ACTA IMEKO
ISSN: 2221-870X
June 2024, Volume 13, Number 2, 1 - 6

The recital assessment of image fusion based on multi-resolution transforms using smoothness approach

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ABSTRACT
Combining the information from the registered source images is the process involved in the image fusion. In this present manuscript, two fusion rules are explored. The first one is based on the weightage-based rule. The second one is the Smoothness and weightage based algorithm. Smoothness is used to reduce the noise from the source images. These two methods are independent of the selection of the transform. In this work, Discrete Wavelet Transform is considered to perform the experimentation. The recital comparison was made between multiresolution transforms using maximum selection method, weightage method, and smoothness along with weightage. The source images are generally multi-focused, satellite, panchromatic, and clinical medical images. The experimental results show that more smoothened (in addition with weightage) images (including edges and curves) provide high visual information. The advantage of this approach is proven using the performance metrics such as PSNR, NCC, MI, ESOP, and FSIM. The blocking artifacts are reduced by decomposing the transforms and the high frequency noise in the source image is smoothened by proposed approaches.

Section: RESEARCH PAPER

Keywords: Image fusion; multi resolution transforms; maximum selection rule; smoothness-based method; weightage method

Citation: R. Vadhi, V. Swamy Kilari, The recital assessment of image fusion based on multi-resolution transforms using smoothness approach, Acta IMEKO, vol. 13 (2024) no. 2, pp. 1-6. DOI: 10.21014/actaimeko.v13i2.1491

Section Editor: Laura Fabbiano, Politecnico di Bari, Italy

Received March 1, 2023; **In final form** May 28, 2024; **Published** June2024

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1. INTRODUCTION

A fused image has included the processes of acquisition and enhancement. Acquisition is capturing the source images from digital sensors. The registered images are considered as source images [1]. For example, fusion of Computerized Tomography (CT) and Multi Resolution Image (MRI) result a fused image that offers better information of dense and soft tissues of a particular part of body.

At the stage of integration of information, the fusion set of rules are classified as Pixel Level [2], Feature Level [3], and Decision Level [4]. Pixel level fusion is the initial level that integrates the visual information from source images [5]. The fused image incorporates more information than any of the source images. Generally, fusion algorithms are classified into two groups. One is spatial domain techniques; the second one is transformed domain techniques.

The transform domain algorithms are designed to represent the sharpness and edges of a photo. The Fused photograph may be created without losing the salient capabilities of source snap shots. The fusion images are built meaningfully with coefficients supplied through image transforms. Many transform kernels are considered for image-fusion. Popular multi resolution transforms are Laplacian pyramid decomposition, Discrete Wavelet Transform (DWT) [6], Stationary Wavelet (SWT) [7], Zhang Bin [8] defined the numerous fusion rules of wavelet transforms. Contourlet Transform (CT) [9], and Nonsub Sampled Contourlet Transform (NSCT) [10].

The classification of multi-scale decomposition-based photo fusion can be installed by way of Gemma paella to attain high excellent of digital camera photos. Multi scale decomposition coefficients are considered from only few simple kinds consisting of Laplacian-pyramid transform, Discrete wavelet rework and discrete wavelet frames to get the fusion photograph. In spatial domain, simple fusion algorithms are an averaging approach, absolute maximum method, absolute minimum method, and weightage-primarily based method [11].

The mathematical standards are used to evaluate the weighted coefficients using the average and well-known deviation of each sub-block.

Do and Martin Vetterli described a directional multi-resolution digital image representation using the contourlet-remodel. Multi scale fusion methodology was explored [12] to make tremendous revolution in image fusion. In this scenario, Discrete cosine transforms are also used in obtaining the fusion results [13]. Further, the techniques developed a region based-fusion algorithms with the use of non-sub sampled contourlet Transform. Radhika et al [14] explained the performance metrics used to measure the quality of the fused images.

