International Journal of Electrical, Electronics and Computer Engineering **6**(1): 16-23(2017)
ISSN No. (Online): 2277-2626

Image fusion using DTCWT with High Boost Filtering

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(Received 27 November, 2016 Accepted 08 January, 2017)
(Published by Research Trend, Website: www.researchtrend.net)

ABSTRACT: Due to the rapid development of sensor technology, it is most plausible to combine two or more images of similar scene to obtain an enhance quality of image on applying image fusion. There have been various approaches proposed for combining or fusing multitasks or multimodal information. Image fusion is classified into two category spatial domain and frequency domain.
In Spatial domain methods, the pixel values of the two or more images to be fused in a linear or nonlinear way while in frequency domain, the input images are decomposed into Multi-scale coefficients primarily. In this paper we apply frequency domain image fusion technique DT-CWT and high pass filter with high boost filter/ Gaussian filter to obtain enhance quality of fused image. The simulation of the proposed methodology is done in MATLAB 2012a toolbox and the comparative analysis is performing using MSE and PSNR performance metric. The experimental results of the proposed methodology for these parameter is much better than the existing methodology. It means that our proposed method produce much improved quality of image.

Keywords: Image fusion, High boost filtering, DT-CWT, MSE, PSNR

I. INTRODUCTION

From the preceding years, with the fast enhancement of sensor technology, it is conceivable to have a few pictures of a similar scene giving analogous and excess information in spite of the fact that the scene is the same. This is on account of every picture has been caught with different sensor. Because of the constrained depth of field of optical focal points in CCD devices, it is regularly difficult to get a picture that contains every single important protest in center, which implies in the event that one question in the scene is in center, another will be out of center (obscured) [1]. The popular approach to take care of this issue is multi-focus image fusion, which coordinates numerous pictures of various centering objective at a similar scene into a composite concentrating sharp picture so that the new picture is more appropriate for representation, identification or acknowledgment undertakings [2]. Up to now, numerous multi-focus image fusion strategies have been produced. Practically corresponding to different types of data fusion, image fusion is normally performed at one of the three distinctive processing levels: signal, features and decision. Signal level image fusion, otherwise called pixel-level image fusion, corresponding to fusion at the lowest level, where a number of raw input image signals are combined to produce a single fused image signal. Object level image fusion, likewise called feature level image fusion, fuses features and object label and property descriptor data that have as of now been separated from individual info images. At long last, the highest level, decision or image level image fusion represents the combination of probabilistic decision data acquired by local decision makers working on the after effects of feature level processing on image information delivered from individual sensors. Image fusion technique can be classified into two categories: spatial domain fusion strategies, transform domain fusion strategy. The spatial domain fusion technique manages the pixels of info images. The fusion strategies, for example, averaging, maximum, minimum, principle component analysis (PCA) and HIS technique [3], [4] go under spatial domain approaches. In the transform image fusion technique, the image is changed to frequency domain. The techniques, for example, DWT, DTCWT and so on. go under the transform domain or spectral domain.

In this paper, we use DT-CWT wavelet transform which decomposes the images into sub-bands then apply high pass filter to sharpen the image and Gaussian filter to remove the noise from images and high-boost filter is used to preserve several of the low-frequency apparatus to abet in the elucidation of an image then apply fusion rule to enhance the quality of image. The general image fusion system is shown in fig.1.

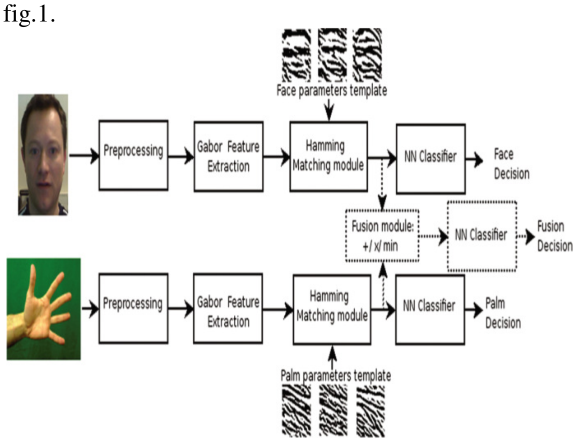


Fig. 1. Image fusion processing system.

