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An Effective Multi-focus Image Fusion Based on Law's of Texture Enegery Measures in Integrated Wavelet Domain

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Abstract*:* Feature extraction provides better description of given image. In computer vision, characterization of images is a challenging task. Due to intensity variations and non-uniformities. In such situations the texture description plays a vital role to extract essential information without any distortion, to attain such information texture energy measures are very useful. This paper concentrates on feature extraction methods by combining NSCT (Non-Subsampled Contourlet Transform) domain with the combination of DTCWT (Dual-Tree Complex Wavelet Transforms). Energy measures are applied in the form of masks to get more efficient features comparing with other approaches. A set of test images are considered to the energy measures which significantly improves correlation of texture for given test dataset. Different kinds of measures are considered like average gradient, edge intensity, gray mean value, standard deviation etc. to show the significance of proposed method with greater time complexity.

Keywords*—NSCT, DTCWT, LTEM, Texture, Image fusion.*

1. Introduction

Nowadays development of multimedia leads to utilization of digital images in various domains. The characteristics of images are very important in various applications like pattern identification, face recognition, character recognition and so on. There is a huge demand in formulating and extracting essential characteristics in image data management. In the field of image fusion feature extraction are extracted by combining the same scene with different orientations. Several algorithms are proposed to define the structural and spatial properties such as wavelets, steerable pyramid shape and [1] texture extractions, anatomical fusion-based measures, etc. all the above-mentioned methods are developed in the last few decades which shows the impact of image fusion and energy measures in the computer vision domain. Recently various works are proposed in image fusion with neural networks like PCNN, PADCPNN, DNN. The utilization of these methods has their impact in image fusion and energy measure evaluation even though these are being computationally expensive. According to approaches mentioned above energy measures are categorized into two types such as statistical and structural. In the statistical category varies matrices are proposed works on principles of Laws of Texture Energy Measures [2] (LTEM). But in case of structural properties, Voronoi picture formations are considered.

In this work hybrid wavelets are considered for feature description using LTEM. The rest of the article as follows:

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The Section background study reviews the existing works related to LTEM and image fusion. The section methodology provides details about proposed method and evaluation of features. The section results and analysis provide the experimental results which are carried out by various parameter like average gradient, edge intensity, gray mean value, standard deviation etc. along with computational complexity. Finally, the conclusion section provides brief remarks of proposed method along with future scope.

2. Background Study

Roman N. Kvyetnyy et al. [3] implemented a method of image texture segmentation with the help of Laws energy measures. This method helps to identify parts of images effectively. In order to acquire these measures, the sixteen masks are considered. Output energy measures are generated by implementing every mask to the image. And stated energy maps remarkably improves the correlation coefficient and therefore increases textural features and makes it to identify the uniformity of textures. To evaluate the method output was compared with existing state-of-art methods

Uma Ranjan Jena and Sonali Dash [4] introduced texture classification by using various-resolution Laws Masks. In this work a modern approach for texture classification is introduced by implementing a integration of Laws masks and wavelet basis functions with dyadic wavelet transform. These Laws masks are referred as Multi-resolution Laws' Masks (MRLM) to further enhance the efficiency of Laws' mask descriptor. Ak-Nearest Neighbour (k-NN) classifier is created to categorize every texture into corresponding category. It is implemented on databases VisTex and Brodatz to evaluate. And stated that Multi-resolution Laws

Masks can acquire improved categorial accuracy when compared with Laws' masks method and traditional dyadic wavelet transforms and.

P. Govindaraj and M.S. Sudhakar [5] done a shape categorization by implementing laws of texture energy measures for retrieval facility. In this work a descriptor developed using LTEM improves the boundaries of structures in a image to generate highly dominant features. Further a feature deception positioning embedded it into universal-constitutional shape histograms which are used for coordinating and retrieval. It is implemented on Kimia's 99, MPEG-7, and Tari-1000 datasets and achieved accuracy of 90%. And stated this method robust regardless of data.

K. Kamal et al [6]. developed a methodology for categorization of wood defects by utilizing supervised learning approach and laws texture energy measures for an automated inspection. This methodology uses GLCM and LTEM for extraction of texture and output is given to FFBPNN to classify. And it is assed that MSE is 0.0718 and accuracy is 90.5% is acquired in training data while for testing data MSE is 0.10728 and accuracy is 84.3%.