The organization of this manuscript is provided as follows. In Section 2, the short descriptions are provided for DWT, SWT, CT, and NSCT. In Section 3, a few descriptions are presented about the existing algorithms and the proposed algorithms. In Section 4, experimental results are presented. The main Conclusion are given in Section 5.

2. MULTI RESOLUTION TRANSFORMS

2.1. Discrete wavelet transforms (DWT)

In the Wavelet-scenario, the source image is sub-sampled and directional filtering operations are performed by means of a component of two [6]. Image down-sampled can be intended with a variable extension of the 1-directional decomposition on the rows and-columns. In Wavelet Transform, the image is down sampled into 4 sub-images. This area has righteous localization in time and frequency. Utilising the scaling property, higher identification, and higher litheness, the image is transformed. The input sign can be a cause for primary variation inside the distribution of energy among DWT because of the lack of shift-invariance.

2.2. Stationary wavelet transforms (SWT)

Stationary Wavelet Transforms (SWT) are the simplest in suppressed down sampling. It has translation invariant property. The sizes of all sub bands are identical as the source. SWT is an intrinsically regularly repeatable scheme due to the fact that every set of coefficients contained the equal quantity of samples as an enter. Hence, it has the value of 2N is repeatedly appear for a decomposition of number of N levels. The translation invariance of the redundancy and Wavelet coefficients that helps the identity of salient capabilities in a signal, specifically for presence of the noise are the advantages of SWT. There is a decrement in directionality and increments in computational problem are the risks.

2.3 Contourlet transform (CT)

The Contourlet Transform is a Multi- Scale and Multi-directional network built by way of compounding the Laplacian pyramid with the Directional Filter Bank (DFB). Minh and Martin Veterly [9] explained that CT not only possesses the most effective functions of wavelets but also gives an excessive diploma of directionality and anisotropy. The advantages of CT have its minute redundancy and provide multi-scale and multi-path decomposition.

2.4 Non sub-sampled contourlet transform (NSCT)

The NSCT is a grouping of the Non-sub-Sampled pyramids and the Non sub–Sampled DFB. It was presented by Tania Stataki, [4]. The non sub-sampled pyramid is specific from the counterpart of the Contourlet Transform. The Building Block of the Non-Sub Sampled pyramid is a channel Non-sub-Sampled clear out bank. It has no down-sampling or up-sampling. Hence, it is far shift-invariant. It has accurate directionality. Non-sub-sampled DFBs are repeated to achieve filter directional down-sampling.

3. IMAGE FUSION TECHNIQUE

In this proposed work, the Authors consider the multi focus natural images and medical images with different modalities. Assume that the source image pair 1 and 2. The general procedure of multi scale image fusion is illustrated in Figure 1. In this procedure, first the source images are decomposed into low-frequency sub bands and a sequence of high-frequency sub band at different orientations and scales according to the transform. Based on the algorithm, the decision will be made and then the fused image is obtained by applying inverse transformation. The more salient features are selected through Shutao et al. [6], the proposed method of maximum selection rule. The following steps describe the maximum selection rule procedure.

3.1. Average and maximum selection fusion

- Decompose the images to be fused by using any multiresolution transform.
- The Low frequency components L_1 and L_2 are fused by the average method using the formula.

$$L = \frac{1}{2}(L_1 + L_2)\,. \tag{1}$$

- The high frequency coefficients H_1 and H_2 are fused by the approach of choosing absolute maximum using the formula.

$$H = \begin{cases} H_1 \text{ if } & H_1 > H_2 \\ H_2 & \text{otherwise}\,. \end{cases} \tag{2}$$

- Compute the inverse transform to generate the fused image by considering low frequency and high frequency components.

