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Multimodal Medical Image Fusion using NSCT and DWT Fusion Frame Work

K. KoteswaraRao, K. Veera Swamy

***Abstract:** Image fusion is the process, which gathers significant details from two or more images. In the image fusion important information is selected from multiple images. Implementation of fusion of images is carried out either in spatial or in transforms domains. In this work, fusion is done in both domains to get better performance. Energy of decomposed bands of NSCT is used to select important bands in NSCT based image fusion. Energy of decomposed bands of DWT is used to select important bands in DWT based image fusion. Fused images of NSCT and DWT are further fused by using spatial domain technique. In spatial fusion ESOP values are taken into consideration to perform fusion. Experiments are done on several medical images .Experiments show that, the proposed method is giving perceptually meaningful fused images. Image metrics like entropy, edge based similarity measure and quality of mutual information have been used for the assessment of performance of the work. In this research work, two medical images (CT, MRI), after pre-processing, will be merged according to the wavelet and NSCT transformations using energy fusion techniques to generate two independent fusion images that will be merged again using spatial domain to get the desired output. In this way the large amount of comprehensive information can be presented in the merged image, all the comprehensive information obtained from the two medical images appears in the final output. The experimental outcomes on different CT and MRI images are analyzed qualitatively and quantitatively. Image fusion has been implemented in the various applications like remote sensing, space research, defence, medical imaging etc. The performance parameters show remarkable improvements.*

***Keywords:** Medical image fusion, DWT, NSCT, Energy and Edge strength orientation preservation.*

I. INTRODUCTION

Now a day, screening programmers focus on digital data and screening techniques are designed for detecting early symptoms of diseases and remedies for treatment. In medical imaging, there are different modalities with different capabilities to get useful information of human body. Even though, there may be many sources, a single source is not able to provide more valuable information in discriminating diseases. The problem with single source is costly, meticulous, causing error, time consuming and it requires more experience. These factors of single image motivated the researchers to get appropriate information. Furthermore, the latest image modalities are more costly, which are the additional burden for the individuals.

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***** Correspondence Author
K.Koteswara Rao*, Research Scholar , JNTU College of Engineering, Kakinada, AP, India. Email: koti_r@yahoo.in
K.Veera Swamy, Professor, Department of ECE, Vasavi College of Engineering, Hyderabad, Telangana, India. E-mail: k.veeraswamy@staff.vce.ac.in

So, it is necessary to combine individual images into a single image, which is more suitable for efficient diagnostic assessment. Many researchers [1], [3] have developed different fusion algorithms Algorithms on image fusion are broadly categorized into two, one is the spatial domain and another one is the transform domain. Spatial methods deal directly with the pixel .Desired result is achieved by manipulating the pixel values. This method fuses source images by using spatial local features. The algorithms based on spatial methods are bravery method, IHS, PCA, averaging method, minimum absolute method [5], [6], averaging method and weighted averaging method, which are focused to reduce unwanted edge information. These methods are simple compared to transform methods. Spatial domain fusion rules like mean, minimum and maximum methods failed to get salient features of images. But, the edge strength and orientation preservation fusion rule gives more comprehensive information of fused image. The selection of block and its size decides the quality of the merged image

Some authors approached transform domain techniques to increase the performance of fusion. In transform domain, images are transferred into frequency domain. In this domain, source images are projected into local bases and these are designed to convey sharpness and edges. Salient features are detected by transformed coefficients. These methods provide good quality spectral content. Image fusion based on the wavelets [7] was proven to be efficient in capturing one-dimensional singularity. DWT is good at isolated discontinuity. It is ideal fusion scheme. DWT captures point wise information at only few directions. DWT is shift variant and it requires down sampling. The drawback with wavelet fusion is limited directionality. Wavelet fusion does not give more information about edges [8]. To avoid the problems of wavelet fusion, the RT [9] was introduced to get edge information, but failed in capturing details of curve edges. Wavelets [7], contourlets[13],[14] curvelets [10],[11] and NSCT[16],[19] come under this category. Donoho introduced curvelets [10], which are capable of capturing 2D singularities of an arbitrary waveform. Srivasthava et al [12] used localized energy fusion rule using curvelets and it was proved as an efficient method than any other fusion of single pixel. After that, other transformation methods such as contourlet transform has been introduced [13],[14]. In this, shift variance and less directionality were observed. To avoid these problems, the NSCT has been presented and is broadly used in the image fusion. Cunha [16] proposed a non sub sampled contourlet transform. Yang [17] introduced a method, which uses wavelet-based NSCT image fusion approach.

