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Image Quality Enhancement Based on Fusion in Dual-tree Complex Wavelet Transform

Vinay Kumar Tiwari
M.Tech (IT) Student, Saroj Institute of Technology & Management, Lucknow, Uttar Pradesh, India

Saurabh Tiwari
Assistant Professor, Saroj Institute of Technology & Management, Lucknow, Uttar Pradesh, India

Abstract: Today, many applications are required a good quality of image. Many similar images which are degraded by blurring can be enhanced and further used for various purposes such as medical examination, analysis of geographic images and so on. With this motivation, a scheme is proposed to enhance the quality of two input images which are degraded by blurring. To enhance the image, a fusion method is proposed using dual tree wavelet transform, DCT and PCA. For result analysis, proposed scheme is verified using mean square error and PSNR. A comparison is also performed to verify the performance of proposed scheme. From experimental evaluation, it was observed that proposed scheme is giving better results in compare to some of recent existing schemes.

Keywords: Wavelet Transform; image fusion; Dual-tree complex wavelet transform.

I. INTRODUCTION

In the last decade significant growth is achieved in current image processing systems, mainly due to the increased variety of image acquisition techniques and because of this image fusion algorithm is a prime focus for researchers. Image fusion is a procedure that aims at the integration of disparate and complementary data to enhance the information present in the source images as well as to increase the reliability of the interpretation. This process leads to more accurate data interpretation and utility. A fusion process is nothing but a combination of salient information in order to synthesize an image with more information than individual image and synthesized image is more suitable for visual perception. We use the term image fusion to denote a process by which multiple images or information from multiple images is combined. These images may be obtained from different types of sensors. With the availability of the multisensor data in many fields, such as remote sensing, medical imaging or machine vision, image fusion has emerged as a promising and important research area.

A hierarchical image merging scheme based on multi resolution contrast decomposition (the ratio of a low-pass pyramid). The composite images produced by this scheme preserve those details from the input images that are most relevant to visual perception. The method is tested by merging parallel registered thermal and visual images. The results show that the fused images present a more detailed representation of the depicted scene. Detection, recognition, and search tasks may therefore benefit from this new image representation proposed by **[1].**

In [2-5] introduced a novel design for personal authentication and for vehicle security using fusion system. Wavelet transform is used for feature point extraction using HAAR mother wavelet. The attracting feature of HAAR transform includes fast implementation and able to analyze the local features. The authors have presented hardware implementation of finger vein recognition system for vehicle security application, a vehicle set up consist of embedded main board module which has AT89C51 microcontroller and communication module consisting of LCD display, alarm and GSM. Purpose of this module is to alert the authorized vehicle user.

In [6-8] proposed a real-time embedded fusion system for authentication on mobile devices. The system is implemented on a DSP platform. The results proved that the system has low computational complexity and low power consumption, thus qualified for authentication on mobile devices. In [9] proposed an embedded system implementation of fusion on FPGA. The system is prototyped on Altera Stratix-II FPGA hardware board with Nios2- Linux operating system running at 100 MHz. In this authentication system, feature extraction is based on minutiae extracted from vein pattern images while biometric matching is based on modified Hausdorff distance technique. The system gives high performance and optimum accuracy by an embedded system implementation on FPGA. In [10], they provided a method for evaluating the performance of image fusion algorithms. We define a set of measures of effectiveness for comparative performance analysis and then use them on the output of a number of fusion algorithms that have been applied to a set of real passive infrared (IR) and visible band imagery.

In [11], work presents a model to support medical diagnosis through the fusion of abnormality/normality in medical brain images, in order to help to specialist as a previous step in the brain pathology, radio graphical and clinical diagnosis. First, GLCM is used to extract texture features from arbitrary shaped regions which is use FCC separated from an image after segmentation to increase the system effectiveness. Using median filter as preprocessing step and then segmentation on region based. To speed up retrieval and similarity computation with the help of SVM classifier, the database images are segmented and the extracted regions are clustered according to their feature vectors. To further increase the retrieval accuracy of the system, combine the region based features extracted from image regions, with global feature extracted from the whole image, which are shape using FCC and texture using GLCM. The proposed system is better than the other existing system, and gives better retrieval results in terms of precision, recall and accuracy. In [12], the actual image is separated from its background and it computes threshold for every pixel. This method converts grayscale image into binary i.e. image with only black or white colors. The most essential thresholding operation will be the selection of a single threshold value. All the grey levels below this value are classified as black i.e. 0, and those above white as 1.

With the motivation from existing methods, the proposed scheme is designed to get the enhanced image from degraded images. This paper has the following structure: section 2 is about wavelet transform, section 3 gives information on the proposed algorithm employed for the fusion process, section 4 represents the results and discussion and section 5 concluded the paper.