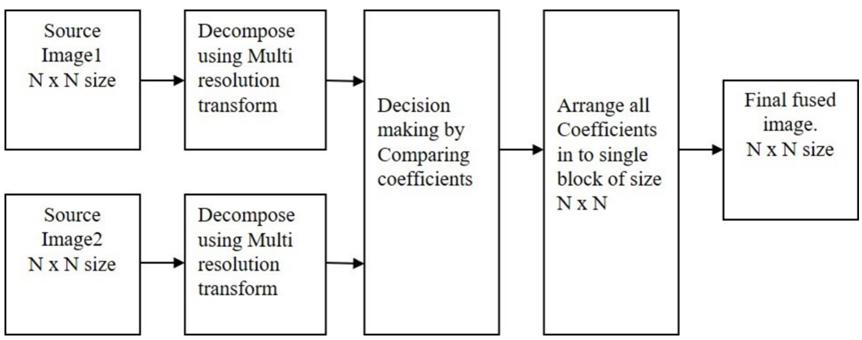


Figure 1. Generalized block diagram for fusion using multi scale transforms.

3.2. Proposed fusion rules

Weight-based method

Here we propose the methods which results better than Shutao et al. [6] method. The first proposed method is weighted base algorithm and the second is uniform based weighted algorithm. The generalized weighted based algorithm is as follows:

- Decompose the Images to be fused using any multiresolution transform.
- The Low frequency components are fused by the average method using the formula as given in equation (1)
- The high frequency coefficients are fused by the approach of adopting weights as follows in below steps.
- Compute the energy of high frequency components $p(i,j)$ which are to be fused by the formula given:

$$E = \sum_i \sum_j p(i,j)^2 \,. \tag{3}$$

- Calculate the average to the energies of high frequency components E_1 and E_2 of the images which are to be fused:

$$E = \frac{1}{2}(E_1 + E_2)\,. \tag{4}$$

- Find the absolute difference between two high frequency coefficient bands (D)
- If the average of energies of high frequency components is less than T and D value is 1 then weightage is equal to w_1 otherwise weightage is equal to w_2.
- If the average of energies of high frequency components is greater than T and D value is 1 then weightage is equal to w_3 otherwise weightage is equal to w_4.
- Apply the given formula for the high frequency bands:

$$\begin{aligned} H = {} & (w_1 \text{ or } w_2 \text{ or } w_3 \text{ or } w_4) \cdot H_1 \\ & + (w_1 \text{ or } w_2 \text{ or } w_3 \text{ or } w_4) \cdot H_2 \,. \end{aligned} \tag{5}$$

- Compute the inverse transform to generate the fused image by considering low frequency and high frequency components.

Smoothness and weight-based method

- Two multi-focused, registered images are contemplated with the equal size {N, N}.
- Split each image into equal number of sub blocks with the size {n, n}.
- Calculate Smoothness of one and all blocks with the following sequence
- The approximation band in DWT is specified in equation (6) is

$$\Psi_\phi(j_0, u, v) = \frac{1}{\sqrt{MM}} \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} f_i(x,y)\, \phi_{j_0.u,v}(x,y)\,. \tag{6}$$

- Smoothness of one and all sub-blocks are determined and is shown as below.

$$S_{i\,\theta=1}(u,v) = 1 - \frac{1}{1 + V_{i\,u,v}}\,. \tag{7}$$

- where $V_{i\,u,v}$ is the variance of the approximation-band. $S_{i\,\theta=1}(u,v)$ is the Smoothness of approximation-band.
- The Smoothness (transform domain) of detailed bands specified in equation (8) is

$$\Psi^i{}_\psi(j_i, u, v) = \frac{1}{\sqrt{MM}} \sum_{x=0}^{M-1} \sum_{y=0}^{M-1} g_i(x,y)\, \psi^i_{j.u,v}\,. \tag{8}$$