The arrangement of the rest part of the research paper is as follows: Section II different levels of image fusion. In section III literature work of the earlier work done in the area of image fusion is discussed. In section IV, describes our proposed methodology to enhance the quality of images. Section V, experimental result and analysis are illustrated. Last section but not least, this section present overall conclusion and future scope of the methodology.

II. LEVEL OF IMAGE FUSION

A. Pixel Level Image Fusion

Pixel level fusion is the combination of the raw data from multiple source images into a single image. In pixel level fusion the fused pixel is derived from a set of pixels in the various inputs. The main advantage of pixel level fusion is that the original measured quantities are directly involved in the fusion process [5].

B. Feature Level Image Fusion

Feature level fusion deals with the fusion of features such as edges or texture while decision level fusion corresponds to combining decisions from several experts. In other word, Feature level fusion requires the extraction of different features from the source data before features are merged together.

C. Decision Level Image Fusion

Decision-level fusion involves fusion of sensor information that is preliminary determinated by the sensors. Examples of decision level Fusion methods include weighted decision methods, classical inference, Bayesian inference, and Dempster–Shafer method. In decision level fusion the results from multiple algorithms are combined together to yield a final fused decision.

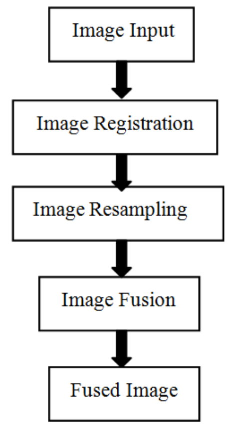


Fig. 2. Preprocessing steps for image fusion.

III. RELATED WORK

This section gives an extensive literature survey on the previous work done in the field of image data compression. We study various research and journal paper related to image data compression using DWT. Most of the paper faced as same problem in the fusion process of image data. Some of review of summary given here with entailed with respective authors.

Bhavana. V, Krishnappa. H.K (2015). In this work, MRI and PET images are pre-processed along with enhancing the quality of the input images which are degraded and non-readable due to various factors by using spatial filtering techniques like Gaussian filters. The enhanced image is then fused based on Discrete Wavelet Transform (DWT) for brain regions with different activity levels. The system showed around 80-90% more accurate results with reduced color distortion and without losing any anatomical information in comparison with the existing techniques in terms of performance indices including Average Gradient and Spectral Discrepancy, when tested on three datasets - normal axial, normal coronal and Alzheimer's brain disease images [6].

Daneshvar *et al.* (2015). Presented a new method based on lifting scheme is suggested to fuse modals of MR. In this algorithm, lifting wavelet transform is used to decompose source images into different sub-bands. Different fusion rules are applied to fuse sub-bands and achieve fused image.

Numerical and visual analyses prove efficiency of propped method in gathering complementally information of source images in one image [7].

Aishwarya *et al.* (2016). Proposed a novel fusion algorithm based on Discrete Wavelet Transform (DWT) and Sparse Representation (SR) is proposed. Initially, DWT is applied to extract the low frequency components and high frequency components of source images. High frequency components are merged using SR based fusion approach and low frequency components are combined using variance as activity level measurement. Finally, inverse DWT is performed on the fused coefficients to get the fused image. Experimental results demonstrate the effectiveness of proposed method in terms of visual perception and quantitative analysis [8].

Nirmala Paramanandham, Kishore Rajendiran (2016). In this, a simple and competent image fusion algorithm based on standard deviation in wavelet domain is proposed and compared with both transform domain as well as spatial domain techniques. The techniques are evaluated with various databases quantitatively and qualitatively [9].