II. DUAL TREE COMPLEX WAVELET TRANSFORM

For the DWT small changes in the input may cause large changes in the wavelet coefficients. Furthermore aliasing occurs due to downsampling. Inverse DWT cancels this aliasing provided if the wavelet and scaling coefficients are not changed. The other disadvantage of DWT is its poor directional selectivity (e.g., inability to distinguish between +45° and −45° spectral features).

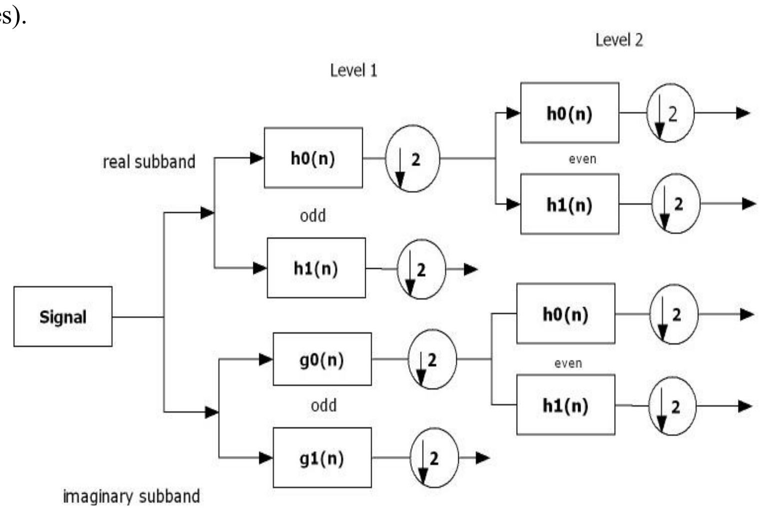

Figure.1. DT- CWT working principle for 1D signal

These problems of Real DWT can be solved using complex wavelets. However, a further problem arises in achieving perfect reconstruction for complex wavelet decomposition beyond level 1. To overcome this, Kingsbury proposed the DTCWT, which allows perfect reconstruction while still providing the other advantages of complex wavelets [13]. DT-CWT provides N multi scales, can be implemented using separable efficient Filter Banks as shown in Fig.1. Here two sets of Filter banks are used, consists of low pass and high pass filters.

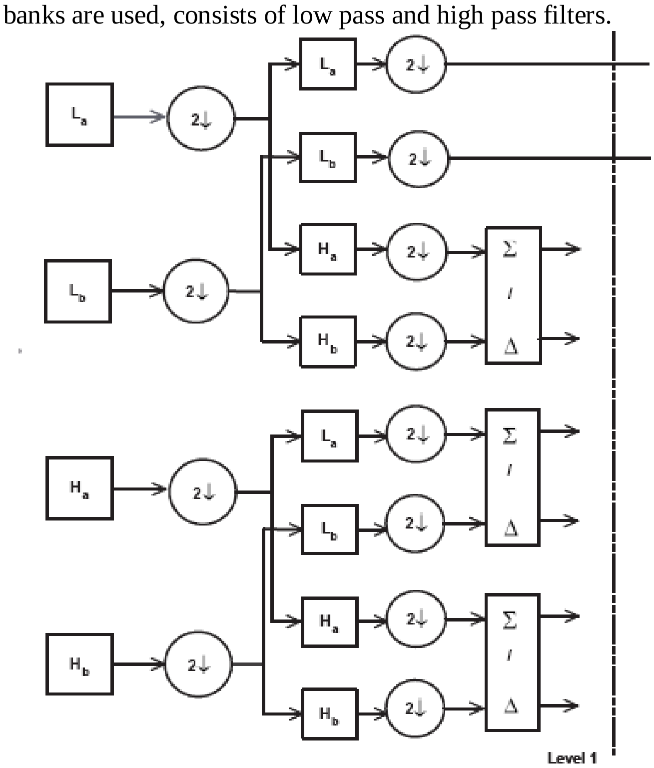

Figure.2. Decomposition of DT-CWT for 2D image

The sub band signals of the upper DWT can be interpreted as the real part of a complex wavelet transform, and sub band signals of the lower DWT can be interpreted as the imaginary part. Equivalently, for specially designed sets of filters, the wavelet associated with the upper DWT can be an approximate Hilbert transform of the wavelet associated with the lower DWT. Then designed, the dual-tree complex DWT is nearly *shift-invariant* and *strong directional* in contrast with the critically-sampled DWT.

2D DTCWT produces six high-pass subbands as well as two low-pass subbands at each level of decomposition, L represents lowpass filters and H represents high-pass filters. Each filtering operation is followed by a downsampling by two. Six directional wavelets of DTCWT are obtained by taking sum (Σ) and difference (Δ) of high-pass subbands which have the same pass bands.