- The equation of Smoothness is given below:

$$S_{\theta=2,3,4}\,(u,v) = \sum_{u,v} \left| \Psi^i{}_\psi(j,u,v) \right|. \tag{9}$$

where $S_{\theta=2,3,4}\,(u,v)$ are the smoothness of the vertical, horizontal, and detailed bands. The DWT, the Smoothness of an image is determined with the help of-equation (6) and equation (7). Average of all pixels is considered for the approximation band. The detailed bands contain the transform coefficients. The Smoothness measures of approximation-band are determined using the mentioned equation (7). $\theta = \{1,\ 2,\ 3,\ 4\}$. For $\theta = 1$, is the approximation-band and $\theta_s = \{2,\ 3,\ 4\}$ signifies the vertical, horizontal and the detailed-bands. Further smoothened blocks are recognized by using the value of S. The blocks which have more value of S are positioned in result image. Processed image and one of the source images are considered for fusion by adopting the weighted method.

4. EXPERIMENTAL RESULTS

In this work, we recall five pairs of supply photos, as given in Figure 2. The source image pairs are (a) and (b), (c) and (d), (e) and (f), (g) and (h), (i) and (j). The source images are multi-resolution and registered photographs. The source image size should be 128 × 128.

4.1. Qualitative analysis

In Figure 1, the decomposition procedure included the filters for each multi-scaling with the general digital image-fusion framework is given. The multi-resolution coefficients - reciprocates largely in pixel values whereas in comparison with the ultimate decomposed levels. Only some decompositions are carried out to lessen the block effect in multi decision transforms. In Figure 2, each multi awareness and medical source picture pair is given. The objective of overall recital evaluation is performed by means of Peak Signal-to-Noise Ratio (PSNR) and Normalized Cross Correlation (NCC). Mutual information (MI). The Edge Strength and Orientation Preservation [8] is the weights of edges and their orientation power. Feature Similarity (FSIM) Index can be measured the similarity be contingent upon the gradient measure.

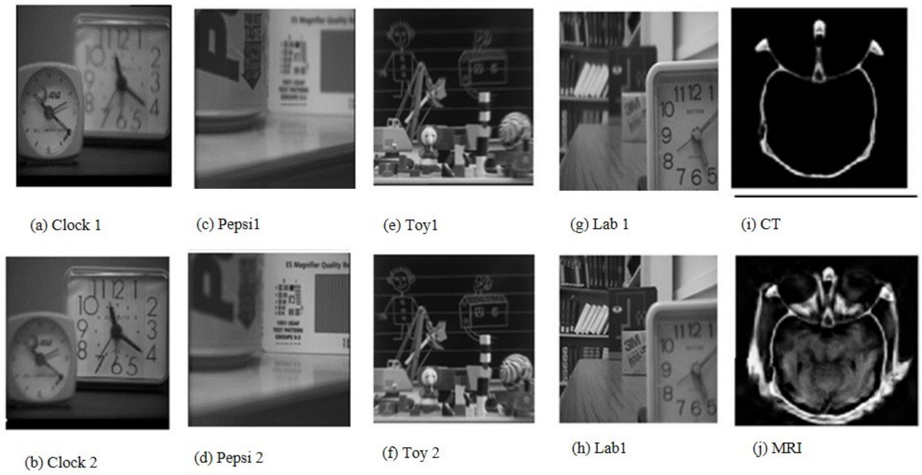


Figure 2. Results of both multi focus and medical images using DWT.

Table 1. Fusion Results for Multi-focus images.