Padma Ganasala and Achanta Durga Prasad [7] proposed a model for medical image fusion with the help of LTEM in SWT area. This model utilizes SWT to acquire detail and approx. information of images along with TEM. It is implemented on datasets which contains images of seven patients suffering from neurological disorders. Further various metric was enhanced in the output of model with less execution time when evaluated with present state-of-the-art methods. It is assessed that this model can be improved for fusion of other imaging modalities.

Padma Ganasala and A D Prasad [8] stated a new strategy for image fusion which work on Texture Energy Measures in NSST area. It is assed that this strategy is a practical and structural image fusion to generate diagnostic data necessary for accurate diagnosis. It is mainly focused on obtaining a fused image that contains practical and structural data without distortion and loss. Further YIQ color model is used to contain data. And structural details are maintained through TEM in NSST area. It is implemented on SPECT and MRI images of brain tumor. It is evaluated by various fusion quality metrics.

Vijayalakshmi G. V. Mahesh et al. [9] initiated a facial expression recognition method with Law's Textures Feature collection and Spatial Pyramid Zernike Moments. This work combines spatial pyramid Zernike moments which works on Law's texture features and shape features to exclusively acquire the micro and macro data of facial expression. It implements multilayer perceptron and radial basis function feed forward artificial neural networks to identify the facial expression. It is executed on KDEF and JAFFE datasets and achieved accuracy of 95.86% and 88.87% respectively.

3. Methodology

The fundamental objective of this work is to investigate the efficiency of LTEM method in the extraction of texture features. By integrating hybrid technique based on Dual-Tree Complex Wavelet Transforms (DTCWT) and Non-Subsampled Contourlet Transform (NSCT). The purpose of this method is to get superior quality images for further analysis. This work examines the feasibility of LTEM with clear structure. The proposed method is divided into 3 subparts. Firstly, implementation of NSCT and DTCWT are introduced to enhance the information by considering multiple orientation images from same source. Further LTEM mask methos are applied on the output of above methods. Finally, the features are extracted from the image. The procedural steps of above methods are described in detail in further of this section.

A. Non-Subsampled Contourlet Transform

The following figure represent the overview of NSCT.

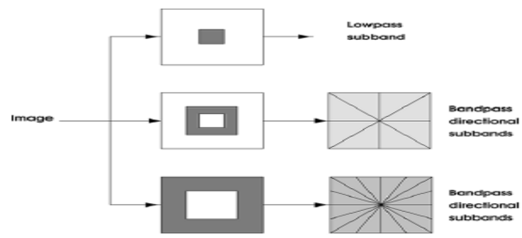

Fig. 1. *NSCT flow diagram*

In the "Fig. 1" a 2d [10] frequency plain is presented to generate the sub-bands to overcome the problem of Shift invariance and directionality. In this transformation multiscale decomposition is achieved by non-subsampled pyramids. This decomposition is similar to Laplacian pyramid further a filter bank which consists two input channels is also applied to carry out the NSP.

The perfect reconstruction is guaranteed in the decomposition of NSCT.

$$A_0(X) * B_0(X) + A_1(X) * B_1(X) = 1 \quad (1)$$

Here A_0, A_1 are up-sampled filters while B_0, B_1 are directional up-sampled filters.

In case of directional filter bank up-sampling is achieved which also ensures perfect reconstruction of same size as input image.

$$K_0(z) * L_0(z) + K_1(z) * L_1(z) = 1 \quad (2)$$

Here K_0, K_1 are decomposition filters while L_0, L_1 are synthesis filters.