Zhang *et al.* (2015). In this paper, proposed an efficient image fusion algorithm which combined with the advantage of space domain and transform domain. they employ the Principal Component Analysis (PCA) in the low frequency domain, and combine the biggest value selection method with weighted mean method in the high frequency domain. Finally, the output image is obtained by inverse wavelet transform. The experimental results show that this algorithm can produce high-contrast fusion images that are clearly more appealing and have more useful information than the PCA and the wavelet transform [10].

Mini *et al.* (2015). Utilized Stationary Wavelet Transform (SWT), modulus maxima and high boost filtering. The image is decomposed using SWT and its modulus maximum is determined. A fraction of the high pass filtered image obtained as the result of SWT decomposition and modulus maxima is added to original image. The scheme is evaluated visually and objectively using measures like contrast, PSNR etc. The performance measures are evaluated for different category of images and found to be suitable to all categories of mammographic images [11].

S. Anbumozhi, P.S. Manoharan (2014). Focused to classify the brain image into normal and abnormal image using minimum distance classifier algorithm. The proposed methodology consists of spatial domain filter, fusion, clipping circuit and minimum distance classifier algorithm. The difference features are extracted from fused image and compared with trained extracted feature set. The low power architecture for the proposed brain image classification method is presented in this paper. The proposed hardware architecture consumes power of 151mW in CMOS 90nm technology.[12]

IV. PROPOSED METODOLOGY

This chapter describes the proposed methodology to obtain the improved quality of using image fusion technique DT-CWT and image fusion rule after that apply filtering technique (High Boost Filter) while various techniques and methodologies has been already implemented. The description of the DT-CWT and fusion rule is discussed below with their proposed algorithm.

A. Dual Tree Complex Wavelet Transform (DT-CWT)

The Dual-tree Complex wavelet transform (DT-CWT) [13, 14] is complex valued extension of the standard wavelet. Complex transform uses complex valued filtering that decomposes the image into real and imaginary parts in transform domain. The real and imaginary coefficients are used to compute magnitude and phase information. The prime motivation for producing the dual-tree complex wavelet transform was shift invariance. In normal wavelet decomposition small shifts of the input signal are able to move energy between output sub-bands. Shift invariance can also be achieved in DWT by doubling the sampling rate. This is affected in the DT-CWT by eliminating the down sampling by 2 after first level filter. Two fully decimated trees are then produced by down sampling, effected by taking first even and then odd samples after the first level of filters. To get uniform intervals between the two trees samples, the subsequent filters need half a sample different delay in one tree. Application to image can be achieved by separable complex filtering in two dimensions.

The real 2-D dual-tree DWT of an image x is implemented using two critically-sampled separable 2-D DWTs in parallel. Then for each pair of sub-bands we take the sum and difference. The complex 2-D DT-DWT also gives rise to wavelets in six distinct directions. The complex 2-D dual-tree is implemented as four critically-sampled separable 2-D DWTs operating in parallel as shown in figure (4.2). 2-D structure needs four trees for analysis and synthesis. The pair of conjugate filters applied to two dimensional images (x, y) can be expressed as:

$$(h_x + jg_x)(h_y + jg_y) = (h_xh_y - g_xg_y) + j(h_xh_y + g_xg_y)$$

The complex wavelets are able to distinguish between positive and negative the diagonal sub-bands can be distinguished and horizontal and vertical sub-bands are divided giving six distinct sub-bands in each scale at orientations $\pm15^0$, $\pm45^0$, $\pm75^0$. The oriented and scale dependent sub-bands are visualized spatially in fig. 3.