Image	Fusion rule	Transform	Filter	PSNR	NCC	MI	$Q^{AB/F}$ (ESOP)	FSIM
Clock	ShutaoLi[6]	SWT	Sym2	31.4087	0.9853	3.1239	0.7544	0.9527
	Weightage	SWT	Sym2	33.3145	0.9906	3.1892	0.7683	0.9656
	Smoothness+weightage	SWT	Sym2	**35.2659**	**0.9940**	**3.5252**	**0.7591**	**0.9750**
	ShutaoLi[6]	DWT	Haar	29.9041	0.9792	2.6823	0.7259	0.9479
	Weightage	DWT	Haar	31.9806	0.9872	3.2042	0.7496	0.9593
	Smoothness+weightage	DWT	Haar	**34.8492**	**0.9934**	**3.2790**	**0.7502**	**0.9740**
	ShutaoLi[6]	Con.T	Pyr	30.4560	0.9816	2.6524	0.7460	0.9543
	Weightage	Con.T	Pyr	33.0305	0.9899	3.0789	0.7349	0.9557
	Smoothness+weightage	Con.T	Pyr	**35.4741**	**0.9943**	**3.4277**	**0.7440**	**0.9740**
	ShutaoLi[6]	NSCT	Pyr	31.4368	0.9854	3.0012	0.7589	0.9526
	Weightage	NSCT	Pyr	33.5793	0.9911	3.2200	0.7612	0.9688
	Smoothness+weightage	NSCT	Pyr	**36.0602**	**0.9950**	**3.3937**	**0.7604**	**0.9785**
Pepsi	ShutaoLi[6]	SWT	Sym2	35.9518	0.9958	3.2823	0.8134	0.9776
	Weightage	SWT	Sym2	**36.6718**	**0.9967**	**3.2590**	**0.7900**	**0.9794**
	Smoothness+weightage	SWT	Sym2	34.5150	0.9945	3.1853	0.7771	0.9578
	ShutaoLi[6]	DWT	Haar	34.6122	0.9942	3.1709	0.8054	0.9754
	Weightage	DWT	Haar	**34.8400**	**0.9948**	**3.0801**	**0.7637**	**0.9739**
	Smoothness+weightage	DWT	Haar	34.0222	0.9938	3.0510	0.7718	0.9556
	ShutaoLi[6]	Con.T	Pyr	30.5097	0.9859	2.7860	0.7360	0.9685
	Weightage	Con.T	Pyr	**36.0594**	**0.9961**	**3.1915**	**0.7669**	**0.9738**
	Smoothness+weightage	Con.T	Pyr	34.5025	0.9944	3.1060	0.7689	0.9576
	ShutaoLi[6]	NSCT	Pyr	32.3626	0.9910	3.0029	0.7393	0.9704
	Weightage	NSCT	Pyr	**36.6773**	**0.9967**	**3.2401**	**0.7870**	**0.9797**
	Smoothness+weightage	NSCT	Pyr	34.6602	0.9946	3.2178	0.7806	0.9586
Toy	ShutaoLi[6]	SWT	Sym2	34.6840	0.9962	3.1207	0.8770	0.9859
	Weightage	SWT	Sym2	**32.0922**	**0.9925**	**2.7756**	**0.8166**	**0.9799**
	Smoothness+weightage	SWT	Sym2	32.0351	0.9924	2.8661	0.8175	0.9790
	ShutaoLi[6]	DWT	Haar	33.7150	0.9950	2.9313	0.8689	0.9846
	Weightage	DWT	Haar	**31.2830**	**0.9908**	**2.7066**	**0.8073**	**0.9731**
	Smoothness+weightage	DWT	Haar	31.2514	0.9907	2.7091	0.8082	0.9742
	ShutaoLi[6]	Con.T	Pyr	30.1363	0.9878	2.5143	0.8150	0.9719
	Weightage	Con.T	Pyr	**31.9022**	**0.9921**	2.7111	0.7843	**0.9730**
	Smoothness+weightage	Con.T	Pyr	31.6379	0.9916	2.7266	0.7884	0.9721
	ShutaoLi[6]	NSCT	Pyr	31.2137	0.9907	2.8105	0.8244	0.9733
	Weightage	NSCT	Pyr	32.3467	0.9930	2.8574	0.8075	0.9792
	Smoothness+weightage	NSCT	Pyr	**32.3467**	**0.9930**	**2.8574**	**0.8075**	**0.9792**
Disk	ShutaoLi[6]	SWT	Sym2	31.5898	0.9888	2.8712	0.8049	0.9609
	Weightage	SWT	Sym2	**32.8919**	0.9925	2.9360	0.7535	0.9717
	Smoothness+weightage	SWT	Sym2	33.5624	**0.9936**	**3.0373**	**0.7585**	**0.9731**
	ShutaoLi[6]	DWT	Haar	30.2334	0.9846	2.6878	0.7904	0.9562
	Weightage	DWT	Haar	30.8893	**0.9879**	2.7410	0.7327	0.9629
	Smoothness+weightage	DWT	Haar	**32.8635**	0.9925	**2.9658**	**0.7468**	**0.9698**
	ShutaoLi[6]	Con.T	Pyr	27.0156	0.9704	2.2792	0.7265	0.9466
	Weightage	Con.T	Pyr	31.7117	0.9901	2.7530	0.7172	0.9556
	Smoothness+weightage	Con.T	Pyr	**33.8895**	**0.9940**	**3.0468**	**0.7393**	**0.9720**
	ShutaoLi[6]	NSCT	Pyr	28.5020	0.9797	2.6394	0.7392	0.9474
	Weightage	NSCT	Pyr	32.8819	0.9925	2.9508	0.7494	0.9695
	Smoothness+weightage	NSCT	Pyr	**33.6980**	**0.9937**	**3.0882**	**0.7571**	**0.9738**

