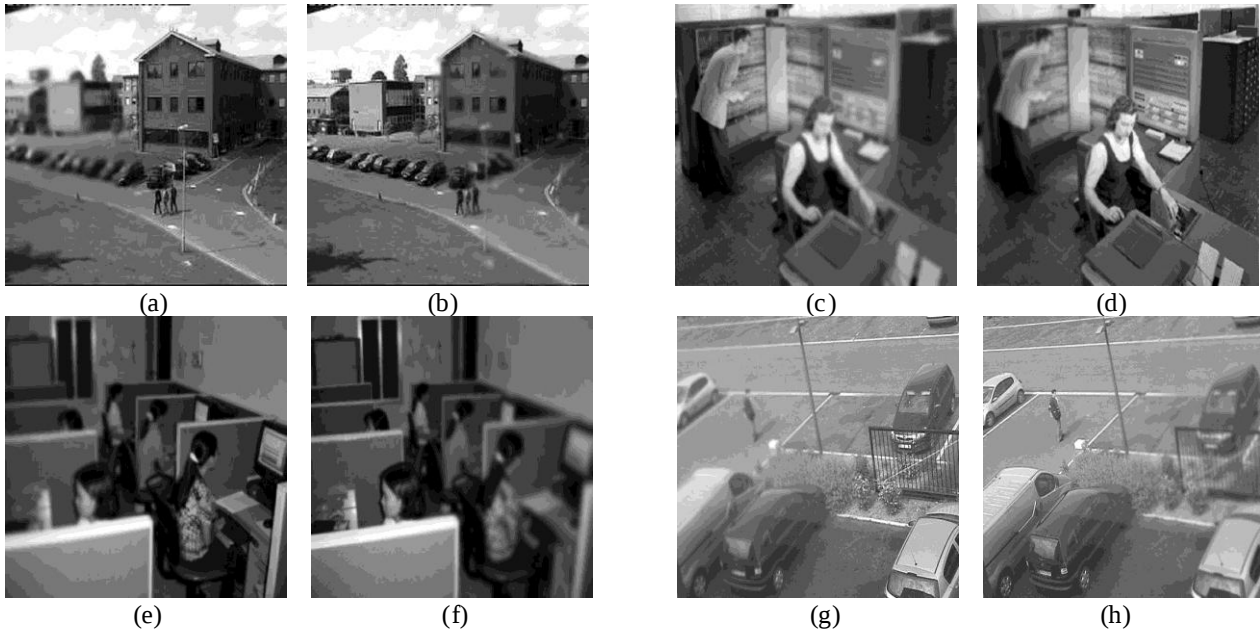


Figure 5 (a)(b),(c)(d),(e)(f),(g)(h) are the set of multi-focus low resolution(256x256) images



(w)



(x)



(y)



(z)

Figure 6 (w)(x)(y)(z) are DCT + VAR + CV fused Images

IV. CONCLUSION

In this paper eight different types of image fusion algorithms based on discrete cosine transform (DCT) were described and compared. Fusion performance is not good while using the algorithms with block size less than 8x8 and also the block size equivalent to the image size itself. DCTe and DCTmx based image fusion algorithms performed well and these algorithms are very suitable for real time applications. The performance of variance based methods are better than other six method and for real time fusion application DCT + Variance + CV fusion method gives the best result with higher block size.

REFERENCES

- [1] VPS Naidu, "Discrete Cosine Transform based Image Fusion Techniques", Journal of Communication, Navigation and Signal Processing, Vol. 1, No. 1, pp. 35-45, 2012
- [2] 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, 2007.
- [3] M. H. Arif and S. S. Shah, "Block Level Multi-Focus Image Fusion using Wavelet Transform," Proceeding of IEEE International Conference on Signal Acquisition and Processing (ICSAP), pp. 213 – 216, April 2009.
- [4] H. Li, B. Manjunath and S. Mitra, "Multi sensor Image Fusion Using the Wavelet Transform," Graphical Models Image Processing, vol. 57, no.3, pp. 235 – 245, May 1995.
- [5] O. Rockinger, "Image sequence fusion using a shift-invariant wavelet transform," Proceedings of IEEE International Conference on Image Processing, vol. 3, pp. 288 – 291, 1997.
- [6] R. S. Blum, and Z. Liu, "Multi-sensor image fusion and its applications", CRC Press, Taylor & Francis Group, 2006.

- [7] A. Goshtasby, and S. Nikolov, "Image fusion: Advances in the state of the art," Information Fusion, vol. 8, no. 2, pp. 114 – 118, April 2007.
- [8] J. Tang, "A contrast based image fusion technique in the DCT domain," Digital Signal Processing, vol. 14,no. 3, pp. 218 – 226, 2004.
- [9] Mohammad Bagher ,Akbari Haghighat, Ali Aghagolzadeh, HadiSeyedarabi, " Multi-focus image fusion for visual sensor networks in DCT domain", Elsevier(Springer) , Computers and Electrical Engineering 37, 789–797,2011