

# Evaluating the performance of integrated DCT and PCA based image fusion for multifocus images

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**Abstract-** The main objective of vision fusion is to collect information from more than two images of the same view in order to capture only the useful information. The principal component averaging based techniques of vision fusion are more proficient and time-saving in real-time systems using PCA based standards of still images. In this paper, a suitable approach is proposed in which multi-focus images based on variance calculated in PCA domain are fused to obtain the final image. This paper proposes a new technique which integrates the higher valued Alternating Current coefficients calculated in discrete cosine transform domain based fusion with illuminate normalization to reduce the artifacts which gets introduced due to the transform domain method. The fusion process may degrades the sharpness of the edges in the digital images so to overcome this problem fuzzy based enhancement has been integrated with proposed algorithm to improve the results further.

**Keywords:** Image fusion, DCT, PCA.

## I. INTRODUCTION

A wide variety of imaging sensors are available, but it is impossible to capture an image that embraces all prominent features with the help of only one sensor. To create a more comprehensive synthetic image for a view, fusing multiple images is still important. Image fusion process is mainly performed

Ellmauthaleret et al. [3] described a novel UWT-based pixel-level image fusion approach. It

at different levels of information representation: pixel, feature, and decision levels. In pixel level fusion, fused pixels are derived from the original pixel information of the source images. The pixel level fusion is viewed as low level fusion. Fusion at feature level is based on the extracted features such as shape, edges, and textures. The decision level fusion correspondingly deals with the decisions from several experts, which is regarded as the high level fusion [1].

Medical image fusion encompasses a diversity of techniques from image fusion and acquires general information from these techniques to depict medical problems reflected through images of human body, organs, and cells. There is an increasing interest and use of the imaging technologies in the area of medical diagnostics, analysis and historical documentation. Since computer aided imaging methods allow a quantitative judgment of the images under assessment, it helps to progress the effectiveness of the medical practitioners in arriving at an unbiased and objective resolution in a very short time. Additionally, the use of multi-sensor and multi-source image fusion techniques present a greater diversity of the qualities used for the medical analysis applications; this often leads to robust information processing that can disclose information that is otherwise imperceptible to human eye. The more information acquired from the fused images can be well exploited for more accurate localization of abnormalities [2].

successfully improves fusion results for images exhibiting features at nearby located or coincident

pixel locations - conditions commonly but not exclusively found in multi-sensor imagery. This leads to a better conservation of features which are located close to each other in the input images. Jang et al. [4] proposed a pixel-level multisensor image fusion algorithm to create a contrast-enhanced fused image while preserving visually salient information carried in source images.. In order to integrate visually salient information effectively, a fusion strategy is proposed that reflects the characteristics of SD retinex outputs well and overcomes the limitations of pixel-based fusion approaches. Haghighat et al. [5] has studied that the objective of vision fusion is to merge information from many images of the same view in order to convey only the useful information and proposed an approach for multi-focus image fusion based on variance calculated in discrete cosine transform domain. Lui et al. [6] has discussed that vision fusion is a very main step for vision mosaic. An adaptive weighted coefficients algorithm for vision fusion has been proposed. Adaptive weighted coefficients algorithm can arrange weighted coefficients adaptively in correspondence to the changes of the variety and shape of the overlapping regions. Cao et al. [7] has proposed multi focus noisy vision fusion algorithm using the contour let transform. Utilizing the confined directional information by the contour let transform, the directional windows are used to examine the fusion weight. Pei et al. [8] has discussed improved discrete wavelet based can efficiently mixture the useful information of the each source vision retrieved from the multi sensor. It can mixture the two or more images into one image which is more accurate and reliable. Tao et al [9] has proposed a new discrete wavelet algorithm of choosing high frequency coefficients, the regional edge intensities of every sub-division are calculated to realize adaptive fusion. Patil et al. [10] has proposed vision fusion algorithm using hierarchical PCA. Hierarchical multiscale and multiresolution vision processing methods, pyramid disintegration are the basis for the majority of vision fusion algorithms. Haozhang et al. [11] vision fusion is one of the important embranchments of data fusion. Its use is to mixture multi-vision information in one view to one image which is more suitable to human image and computer vision or more adapt to further vision processing, such as target