B. Dual-Tree Complex Wavelet Transforms

In the implementation of DTCWT [11] tree-based decomposition are calculated which separates the signals into two parts. Further these parts produce real and imaginary representations. The design of DTCWT includes filters to define particular characteristics. The two trees are differed by half in a sample period using low-pass filters. Reverse analysis is used for reconstructing filters. Filters of one tree is reverse of other tree both the trees are having same frequency the block diagram of DTCWT Is as follows:

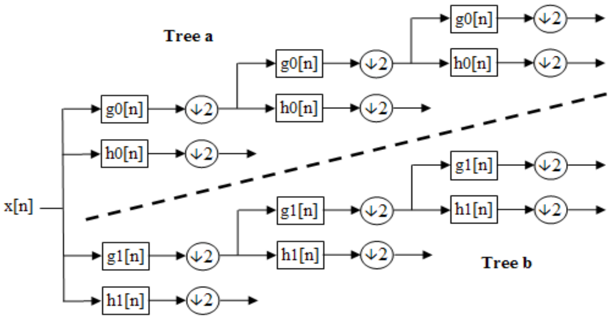

Fig. 2. *DTCWT flow diagram*

C. Texture Energy Measures

The Texture energy measures are implemented to quantify the texture in an image. Texture energy measures are based on the [12] principle of local energy, which refers to the amount of energy in a signal within a particular frequency band. In image processing, local energy can be measured using a filter bank that separates the image into various frequency bands. The energy of these band is then measured and summed to give the overall texture energy of the image.

Texture energy measures can be used to analyze different types of texture patterns, including periodic, random, and mixed patterns. They can also be used to quantify the degree of anisotropy in an image, which refers to the extent to which the texture patterns are oriented in a particular direction.

Normally approx. sub-bands contain more data from a original image. It is necessary to transfer this data into a fused image. To acquire properties like waves, ripples, sparks and edges. The three primary vectors are utilized. $\boldsymbol{L} = [\mathbf{1}, \mathbf{2}, \mathbf{1}]$, $\boldsymbol{E} = [-\mathbf{1}, \mathbf{0}, \mathbf{1}]$, $\boldsymbol{S} = [-\mathbf{1}, \mathbf{2}, -\mathbf{1}]$. With the help of three vectors, nine convolution matrixes are generated as follows:

$$M_1=\begin{bmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{bmatrix}$$

$$M_2=\begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

$$M_3=\begin{bmatrix} -1 & 2 & -1 \\ -2 & 4 & -2 \\ -1 & 2 & -1 \end{bmatrix}$$

$$M_4=\begin{bmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & -1 \end{bmatrix}$$

$$M_5=\begin{bmatrix} 1 & -2 & 1 \\ 0 & 0 & 0 \\ -1 & 2 & -1 \end{bmatrix}$$

$$M_6=\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix}$$

$$M_7=\begin{bmatrix} 1 & -2 & 1 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{bmatrix}$$

$$M_8=\begin{bmatrix} -1 & -2 & -1 \\ 2 & 4 & 2 \\ -1 & -2 & -1 \end{bmatrix}$$

$$M_9=\begin{bmatrix} 1 & 0 & -1 \\ -2 & 0 & 2 \\ 1 & 0 & -1 \end{bmatrix}$$

The except mask of M1 all other are zero-sum while M1 is zero sum. The mask M1 generates energy average. M2 and M3 generates first and second-order vertical boundaries. M6 produces horizontal boundaries. M4 indicates waves. M5, M7, and M9 indicates ripples. Additionally, TEM referred as TEM1 to TEM9 corresponding to traditional matrices: M1 to M9 as follows

$$\mathrm{TEM}_1(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_1(k+2,l+2) \quad (4)$$

The traditional M1 should be implemented on the approx. sub-band respective block; the TEM1(r, c) contains results. Similarly, the other traditional matrices are implemented to the corresponding blocks of approx. sub-bands.

$$\mathrm{TEM}_2(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_2(k+2,l+2) \quad (5)$$

$$\mathrm{TEM}_3(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_3(k+2,l+2) \quad (6)$$

$$\mathrm{TEM}_4(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_4(k+2,l+2) \quad (7)$$

$$\mathrm{TEM}_5(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_5(k+2,l+2) \quad (8)$$

$$\mathrm{TEM}_6(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_6(k+2,l+2) \quad (9)$$

$$\mathrm{TEM}_7(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_7(k+2,l+2) \quad (10)$$

$$\mathrm{TEM}_8(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_8(k+2,l+2) \quad (11)$$

$$\mathrm{TEM}_9(x,y) = \sum_{k=-1}^{1}\sum_{l=-1}^{1} \mathrm{ASX}(x+k,y+l)^2 M_9(k+2,l+2) \quad (12)$$