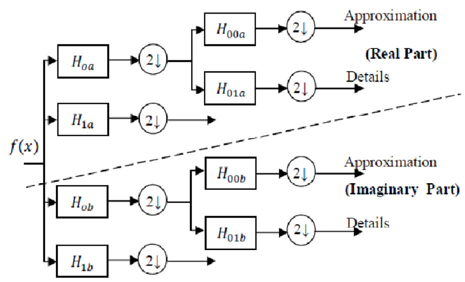


Fig. 3. Image fusion using DT-DWT.

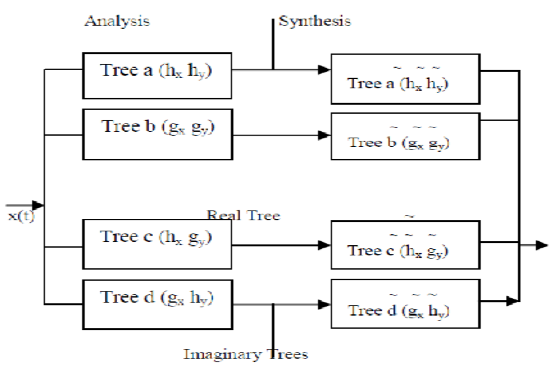


Fig. 4. Filter bank structure for 2-D DT-DWT.

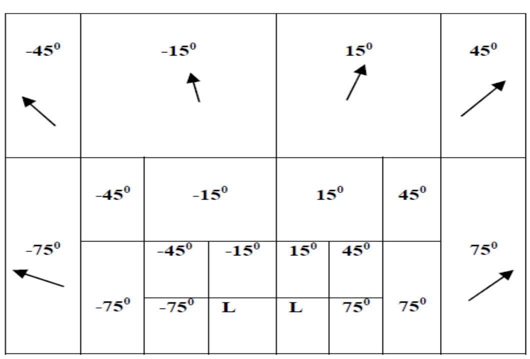


Fig. 5. Complex Wavelet Transform Scale Orientation labelled sub- bands.

The DWT have three sub-bands in 0°, 45° and 90° directions only but DT-CWT having six sub-bands in ±150, $\pm45^0$ and $\pm75^{\circ}$, thus DT-CWT improves the directional selectivity which is the prime concern in the application like image fusion.

B. Image Fusion Rule

Three previously developed fusion rule schemes were implemented using discrete wavelet transform based image fusion:

1. Maximum Selection (MS) scheme: This simple scheme just picks the coefficient in each subband with the largest magnitude;

2. Weighted Average (WA) scheme: This scheme developed by Burt and Kolczynski uses a normalised correlation between the two images' subbands over a small local area. The resultant coefficient for reconstruction is calculated from this measure via a weighted average of the two images' coefficients;

3. Window Based Verification (WBV) scheme: This scheme developed by Li et al. [15] creates a binary decision map to choose between each pair of coefficients using a majority filter.

High pass filters: A high pass filter is mostly used for sharpening purpose. When an image is sharpened and contrast is superior between bordering areas with little variation in brightness or low eminence information.

High pass = f(x, y) – low pass eq1

High-boost Filtering: A high-boost filter is also identified as a high-frequency prominence filter. A high-boost filter is used to preserve several of the low-frequency apparatus to abet in the elucidation of an image. In high-boost filtering input image h (m, n) is multiplied by an amplification factor *A* prior to subtracting the low-pass image. Accordingly, the high-boost filter expression is:

*High boost = A *f(m,n) – low pass*.......................eq2

Adding and subtracting 1 with gain factor, then

*High boost = (A-1) * f(x, y) + f(x, y) – low pass*

So

*High boost = (A-1) * f(x, y) + high pass eq3*

Major Steps of Proposed Methods:

1. Select first image from source data, then assign into variable A.
2. Select second image from source data, then assign into variable B.
3. Apply layer 1 dual tree wavelet into image to decompose in sub-bands (LL, LH, HL, HH).
4. Again decomposed band LL into sub bands (LLLL, LLLH, LLHL, LLHH).
5. Measurement of the wavelet coefficient of A and B.
6. Apply transform function on selected image A and B.
7. Apply high pass filter into decomposed layers of images.
8. Apply Gaussian filter to removes extra noise from the images.
9. Then apply high boost filter to enhancement of decomposed layers.