Ganasala [19] implemented image fusion by taking CT and MRI images in NSCT domain. Padma *et al.* introduced a fusion approach which is also NSCT based and proved better performance measures [18]. In NSCT shift is not varied, image is viewed at different resolutions, scale is multiple and high directionality is achieved. It avoids the usage of up-sampling and down sampling. It gives more information about edges. Murphy, Azam and Sun revised the shearlet transform as non subsampled scheme named as non sub sampled shearlet transform. It avoids the usage of samplings in decomposition and inversion by keeping high directionality [28]. In [29], Guoronga revealed the superiority of NSST compared to NSCT and other wavelet fusion techniques. Recently, different fusion techniques with merits and demerits were stated [30]. By considering the outcomes of various methods, it is understood that still there are some parameters, which are to be improved so that the loss of meaningful information is reduced. These problems are addressed in the proposed method.

In this work, dual level fusion is framed by taking the concepts of NSCT [16] and DWT [7] at the first level and the concepts of spatial domain [6] in the second level. Energy fusion rule is taken for all the frequency coefficients of both NSCT and DWT at first level. Edge strength and orientation preservation fusion rule is appli————————ed to sub blocks of spatial domain. CT and MRI images are the inputs to both NSCT and DWT, and these are fused in NSCT domain and DWT domain independently. The outputs of both NSCT and DWT are again fused using spatial domain principles. The dual level fusion framework preserves relevant information and enhances visual quality of output image. The performance is analyzed subjectively and objectively. For fusing all frequency co-efficients of both NSCT and DWT at the first stage, energy fusion rule is used and in the consequent stage ESOP fusion rule is used

Existing methods on spatial domain like mean, minimum, maximum were failed to give comprehensive information and to design good fusion algorithm but edge strength and orientation preservation fusion rule gives more meaningful information in the final fused output

This paper is organized by presenting DWT, NSCT details in second section, proposed fusion frame work in third section, discussion of results in fourth section and finally Conclusions are in the fifth section.

II. METHODOLOGY

This part brings the depiction of concepts based on which the recommended framework is formed.

A. Non-Subsampled Contour let Transform

NSCT is one type of multiscale, multidirectional and multiresolution framework for the computation of discrete images [16]. It comprises two stages which are, pyramid without subsampling (NSP) and bank of directional filters without subsampling (NSDFB).The first stage provides a multi-scale property using a non subsampled two-channel filter bank. Every NSP decomposition stage produces one LF and one HF components. The consequent stage NSP decomposes the low frequency components in the iterative manner to bring uniqueness. With this outcome, NSP produces N+1 sub images, with N high- frequency images and single low-frequency and N represents number of levels of decomposition. After decomposition the sizes of source and sub images must be same. NSP decomposition with N = 3 levels is shown in Fig.1. The combination of fan filter banks produce NSDFB (Non sub sampled directional filter bank),which is a two-channel filter, that accepts directionality decomposition. For M levels, 2^M directional sub images are produced by NSP at every scale. As a consequence, the NSDFB provides NSCT a multi-directional ability that gives extra decisive information about the directionality. These details are illustrated in Fig .2