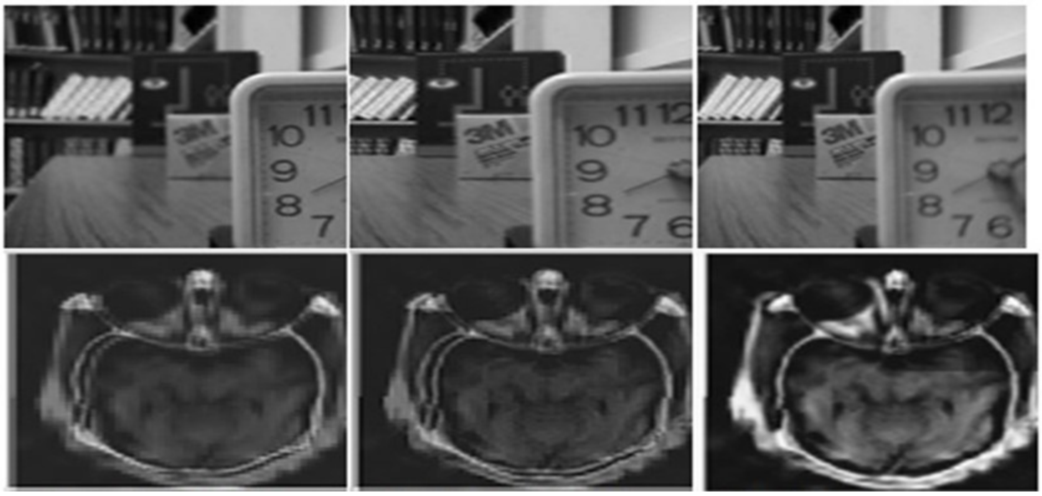
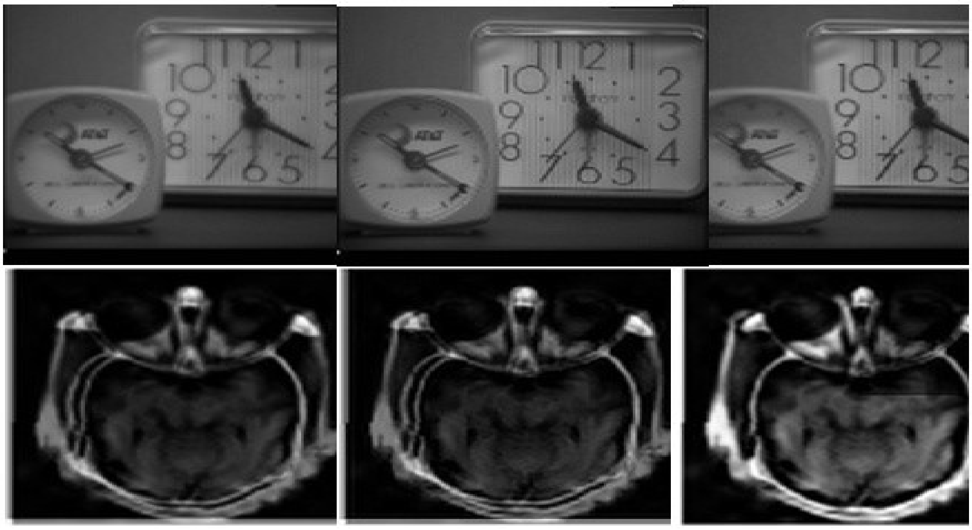