Absolute values of TEMs are calculated by utilizing following formula. Assume that normalized TEMs be NTEMY1, NTEMY2, NTEMY3, NTEMY4, NTEMY5, NTEMY6, NTEMY7, NTEMY8, NTEMY9

$$NTEMY_i = \text{normalized}\ (|TEMY_i|) \qquad (13)$$

D. Algorithm

Input: Multi-focus images

Output: Fused image

Step 1: Consider images with various focuses.

Step 2: In the first level apply NSCT which generates lowpass and approx. sub-bands.

Step 3: Consider lowpass sub-band as an input for DTCWT for second level of decomposition in this also low pass and approx. sub-bands are generated.

Step 4: Apply max function rule for lowpass sub-bands and in the second level of decomposition calculate perfect value for approx. sub-bands.

Step 5: Implement inverse DTCWT for the output of perfect value and max fusion rule

Step 6: Calculate weighted average for approx. sub-bands generated in first level decomposition using NSCT.

Step 7: Implement inverse NSCT for the output of inverse DTCWT and weighted average to generate fused image

Step 8: To extract features, apply LTEM on fused image to attain final image.

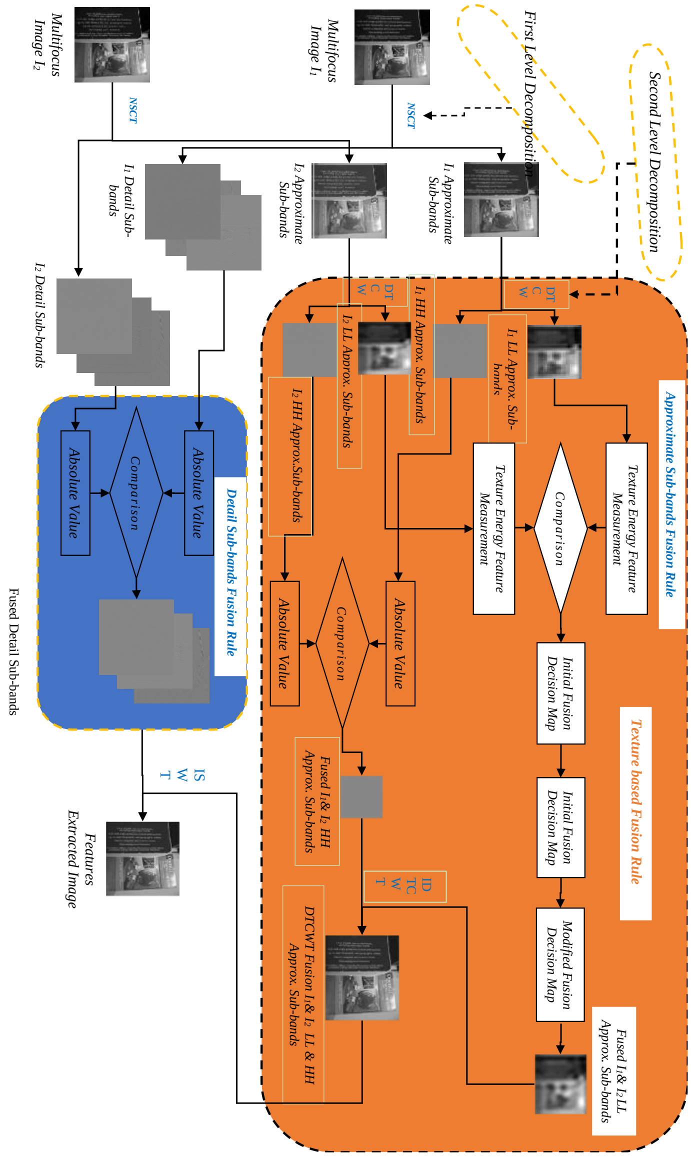

Fig. 3. Proposed flow diagram

4. Results and Analysis

The following metrics [13][14] are considered to evaluate the proposed method: image definition (ID), average gradient (AG), edge intensity (EI), standard deviation (SD), grey mean value (GM), and $Q_{AB/F}$, Q_E, Q_0. A total of 10 images are considered for the evaluation of the proposed method. The following "Fig. 4" show the output of the proposed method.