### ***B. DCT Method***

DCT method is efficient in performing image fusion for Joint Phtographic Experts Group (JPEG) format

identification. Mohamad et al. [12] studied vision fusion is a technique which merges the data from two or more source images from the same view to generate one single vision containing more precise details of the view than any of the source images. This method addresses these issues in vision fusion. Lavanya et al. [13] proposed a new vision fusion scheme using wavelet combined IHS and PCA transformations for remotely sensed lunar vision data in order to extract features correctly. Albuquerque et al. [14] has discussed that it is impossible to get a clear basis in all regions simultaneously. So there are two vision fusion algorithms in the frequency domain that are based on focus- DCT and spatial frequency which divides image into blocks.

## **II. IMAGE FUSION TECHNIQUES**

Two of the commonly used image fusion techniques are:

### ***A. PCA Method***

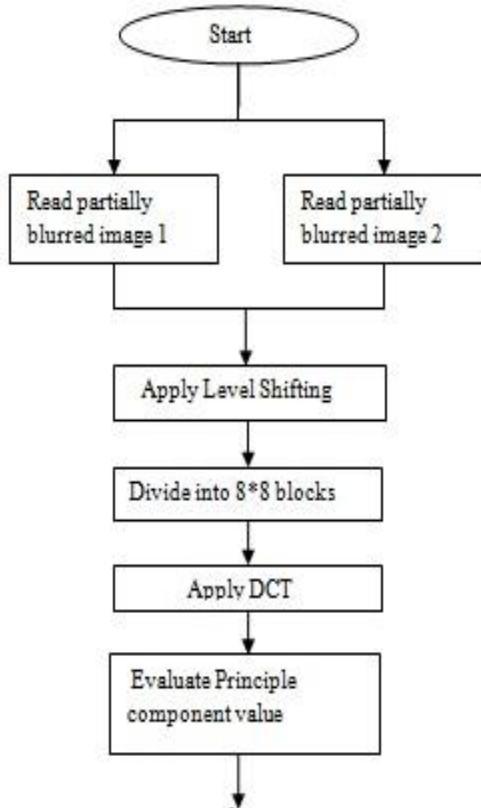
Principal component analysis provides a powerful tool for data analysis and pattern recognition which is used in image processing as a technique for data dimension reduction. Principal component analysis is appropriate when you have obtained measures on a number of observed variables and wish to develop a smaller number of artificial variables (called principal components) that will account for most of the variance in the experimental variables. The PCA involve a mathematical formula that transforms a number of correlated variables into a number of uncorrelated variables called principal components [15]. The PCA is used extensively in image classification and image compression. It computes a compact and optimal depiction of the data set. The first principal component gives description for as much of the variance in the data as possible. First principal component is taken along the way with the maximum variance. The proceeding component i.e. second principal component points the direction of maximum variance as perpendicular to the first. The third principal component is taken along the direction of maximum variance in the subspace upright to the first two and so on [16].

type images. To perform the JPEG coding, an image is first sub-divided into blocks of 8x8 pixels [17]. The

Discrete Cosine Transform (DCT) is then executed on every block. This generates 63 ac coefficients then the

fusion rule is applied where in the transformed block with more number of higher valued AC coefficients is

### III. PROPOSED METHODOLOGY



absorbed into the fused image. Higher the value of AC coefficients implies finer image information. From these coefficients, then variance is calculated and high values variance values are fused in the final image [18].