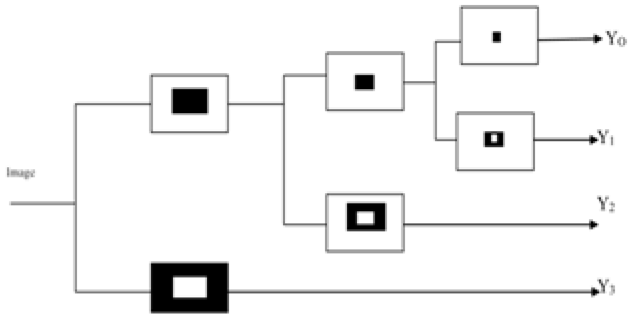

Fig.1. Three Stage NSP decomposition

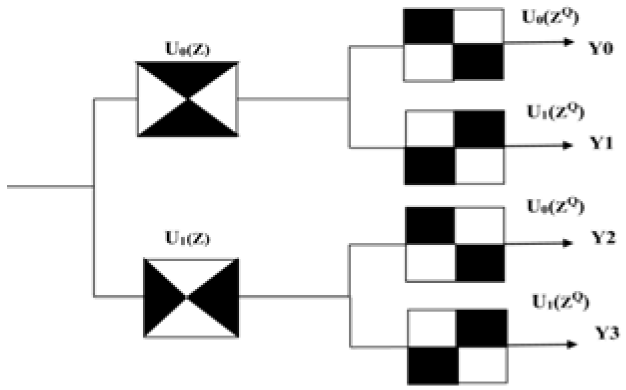

Fig.2. Four Channel NSDFB

Mathematically Energy of each sub band is calculated using the formula

$$E1(j,k) = \sum_{j-1}^{j+1} \sum_{k-1}^{k+1} A(j,k) \qquad (1)$$

$$E2(j,k) = \sum_{j-1}^{j+1} \sum_{k-1}^{k+1} B(j,k) \qquad (2)$$

Where A and B are two source images

B. Discrete Wavelet transform

The theory and concept of wavelets have come from Mallat. Wavelet transform quantifies the matching of the signal with the wavelets. If the shape of the signal matches with wavelet, then higher value of transform is obtained. If the signal is not correlated well with wavelet, low transform value is obtained. The Transform is computed at various scales and locations.

The wavelet transform is useful as a tool which detects regional characteristics in the processing of images. This transform gives time-frequency representation of an image. This transform conquers the defects of STFT, and it analyses non stationary signals also.
In this, signal is viewed at different resolutions. This transform is treated as mathematical microscope. The DWT decomposes the input sequence as low and high pass sub-bands. Each sub band consists of half samples of the original input. In DWT the input is analyzed with analysis filter bank succeeded by the operation called decimation. A 2D transform is obtained by using two one dimensional transforms. Firstly the input image is filtered along rows and decimated by two. Then it is followed by filtering sub image along column. This process separates the input into sub bands those are shown in the Fig.3.

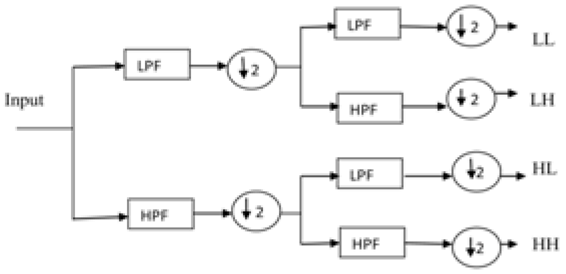

Fig.3. DWT Decomposition

The two dimensional DWT is expressed
as$\Psi_{\varphi}(j_0,u,v)=\frac{1}{\sqrt{N\times N}}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y)\emptyset_{j0,u,v}(x,y)$ (3)
$\Psi_{\Psi}^{i}(j,u,v)=\frac{1}{\sqrt{N\times N}}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y)\Psi_{j,u,v}^{i}(x,y)$ (4)
where $\emptyset_{j_0,u,v}(x,y)=2^{\frac{j}{2}}\emptyset(2^jx-u,2^jy-v)$ is the scaling function
$\Psi_{j,u,v}^{i}=2^{\frac{j}{2}}\Psi^{i}(2^jx-u,2^jy-v)$ is the translated function,$N\times N$ is the size
i assumes row ,column and diagonal values
j indicates scale function and u, v values are ranging from 0,1,2…..2^j-1
$\Psi_\varphi(j_0,u,v)$ coefficients resemblances f(x,y) and $\Psi_\Psi(j,u,v)$ co-efficients describe detailed components of f(x,y)