(a) (b) (c) (d)

Fig. 4. Multi-focus image from various perspectives. Original Image: (a), Multi-focus Input Images: (b, c), and Proposed Fusion: (d).

Graphical representation of results corresponding to the proposed and existing [15] are as follows:

Fig. 5. Graphical representation of evaluation of AG between proposed and existing.

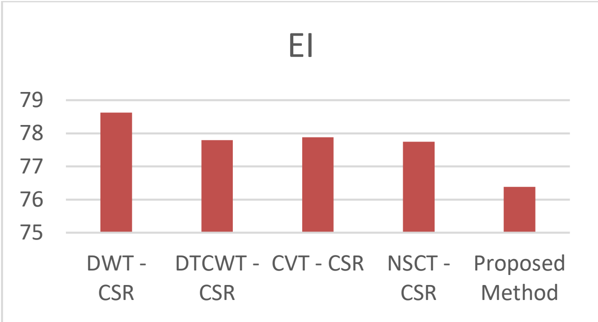

Fig. 6. Graphical representation of evaluation of EI between proposed and existing.

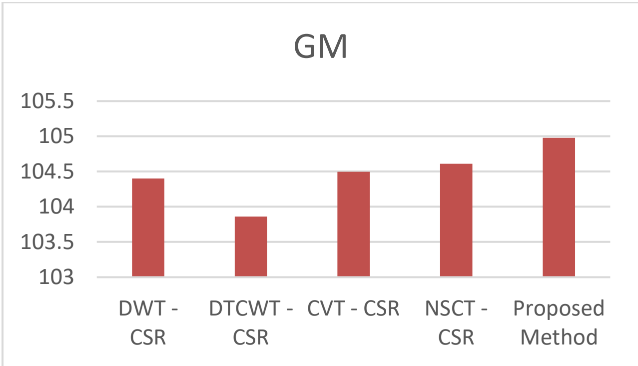

Fig. 7. Graphical representation of evaluation of GM between proposed and existing.

Fig. 8. Graphical representation of evaluation of SD between proposed and existing.

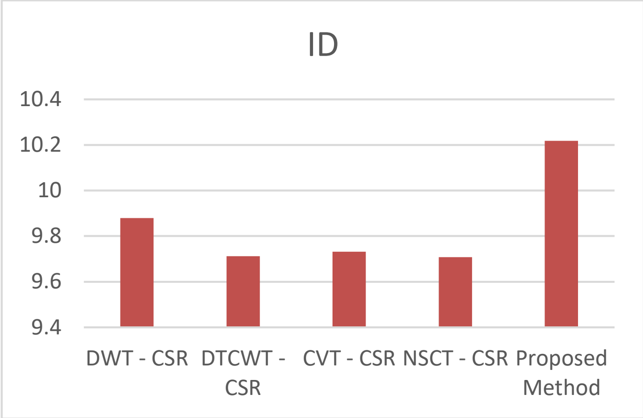

Fig. 9. Graphical representation of evaluation of ID between proposed and existing.

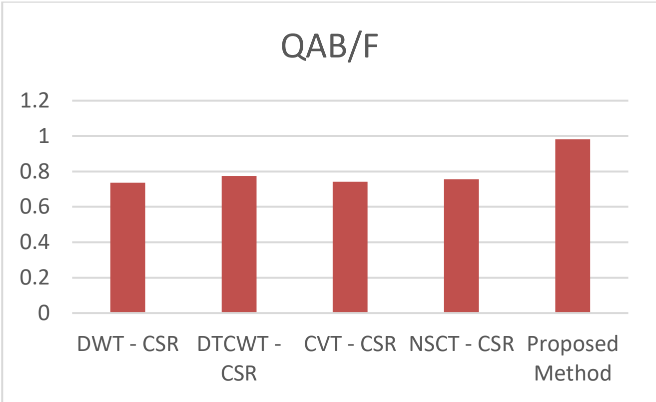

Fig. 10. Graphical representation of evaluation of $Q^{AB/F}$ between proposed and existing.