10. Followed fusion rule:

$$F_p^k(i,j) = \begin{cases} A_p^k(i,j), if \;\; A_p^{km}(i,j) \; > B_p^{km}(i,j) \\ B_p^k(i,j), \qquad\qquad\qquad x \geq 0 \end{cases}$$

11. Fused wavelet coefficients.
12. Apply INV-WAVELET.
13. Measurement of MSE is as follows:

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

14. Measurement of PSNR as follows:

$$\mathrm{PSNR} = 10 \times \log_{10}(\frac{\mathrm{peak}^2}{\mathrm{MSE}})$$

C. Proposed Steps

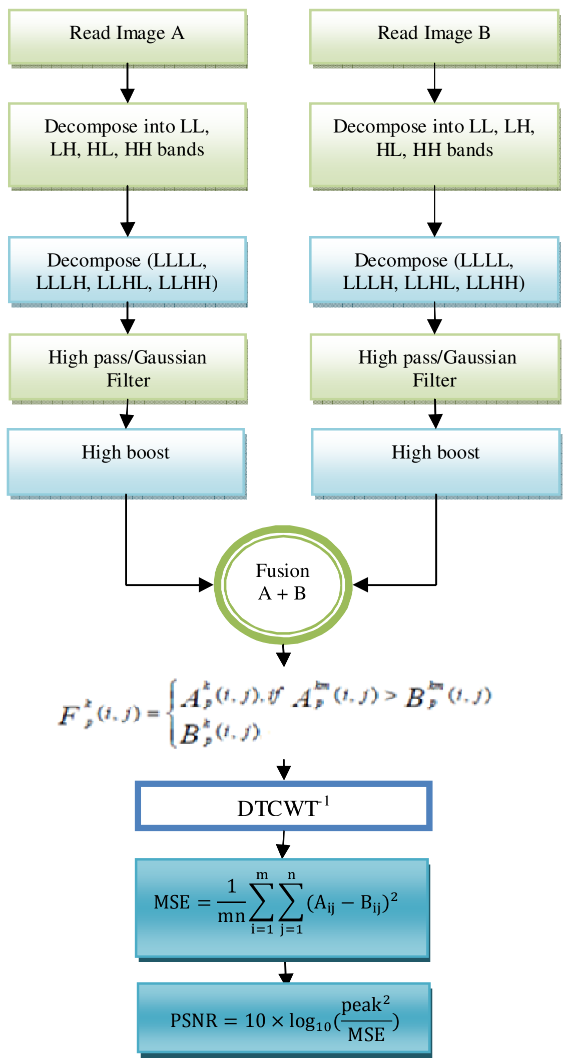


Fig. 6. Block diagram of proposed algorithm.

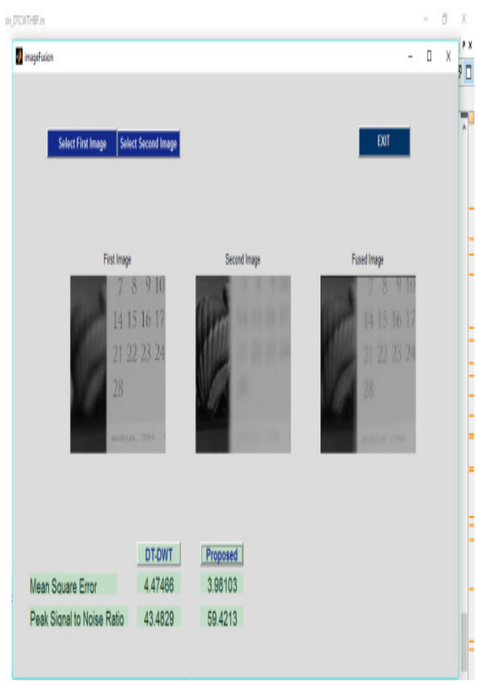
V. EXPERIMENTAL RESULTS

This section contains information of tools used while implementing the proposed methodology as well as some other traditional methods. It is used MatLab2012A in Intel I3 800X4 core processor with 4GB primary memory and NVIDIA graphics adapter, which makes our work more reliable and fast performance. MATLAB [16] is a software package for high performance numerical computation and visualization.