C. Spatial domain

Spatial domain directly manipulates the pixels. This domain is easier to understand, it is cheaper and it takes less time. The edge based similarity measure provides the analogy among the edges carried and is expressed as

$$Q^{AB/F}=\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}\left[Q_{j,k}^{AF}w_{j,k}^{x}+Q_{j,k}^{BF}w_{j,k}^{y}\right]}{\sum_{j=1}^{M}\sum_{k=1}^{N}\left[w_{j,k}^{x}+w_{j,k}^{y}\right]} \quad (5)$$

A,B, and F are the inputs and output images respectively. The individual parameters are same and these are given as

$$Q_{j,k}^{AF}=Q_{g,j,k}^{AF}Q_{\alpha,j,k}^{AF} \quad (6)$$
$$Q_{j,k}^{BF}=Q_{g,j,k}^{BF}Q_{\alpha,j,k}^{BF} \quad (7)$$

Where Q_g^{*F} and Q_α^{*F} are ESOP values. The normal range is from 0 to1. Higher value of this better is the fusion.

III. PROPOSED FUSION FRAMEWORK

This part shows the discussion of some of motivational factors in designing our idea for fusing medical images. The suggested work is taken into account, which requires two different images of the same source to get the compound image. The essential requirement of this framework is the source images must be registered for the alignment of pixels.

Proposed dual fusion Methodology steps

To test the suggested fusion method, the image data typical of CT and MRI are taken and these are named A and B. The following steps are followed in our proposed algorithm.

Step 1: Take the images that will be merged from the database and the pre-processing treatment is done. As a general rule, images of 256 x 256 sizes are selected for evaluation.

Step 2: First level merge: Apply NSCT on the input images, it results one LF and set of HF coefficients in every level and orientation. In this decomposition, number of levels(n) taken are [2, 2, 4]. With these levels no. of sub bands formed are 4,4,16. For the pyramidal filter and directional filters, maxflat filter and dmaxflat7 filters have been used respectively

Step 3: Energy of each co-efficient is calculated using the formula

$$E1(j,k)=\sum_{j-1}^{j+1}\sum_{k-1}^{k+1}A(j,k) \quad (8)$$
$$E2(j,k)=\sum_{j-1}^{j+1}\sum_{k-1}^{k+1}B(j,k) \quad (9)$$

Step 4: Low frequency fusion: The approximation of source images is represented by sub images of low frequency. Simple average methods are used for merging. However, because of low contrast, a high quality merged image cannot be obtained. So we use a Energy fusion rule

$$F_l^F(j,k)=\begin{cases}F_l^A(j,k), & if\ E_l^A(j,k)>E_l^B(j,k)\\ F_l^B(j,k), & if\ E_l^A(j,k)<E_l^B(j,k)\\ \frac{\sum_{k\in A,B}F_l^K(j,k)}{2}, & if\ E_l^A(j,k)=E_l^B(j,k)\end{cases} \quad (10)$$

Step5: High-frequency fusion: The detailed components of source images correspond to sub images of high frequency. Energy of each sub band is calculated as

$$F(j,k)=\begin{cases}F_{l,\theta}^A(j,k),\ if\ \ E_{l,\theta}^A(j,k)\geq E_{l,\theta}^B(j,k)\\ F_{l,\theta}^A(j,k),\ if\ E_{l,\theta}^A(j,k)<E_{l,\theta}^B(j,k)\end{cases} \quad (11)$$

Step 6: Inverse operation of NSCT is done on all frequency sub bands to achieve the first level fused image F.

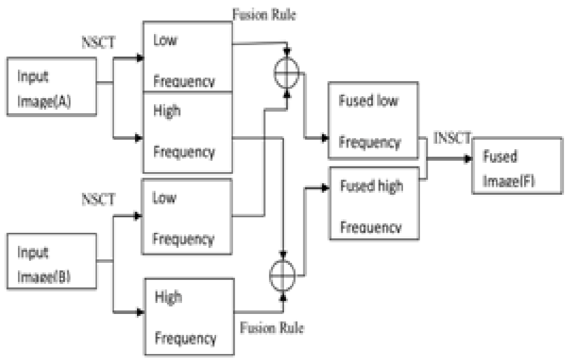

Fig.4. NSCT fusion

Step 7: First level fusion based on DWT: DWT is applied on both source images. Both the source images are resized to 256×256. These 256×256 images are decomposed at five levels as 128×128, 64×64, 32×32, 16×16 and 8×8 . Haar wavelet is used in the decomposition. All frequency components from both images are fused by using energy fusion rule. By applying inverse DWT reconstructed image C is obtained. The LF sub-bands are related to thick part of the images while the high frequency corresponds to edges and contours.