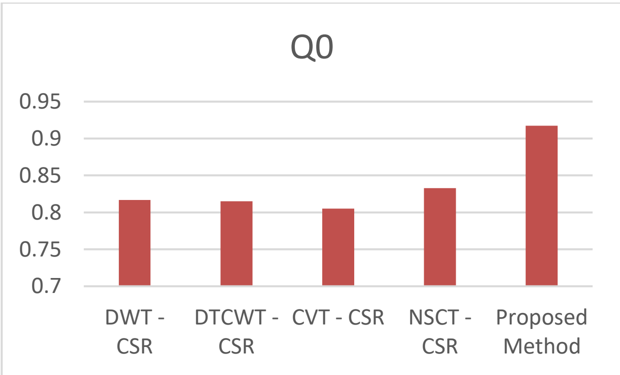

Fig. 11. Graphical representation of Evaluation of Q^0 between proposed and existing.

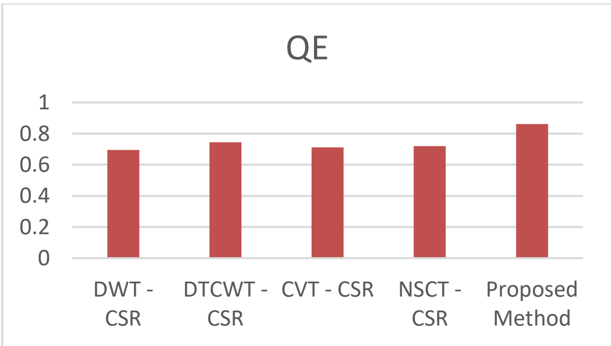

Fig. 12. Graphical representation of evaluation of Q_E between proposed and existing.

The result of the proposed method has enhanced output in the six metrics considered to evaluate when compared to existing method. The comparisons of metrics between existing method and proposed are tabulated and enhanced results are bolded.

Table. 1. Evaluation of metrics between proposed and existing methods

S. No	IF Quality Metrics	Existing Method (MT & CSR) (Average Value)				Proposed Method (NSCT+DTCWT with Law's of TEM) (Average Value)
		DWT – CSR (Method 1)	**DTCWT – CSR (Method 2)**	***CVT – CSR (Method 3)***	***NSCT – CSR (Method 4)***	
1	AG	7.7793	7.6828	7.6924	7.6807	**14.9397**
2	EI	78.6239	77.7976	77.8838	77.7429	76.3851
3	GM	104.401	103.861	104.497	104.613	**104.977**
4	SD	52.323	52.0522	52.1355	52.2404	51.079
5	ID	9.8798	9.7117	9.732	9.7074	**10.2188**
6	$Q^{AB/F}$	0.736	0.7745	0.742	0.7571	**0.98326**
7	Q^0	0.8168	0.8152	0.8051	0.8327	**0.91726**
8	Q_E	0.6941	0.7433	0.712	0.7186	**0.86071**

Table. 2. Percentage increase of metrics between proposed and existing methods

Percentage of improvement than Existing Methods			
DWT – CSR (Method 1)	**DTCWT – CSR (Method 2)**	***CVT – CSR (Method 3)***	***NSCT – CSR (Method 4)***
47.92	48.57	48.51	48.58
-2.93	-1.84	-1.96	-1.77
0.54	1.06	0.45	0.34
-2.43	-1.9	-2.06	-2.27
3.31	4.96	4.76	5
25.14	21.23	24.53	23
10.95	11.12	12.22	9.21
19.35	13.64	17.27	16.51

5. Conclusion

The proposed method has the enhanced results when evaluated with existing state-of-art methods. This method shows the improved performance in average gradient (AG), grey mean value (GM), image definition (ID), QAB/F, QE and Q0. From this work, the TEM and LTEM can enhance the texture analysis of images. Implementation of TEM on texture analysis not only enhance the output but can also improve the application scope of image analysis. The further works of this method can implement GLCM for texture analyzing. Using other image fusion methods. The output of this implies that utilizing of TEM can improve image processing techniques.

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