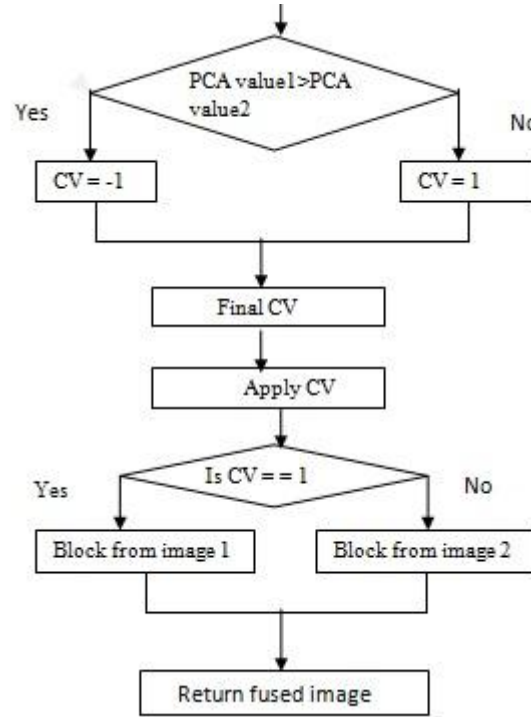


Fig 1: Flow chart of proposed technique

### IV. PROPOSED ALGORITHM

Steps of the algorithm:

1. First of all two images which are partially blurred are passed to the system.
2. Apply level shifting by 8 to them.
3. Divide images into 8\*8 blocks.
4. Now apply DCT.
5. DCT transform of an N\*N image block f(x,y) is given by:

$$F(u,v) = \frac{2}{N} c(u)c(v) \sum_{y=0}^{N-1} \sum_{x=0}^{N-1} f(x,y) \cos\left[\frac{(2x+1)u\pi}{2N}\right] * \cos\left[\frac{(2y+1)v\pi}{2N}\right]$$

(a) Extract AC coefficients from both images.

(b) Initialize  $C_n^t = 0$ , where  $C_n^t$  represents number of maximum valued ac coefficient found in a particular block.

6. Evaluate principle component value, i.e. maximum ac value.
7. Check for consistency verification value.
8. Apply consistency verification.
9. If  $CV = -1$ ,

- Take block from image 1
- Else  $CV = 1$
- Take block from image 2
10. Return fused image.

## V. RESULTS AND DISCUSSIONS

Input and partially blurred images of Lena, traffic and lake has been considered and outputs for three

images have been evaluated. The proposed method shows better results.



Fig 2: Input Image of Lena

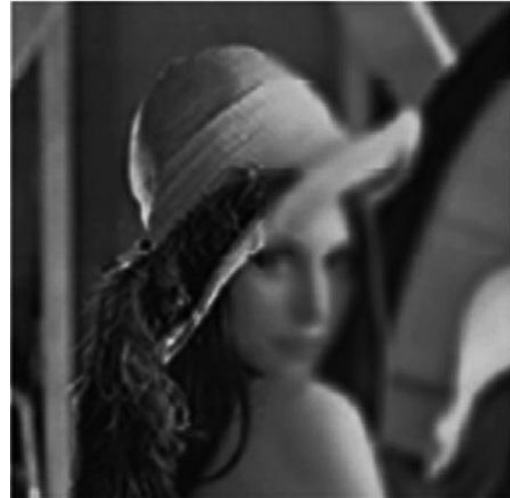


Fig4: Right partially blurred image of Lena



Fig 3: Left partially blurred image of Lena

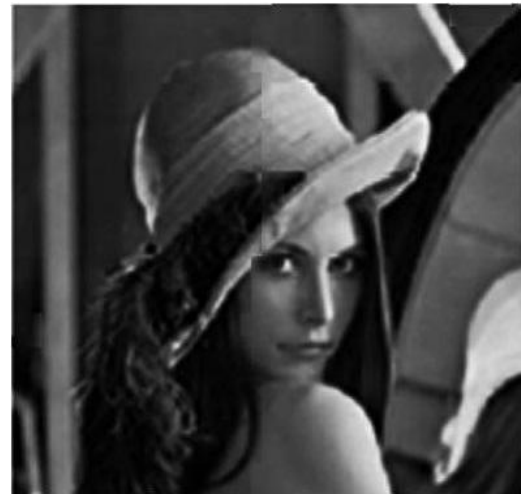


Fig5: Output of proposed technique.



Fig 6: Input image of traffic



Fig 9: Output of proposed method



Fig 7: Left partially blurred image of traffic



Fig 10: Input Image of Lake



Fig 8: Right partially blurred image of traffic



Fig 11: Left partially blurred image of lake



Fig 12: Right partially blurred image of lake



Fig 13: Output of proposed method

Table 1: The MSE, PSNR and MSSIM comparison of various image fusion approaches on reference images.