Figure 3. Fusion results of both-multi focus and medical images using NSCT.



a) Shutao Li method, b) Weightage method, c) Smoothness + Weightage

Figure 4. Fusion results of both-multi focus and medical images using existing and proposed approach (Smoothness + Weightage).

4.2. Image fusion using multi-resolution transform

Image-fusion using DWT to calculate the recital of DWT, Haar-family group is adopted. The unsurpassed results are highlighted/bolded in Table 1.

When compared with other approaches, Smoothness based weighted approach results best, shown in Figure 3. The estimation of CT is based on pyramidal- filters and directional filters.

Image-fusion the use of NSCT is primarily based on pyramidal clear out (maxflat) and directional_ filters Also, there are twelve classes of orientation filters, i.e., 'Haar', (dmaxflat7). Every one of measuring metric of assessment for all methods and source images are specified in Table 1. These filters are up-sampled at every level. In popular, they're four sorts of filters, that is., '9-7', 'maxflat', 'pyr' and 'pyrexc'. McClellan', '17-17', '9-nine', 'dvmlp', '7-9', 'ladder', 'perfect', 'dmaxflat7''dmaxflat6',

Table 2. Fusion Results for medical images.

Fusion rule	Transform	Filter	PSNR	NCC	MI	$Q^{AB/F}$ (ESOP)	FSIM
ShutaoLi [6]	SWT	Sym2	15.0366	0.8185	2.2407	0.5871	0.7730
weightage			14.3456	0.7880	1.7776	0.5456	0.7536
Smoothness+weightage			18.9407	0.9268	2.1401	0.6886	0.8681
ShutaoLi [6]	DWT	Haar	14.7543	0.8040	1.7385	0.5631	0.7741
weightage			14.1686	0.7832	1.4666	0.5600	0.7624
Smoothness+weightage			18.8228	0.9243	2.0484	0.6968	0.8586
ShutaoLi [6]	Con.T	Pyr	14.1733	0.7763	1.4051	0.4928	0.7459
weightage			14.2157	0.7806	1.4219	0.5004	0.7331
Smoothness+weightage			18.8590	0.9262	2.0020	0.6610	0.8750
ShutaoLi [6]	NSCT	Pyr	14.3936	0.7885	1.6546	0.5341	0.7489
weightage			14.2479	0.7828	1.5235	0.5445	0.7488
Smoothness+weightage			19.0482	0.9291	2.0053	0.6965	0.8774

'dmaxflat5', and 'dmaxflat4'. While comparison with all other mentioned multi resolution transforms, NSCT results best. The fused images developed by Shutao Li method, weightage method and Smoothness based weighted methods are shown in Figure 4. Results for the medical images are presented in Table 2.

5. CONCLUSIONS

In this paper, the performance comparisons are made among the algorithms existed using multiresolution transforms with the proposed approaches. The high frequency noise in the source image is tremendously smoothened by proposed Smoothness+ Weightage approach. The blocking artifacts are reduced by decomposing four times of the chosen transforms, i.e. not more than four decompositions. Among the multi-resolution transforms NSCT results best for medical images/multi-modality images. For the proposed algorithm, the NSCT with pyr filter results surpass the other approaches. Smoothness along with weightage method is producing promising results.

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