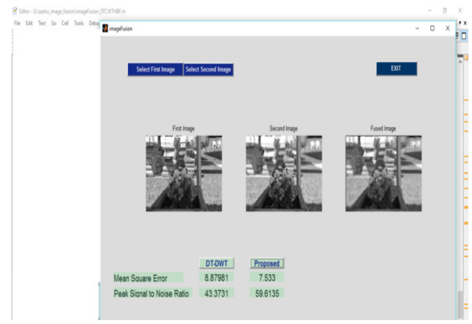
It provides an interactive environment with hundreds of built-in function for technical computation, graphics and animations In MATLAB the M-files are the standard ASCII text files, with a .m extension to the file name. There are two files of this file: script file and function file. Most programs we write in MATLAB are saved in M-files. Fig-files are binary files with a .fig extension that can be opened again in MATLAB as figures. Such files are created by saving a figure in this format using save or save as option from File menu or using the save as command in command window-files are compiled M-files with a .p extension that can be executed in MATLAB directly. There are several optional toolboxes are available from developers of MATLAB. These toolboxes are collection of function written for special applications such as symbolic computation, image processing, statics, control system, neural network, etc.

A. GUI Environment

Here some of the snapshot of the simulation environment is presented for different image dataset in which it shows proposed methods is much better than the DT-DWT technique to improve the quality of the images. The proposed method analysis is done using the performance metric MSE and PSNR image processing parameter and for these parameter this proposed method is very much suitable for enhancing the image quality.



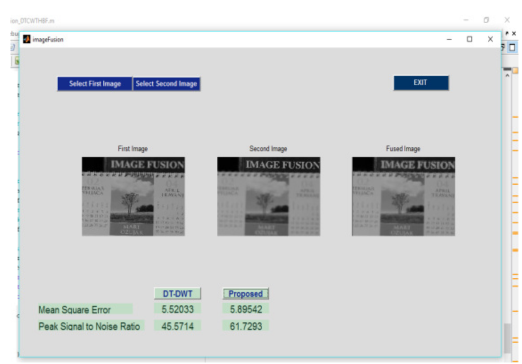
(a)



(b)

(c)

(d)



(e)

Fig. 7. Shows the simulation environment for the proposed method using different image dataset.

B. Results Analysis

The simulation result of the proposed is analyzed using well known image processing parameter MSE and PSNR. The MSE is the measure of error between the original image and the compressed image. Mean Square Error is the cumulative squared error between the compressed image and the original image. Mean Square Error may be calculated using following expression:

$$\mathrm{MSE} = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y) - I'(x,y)]^2$$

Table 1: MSE comparison between proposed method and DT-CWT.

MSE comparison		
Method/image	**DTCWT**	**Proposed**
p27a-b	4.4746	3.981
t3a-b	8.8798	7.533
t6a-b	12.9264	10.1499
t9a-b	11.2079	6.81032

Here, table 1 shows the simulation results of proposed method and DT-CWT for MSE parameter and it is found that the results of proposed method for MSE parameter is about 23% is less than the DTCWT method. It means that our proposed method is more effective than DTCWT for diminishing the effort from the different image dataset and the comparative analysis of the simulation results is shown in fig. 8.