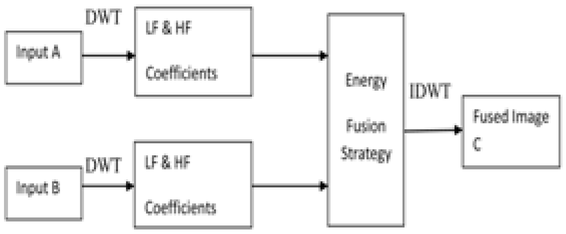

Fig.5. DWT fusion

The energy of all sub bands is calculated using (1). Compare energy of each sub band of both source images using the following relation

$$C_l^F(j,k) = \begin{cases} C_l^A(j,k), & if\ E_l^A(j,k) > E_l^B(j,k) \\ C_l^B(j,k), & if\ E_l^A(j,k) < E_l^B(j,k) \\ \frac{\sum_{k\in A,B} C_l^K(j,k)}{2}, & if\ E_l^A(j,k) = E_l^B(j,k) \end{cases} \quad (12)$$

Fusion of High-frequency Sub-images: The HF sub-images correspond to detail components of the input images. Energy of each sub band is calculated as

$$C_{l,\theta}^F(j,k) = \begin{cases} C_{l,\theta}^A(j,k),\ if\ E_{l,\theta}^A(j,k) \geq E_{l,\theta}^B(j,k) \\ C_{l,\theta}^A(j,k),\ if\ E_{l,\theta}^A(j,k) < E_{l,\theta}^B(j,k) \end{cases} \quad (13)$$

The general principle is to keep the essential characteristics of new images, such as regions and contours. The largest energy transformation values in these sub bands correspond to sharper intensity variations.

Step 8: The two merged images which are F and C are again fused to get another fused image. This is the second level fusion. Spatial method is used to perform second level fusion. Both images F and C of sizes 256×256 are divided into 32 non overlapped 8×8 blocks

Step 9: For every block apply edge strength and orientation preservation ESOP using (3)

Step 10: Select corresponding block from every source image according highest ESOP

$$D_F(j,k) = \begin{cases} D_1(j,k)\ ESOP_1\ (j,k) \geq ESOP_2(j,k) \\ D_2(j,k)\ ESOP_1\ (j,kj) \leq ESOP_2(j,k) \end{cases} \quad (14)$$

Where $ESOP_1$ (j, k) and $ESOP_2$ (j, k) are respective blocks with highest ESOP (j, k). D_F (j, k) is the selected block. Fuse the corresponding block into the empty block

Step 11: The entropy,edge based similarity measure and quality of mutual information values of the final merged images were recorded and presented in the table .

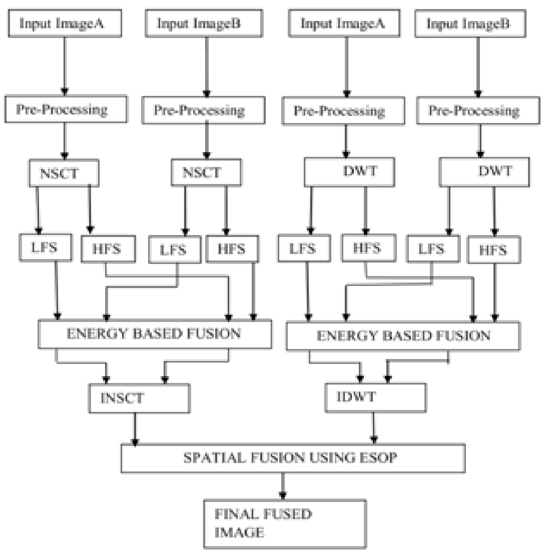

Fig.6. Suggested System Block Diagram

IV. EXPERIMENTAL RESULTS AND PERFORMANCE MEASURES

This part shows the performance of the suggested fusion method. Fusion algorithm needs some requirements 1). It must extract comprehensive features from both input images 2). Inconsistencies or artefacts should not be appeared 3). It must be reliable. In general these are evaluated subjectively as well as objectively. Result analysis reveals remarkable improvements in the proposed method at the second level. In all the sets of images, all performance indices which are Entropy, Edge based similarity measure and Quality of mutual information using dual level fusion have been improved. Among all performance indices Entropy plays an important role and it is good for all sets of images in the second level fusion. Edge based similarity measure has been improved in all cases in the second level fusion. Quality of mutual information also has been improved at the second level fusion compared to DWT and NSCT.