Fusion method	Lena			Traffic			Lake		
	MSE	PSNR(db)	MSSIM	MSE	PSNR(db)	MSSIM	MSE	PSNR(db)	MSSIM
DCT+Average	39.11	32.20	0.9383	112.6	27.62	0.8997	145.43	26.50	0.8343
DCT+Variance	8.90	38.73	0.9854	4.2	41.89	0.9920	13.64	36.78	0.9849
DCT+Variance+CV	1.88	45.38	0.9982	0.797	49.12	0.9997	0.297	53.40	0.9999
DWT with DBSS(2,2)	5.62	40.63	0.9906	12.81	37.05	0.9901	14.58	36.49	0.9836
SIDWT with Haar	5.48	40.74	0.9899	10.33	37.99	0.9905	33.67	32.86	0.9759
Proposed(PCA+DCT)	0.933	48.4318	0.9520	0.116	57.4777	0.9110	0.330	52.9404	0.9466

From the table, it is clear that proposed DCT-PCA method gives better results in comparison to some existing methods. Proposed method has high peak

## VI. PERFORMANCE EVALUATION

### A. Mean square error (MSE)

In image processing mean square error is the most general measure for performance measurement of the existing method and the coded images. It is computed by using equation.

$$MSE = \frac{1}{mn} \sum_{i=1}^m \sum_{j=1}^n (A_{ij} - B_{ij})^2 \quad \dots (6.1)$$

signal to noise ratio value as compared to others and also lesser mean square error.

Where  $A_{ij}$  and  $B_{ij}$  are the image pixel value of reference image and fused image respectively.

Table 1 shows the comparison of various techniques and proposed technique in terms of mean square error. From the table it is clear that as MSE of proposed is less as compared to other methods, therefore the proposed technique performs effectively as compared to others.

### B. Peak signal to noise ratio (PSNR)

The PSNR block calculates the peak signal-to-noise ratio, between two images. As a quality measurement between the original and a fused image, PSNR ratio is used. The higher the PSNR shows the better the quality of the fused or reconstructed image. PSNR value is computed by following equation:

$$PSNR = 10 \log_{10} \left( \frac{255^2}{MSE} \right) \quad \dots (6.2)$$

Table 1 shows the comparison of existing and proposed technique in terms of peak signal to noise ratio. From the table it is clear that as PSNR of proposed is more as compared to existing techniques, therefore the proposed technique performs effectively.

### C. Mean structural similarity index (SSIM)

## VII. CONCLUSION AND FUTURE WORK

In this paper, a new method which integrate the higher valued Alternating Current (AC) coefficients calculated in discrete cosine transform domain based fusion with illuminate normalization and fuzzy enhancement to decrease the artifacts has been introduced due to the transform based method. Also variance is calculated using PCA method. As the fusion process may degrades the roughness of the edges in the digital images so to overcome this problem fuzzy based enhancement has been used to improve the results further. The design and implementation has been done in MATLAB. To do the performance analysis dissimilar metrics has been considered in this paper. The performance of vision fusion has usually been evaluated in terms of accuracy, PSNR and speed etc. From the comparison, it has been proved that proposed technique performs much better as compared to existing algorithm.

## REFERENCES

- [1] Xiaoyan Luo, Jun Zhang, Qionghai Dai "A regional image fusion based on similarity characteristics" Signal Processing 92 (2012) 1268–1280 Volume 92 Issue 5.
- [2] Alex Pappachen James, Belur V. Dasarathy "Medical image fusion: A survey of the state of the art" Information Fusion 19 (2014) 4–19 volume 19.

The structural similarity measure, as a quality criterion issued for objective evaluation of fused image. The general form of metric that is issued to measure the structural similarity between reference image and fused image. The average of the SSIM values across the image (mean SSIM or MSSIM) gives the final quality measure.

$$MSSIM(x_i, y) = \frac{1}{L} \sum_{s=1}^L [SSIM(x_s, y_s)] \quad \dots (6.3)$$

$x_i$  and  $y$  are the one of the input images and fused image respectively.

$x_s, y_s$  = Contents of image at the  $s_{th}$  local window

where,  $L$  = Number of local windows in the image.