III. PROPOSED ARCHITECTURE OF IMAGE FUSION

We have proposed a new approach for efficient and reliable image fusion in multi-focus images, which is a challenging task due to blurring effect.

The first aspect of this work is to use Dual Tree Complex Wavelet transform, where multiscale analysis and extraction of features oriented in different directions are possible. The decomposition level of the wavelet transform is decided by the imagery details which we need. In this work first level decomposition is satisfactory to preserve the details. The Second and important aspect of this work is to extract the features from *low frequency sub bands and high frequency sub bands using DCT and* PCA, respectively.

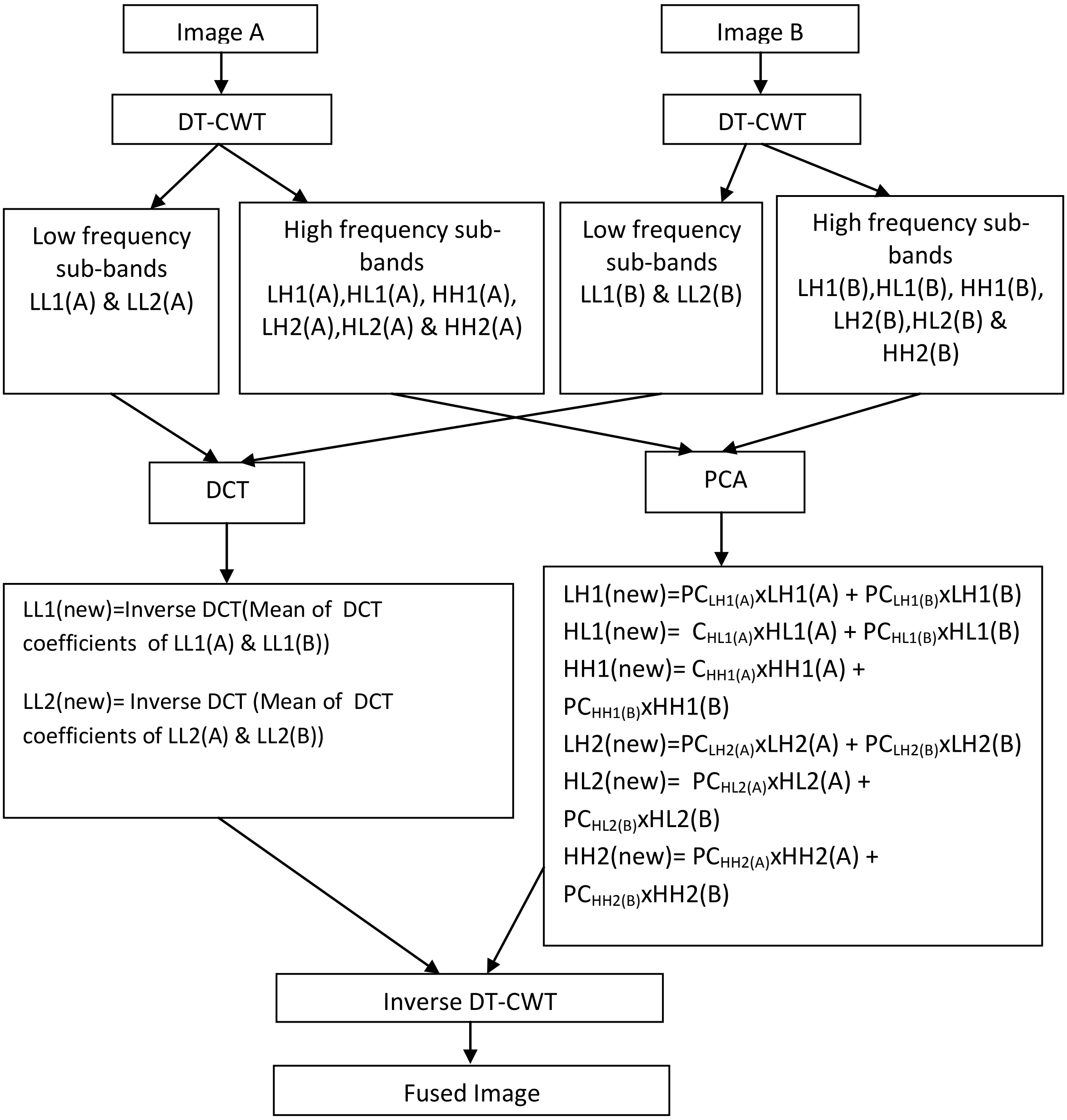

Figure 3: Block diagram for proposed method

The propose scheme is processed using following steps:

Step 1: Two input images (A and B) are taken which are defocused.