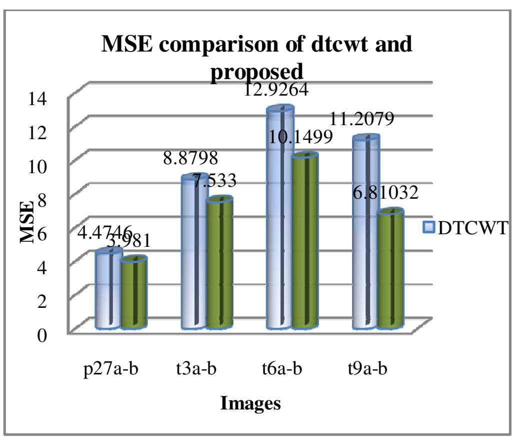


Fig. 8. Comparative analysis of proposed and DTCWT method for MSE parameter.

Here, table 2 shows the simulation results of proposed method and DT-CWT for PSNR parameter. PSNR is the ratio of maximum power of the signal and the power of unnecessary distorting noise. Here the signal is the original image and the noise is the error in reconstruction. For a better compression the PSNR must be high. The PSNR can be expressed as:

$$\mathrm{PSNR} = 20 \times \log_{10}\left[\frac{255}{\sqrt{\mathrm{MSE}}}\right]$$

It is found that the result of proposed method for PSNR parameter is about 17% is more than the DTCWT method. It means that our proposed method is more effective than DTCWT for diminishing the effort from the different image dataset and the comparative analysis of the simulation results is shown in fig. 9.

Table 2: PSNR comparison between proposed method and DT-CWT.

PSNR comparison		
Method/image	**DTCWT**	**Proposed**
p27a-b	43.4829	59.4213
t3a-b	43.3731	59.6135
t6a-b	41.624	57.0567
t9a-b	42.2692	60.3501

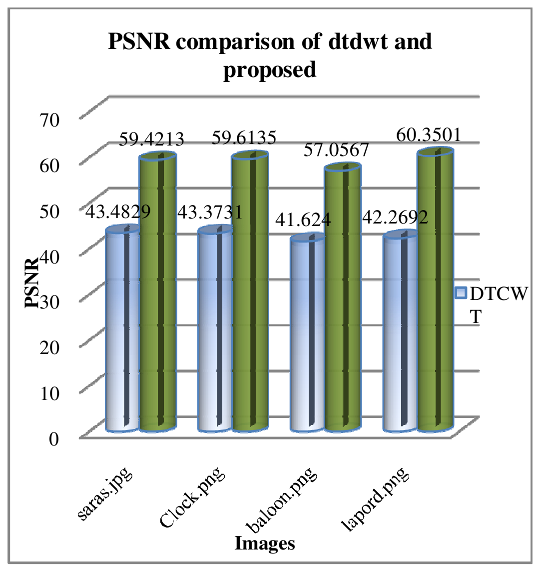


Fig. 9. Comparative analysis of proposed and DTCWT method for PSNR parameter.

VI. CONCLUSION

In digital image processing, the image enhancement is the major area of research in which image fusion is one of the process which helps in improving the quality of images. In this, two or more image of same scene is combine/fused to get improved quality of image.

From the single image it is not possible to extract the essential or more information so to obtain more information the multiple images are fused together. Various techniques have been developed for image fusion the images. In this dissertation, we apply wavelet transform based DT-CWT image fusion technique with high boost filtering technique to acquire enhance image quality. The analysis of this work is done using MSE and PSNR measuring parameter and the simulation results of proposed method gives better results than the existing methods. The results of the MSE parameter of the proposed and DTCWT method is approximately 23% less while for PSNR result it is approximately 17% more than the DTCWT method which must be high. Image fusion is exceptional process to get better quality of image. This proposed approach is simulated only for MSE and PSNR performance parameter. In future work, this methods must be tested for another image processing parameter and also apply the best features of two or more image fusion technique due to which, we obtained very good quality of image and it can be practical for different area of image processing.

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