[3] Andreas Ellmauthaler, Carla L. Pagliari, Eduardo A. B. da Silva "Multiscale Image Fusion Using the Undecimated Wavelet Transform with Spectral Factorization and Nonorthogonal Filter Banks" IEEE transaction on image processing, vol. 22, no. 3, march 2013.

[4] Jae Ho Jang, Jae Ho Jang, Jong Beom Ra "Contrast-Enhanced Fusion of Multisensor Images Using Subband-Decomposed Multiscale Retinex" IEEE transaction on image processing, vol. 21, no. 8, august 2012.

[5] Haghightat, Mohammad Bagher Akbari, Ali Aghagholzadeh, and Hadi Seyedarabi. "Real-time fusion of multi-focus images for visual sensor networks." In Machine Vision and Image Processing (MVIP), 2010 6th Iranian, pp. 1-6. IEEE, 2010.

[6] Liu, Haifeng, Mike Deng, Chuangbai Xiao, and Xiao Xu. "Image fusion algorithm {based on|centered on|predicated on} adaptive weighted coefficients." In Signal Processing (ICSP), 2010 IEEE 10th International Conference on, pp. 748-751. IEEE, 2010.

[7] Cao, Jian-zhong, Zuo-feng Zhou, Hao Wang, and Weihua Liu. "Multifocus Noisy Image Fusion Algorithm {Using the|Utilizing the|Utilising the} Contourlet Transform." In Multimedia Technology (ICMT), 2010 International Conference on, pp. 1-4. IEEE, 2010.

[8] Pei, Yijian, et al. "The improved wavelet transform based image fusion algorithm and the standard assessment." Image and Signal Processing (CISP), 2010 3rd International Congress on. Vol. 1. IEEE, 2010.

[9] Tao, Ling, and Zhi-Yu Qian. "A better medical image fusion algorithm centered on wavelet transforms." *Natural Computation (ICNC), 2011 Seventh International Conference on*. Vol. 1. IEEE, 2011.

[10] Patil, Ujwala, and Uma Mudengudi. "Image fusion using hierarchical PCA." In *Image Information Processing (ICIIP), 2011 International Conference on*, pp. 1-6. IEEE, 2011.

[11] Ren, Haozheng, Yihua Lan, and Yong Zhang. "Research of multi-focus image fusion predicated on M-band multi-wavelet transformation." In *Advanced Computational Intelligence (IWACI), 2011 Fourth International Workshop on*, pp. 395-398. IEEE, 2011.

[12] Mohamed, M. A., and B. M. El-Den. "Implementation of image fusion procedures for multi-focus images using FPGA." In *Radio Science Conference (NRSC), 2011 28th National*, pp. 1-11. IEEE, 2011.

[13] Lavanya, A., K. Vani, S. Sanjeevi, and R. S. Kumar. "Image fusion of the multi-sensor lunar image data using wavelet combined transformation." In *Recent Trends in Information Technology (ICRTIT), 2011 International Conference on*, pp. 920-925. IEEE, 2011.

[14] Albuquerque, Hugo R., Tsang Ing Ren, and George DC Cavalcanti. "Image Fusion Combining Frequency Domain Techniques Centered on Focus." *Tools with Artificial Intelligence (ICTAI), 2012 IEEE 24th International Conference on*. Vol. 1. IEEE, 2012.

[15] Parmar, K., & Kher, R. (2012, May). A comparative analysis of multimodality medical image fusion methods. In *Modelling Symposium (AMS), 2012 Sixth Asia* (pp. 93-97). IEEE.

[16] R. Vijayarajan, S. Muttan "Iterative block level principal component averaging medical image fusion" *Optik* 125 (2014) 4751–4757.

[17] Desale, Rajenda Pandit, and Sarita V. Verma. "Study and analysis of PCA, DCT & DWT based image fusion techniques." In *Signal Processing Image Processing & Pattern Recognition (ICSIPR), 2013 International Conference on*, pp. 66-69. IEEE, 2013 Volume 114 – Number 4.

[18] Phamila, Y., and R. Amutha. "Discrete Cosine Transform based fusion of multi-focus images for visual sensor networks." *Signal Processing* 95 (2014): 161-170.

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