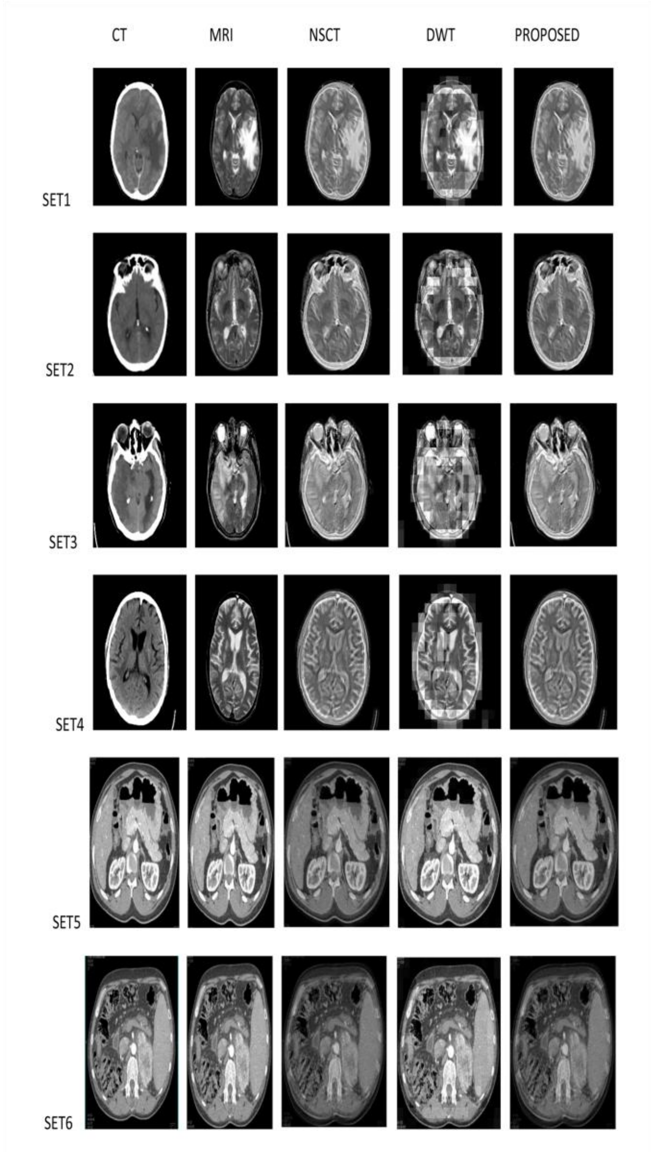

Fig.7. The multimodal medical image fusion results

Table- I: Performance indices of various algorithms

Set No.	Parameter	DWT	NSCT	PROPOSED METHOD
SET-1	Entropy	1.09564	2.452802	2.373966
	ESSIM	0.995825	0.997448	0.999989
	Q_{MI}	0.813499	0.688269	1.342295
SET-2	Entropy	1.001128	2.743131	4.901662
	ESSIM	0.994149	0.996964	0.99987
	Q_{MI}	0.7349	0.631618	1.318422
SET-3	Entropy	1.022532	2.755485	5.013938
	ESSIM	0.993946	0.996632	0.999869
	Q_{MI}	0.711381	0.551477	1.305525
SET-4	Entropy	1.051860	2.308314	5.098267
	ESSIM	0.994832	0.996891	0.999819
	Q_{MI}	0.736539	0.544445	1.297531
SET-5	Entropy	0.794191	1.251708	7.125139
	ESSIM	0.994797	0.998579	0.999884
	Q_{MI}	0.749836	0.619237	1.268498
SET-6	Entropy	0.584880	0.935982	7.282470
	ESSIM	0.994080	0.996850	0.999919
	Q_{MI}	0.644372	0.538880	1.257462