Step 2: Over the both images, perform Dual-tree Complex Wavelet Transform (DT-CWT).

Step 3: Apply Discrete Cosine Transform (DCT) over the approximation parts of both input images.
Step 4: Compute average pixel by pixel of both DCT coefficients obtained by step 3.
Step 5: Apply Inverse Discrete Cosine Transform (IDCT) to obtain filtered approximation part.
Step 6: Perform PCA over the detail parts (LH1, HL1, HH1, LH2, HL2 and HH2) of both input images.
Step 7: Obtained principal components (PCs) of the detail parts are multiplied with their respective sub bands.
Step 8: Both modified detail parts are added with their respective sub bands to obtain filtered detail part.
Step 9: To obtain fused image, apply inverse DT-CWT over filtered approximation parts (obtained from step 5) and filtered detail parts (obtained from step 8).

IV. RESULTS OF EXPERIMENT AND ANALYSIS

The proposed method is tested on various images of size 512×512. The results are tested using images as shown in figs. 4(a)-(b), 5(a)-(b) and 6(a)-(b). In fig. 4-5, the images 4(a) and 5(a) are highly concentrated on the right part and 4(b) and 5(b) highly concentrated on left part. Whereas in fig. 6 (a) the image is focused on the front leaves and 6(b) is focused on background leaves. The noisy images are obtained by adding salt and pepper noise. Over the input images, the fusion is performed based on wavelet transform using DCT and PCA as discussed in proposed methodology. The resultant fused images of proposed scheme are shown in figs. 4(c), 5(c) and 6(c). The visual quality of results is good in compare of input images. To measure the quality of proposed scheme in terms of MSE and PSNR, the results are compared with existing schemes, as shown in table 1. For comparison, the existing schemes are DWT with maximum, DWT with minimum, DWT with average and DWT with PCA.

(a) (b) (c)

Figure 4: Clock images: (a) first input image (b) second input image (c) fused image

(a) (b) (c)

Figure 5: Pepsi images: (a) first input image (b) second input image (c) fused image

(a) (b) (c)

Figure 6: Leaves images: (a) first input image (b) second input image (c) fused image

Table 1: PSNR and MSE

Input Images	**Fusion methods**	**PSNR with first input image**	**PSNR with second input image**	**MSE with first input image**	**MSE with second input image**
	DWT + maximum method	34.9095	33.1916	29.4956	29.4652

Clock (512x512)	DWT + minimum method	33.1948	34.9022	29.3432	29.8347
	DWT + average method	36.9722	36.9722	29.3258	29.1681
	DWT + PCA	36.9504	36.9990	29.2635	29.3533
	Proposed Method	37.0060	37.0430	30.2674	30.4981
Pepsi (512x512)	DWT + maximum method	35.9001	37.0010	29.7677	29.0838
	DWT + minimum method	36.9859	35.8987	29.8237	29.7623
	DWT + average method	39.4204	39.4204	29.4861	29.8622
	DWT + PCA	39.4366	39.3109	29.2871	29.2701
	Proposed Method	39.5406	39.5101	30.1517	30.7077
Leaves (512x512)	DWT + maximum method	28.6968	31.3334	30.2371	29.364
	DWT + minimum method	31.3337	28.6891	29.7118	29.3623
	DWT + average method	32.8258	32.8258	30.3012	29.8324
	DWT + PCA	32.8058	32.8384	29.3254	29.3124
	Proposed Method	33.5267	33.4085	31.3244	30.1463

Peak Signal to Noise Ratio (PSNR) is the ratio between the maximum possible value of a signal and the power of distorting noise that affects the quality of its representation. The PSNR is usually expressed in terms of the logarithmic decibel scale. Higher PSNR value indicate high quality image and our approach is to increase the PSNR.

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

$$MSE = \frac{1}{mn}\sum_{x=0}^{\infty}[I(i,j) - P(i,j)]^2$$

Where, $I(i, j)$ is the input image of size $m \times n$ and $P(i, j)$ is processed image.

V. CONCLUSIONS

In this research work, attention was drawn towards the current trend of the use of multi-resolution image fusion techniques, especially approaches based on discrete wavelet transforms and Dual Tree Complex Wavelet Transforms. The proposed scheme is applicable for similar images, which differ in terms of focus. The fusion is performed over the defocused images as proposed in scheme. The proposed scheme is based on the combination of transform and spatial domain, which provides more informative results. In compare of existing schemes, the proposed scheme gives better results in terms of MSE and PSNR.

The number of decomposition levels in the Multi-resolution analysis has a great impact on image fusion performance. However, using more decomposition levels do not necessarily implies better results. Therefore methods for selection of optimized number of decomposition levels can be explored.

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