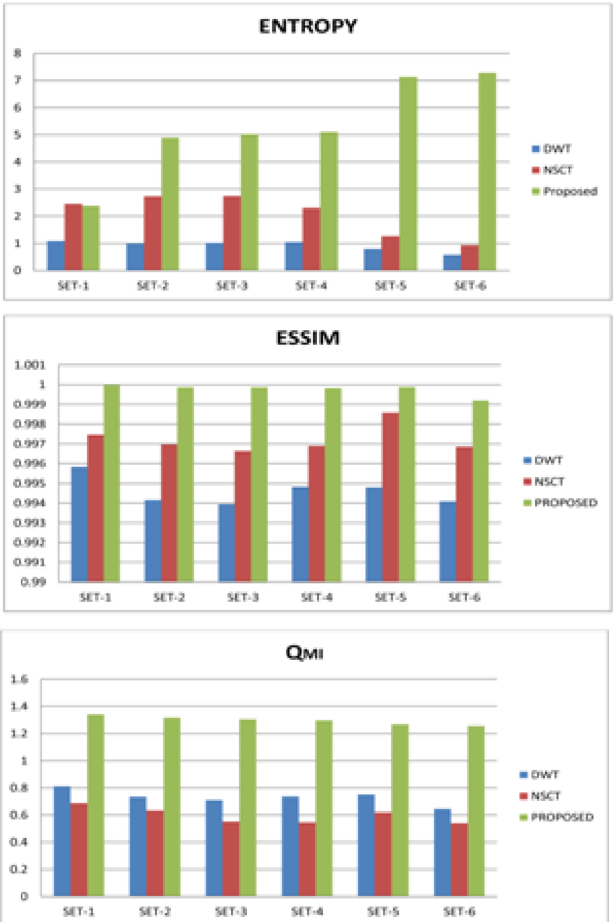

Fig. 8. Chart for the table- I

V. CONCLUSIONS

Fusion of medical images from various modalities is examined as a topic of study for researchers due to its importance and usefulness for the health sector and a better diagnosis with merged images of quality information. Ideally, merged images should contain more comprehensive information than any input image, even if the redundant information is present. Typical images of MRI and CT and two transforms are made, namely a DWT and NSCT with different fusion rules at the first level, spatial domain method at the second level and their performance measures were studied. In this study, the authors tested a double fusion scheme by fusing the two merged images generated independently with DWT and NSCT .Performance indices, which are Entropy(E), Edge based similarity measure($Q^{AB/F}$) and Quality of mutual information (Q_{MI}) for DWT,NSCT and proposed method have been compared. By comparison, it has been observed that, the suggested algorithm which is dual level fusion given good results.

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AUTHORS PROFILE

K.Koteswara Rao has been working as assistant professor in ECE department in Prakasam Engineering College, Kandukuru, Prakasam district, Andhra Pradesh, India. He received his B.E from Andhra University college of engineering Visakhapatnam. He received M.Tech post graduation from JNTUH Hyderabad. He has fifteen years of teaching experience for under graduate students. He guided many M.Tech students. He is member of International Association of Engineers with ID NO:223686 and he is also member of Institute of Research Engineers and Doctors with Membership No:SM101000602506.His research areas include signal processing, edge detection and image fusion.

Dr. Veera Swamy is a Professor at Vasavi College of Engineering, Hyderabad, Telengana, India. He received M.Tech and Ph.D. degrees from JNTUK, Kakinada in 1999 and 2009 respectively. He worked 10 Years at Bapatla Engineering College, Bapatla. He served as a Princiapl at QIS College of Engineering and Technology, Ongole from 2010 to 2018. He is having 20 years of teaching experience and 9 years of research experience. He received a grant worth of 12.5 lakhs from AICTE under RPS Scheme during 2013-16 as PI. He executed one MODROBS and one consultancy project. He published 86 research papers in various reputed international journals and conferences. He published one paper in the patent journal. His interesting research areas are Digital Image Processing, Image fusion, Image Compression, image Watermarking, and Networking Protocols.