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A Fuzzy Based Multiresolution Method for Multimodal Image Fusion

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Abstract: In this study, a Pixel Image Fusion Method that combines multiple sensor images using Non-Subsampled Contourlet Transform (NSCT) and fuzzy Logic is proposed. The objective of this study is to improve the efficiency and performance NSCT based Fusion Method using fuzzy logic. As the Wavelet Transform Based Methods widely used for fusion can not represent smooth contours and edges in images accurately, the proposed method uses NSCT for multiresolution decomposition. The multisensor image information from different sensors is often complementary, uncertain, vague and redundant. As fuzzy logic is a powerful tool that can handle the uncertainty associated with vagueness, it is employed to determine the fusion weight for each NSCT low-pass coefficient based on the activity measures spatial frequency and entropy. In order to combine the NSCT high-frequency directional coefficients the local energy measure is employed. Experimental results demonstrate that the fused images of the proposed NSCT-Fuzzy scheme are with best visual quality and achieve higher scores than the Multiresolution-Based algorithms Discrete Wavelet Transform (DWT), NSCT and hybrid NSCT in terms of the fusion evaluation metrics.

Key words: Image fusion, multiresolution, non-subsampled contourlet transforms, fuzzy logic, fusion metrics

INTRODUCTION

With the rapid growth in the field of sensor technology, multiple visual sensors are employed in image processing applications such as medical imaging, defense, surveillance, remote sensing and object tracking. In these systems, image fusion is employed to combine information from several sensors. These sensor data are often redundant, incomplete and complementary and hence fusion is performed to generate a highly informative fused image with all significant information from the inputs. The new images created are highly appropriate for human understanding and/or to carry out more image processing tasks (Drajic and Cvejic, 2007; Liang *et al*., 2012). Combining multimodal images like Infrared (IR) and visible in surveillance applications, results in improved system performance and reliability even in tough atmospheric conditions (Chen *et al*., 2008). In medical imaging, images from modalities such as Magnetic Resonance Image (MRI) and Computer Tomography (CT) is integrated to get more enhanced information about a part under study. In remote sensing applications, complementary information from multiple modalities are fused in order to facilitate subsequent processing tasks.

There are two widely used classes of Image Fusion algorithms namely, pixel based and feature based. Pixel based schemes combine either the pixels from the imaging sensors or their multiscale transform coefficients using certain fusion rules. Feature level fusion is performed with a region based approach that requires feature extraction. Some important region features or attributes extracted either in spatial domain or transform domain are used for fusion. The most widely used image fusion methods are pixel based and these algorithms fuse image information from the inputs selectively to produce a fused image (Saha *et al*., 2013). The pixel based fusion algorithms are more time efficient and easy to perform than region based fusion (Blum and Liu, 2005) and the fused images obtained by these algorithms were found to have more original information from the sources. These pixel based algorithms are mostly based on multiscale and multiresolution transforms since the salient characteristic features of images are more clearly described in transform domain than in the spatial domain (Ellmauthaler *et al*.,

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2013). The most widely applied multiresolution transforms for fusion include Laplacian Pyramid (Burt and Adelson, 1983), Discrete Wavelet Transform (Li *et al*., 1995) and Independent Component Analysis (ICA) (Mitianoudis and Stathaki, 2007). Wavelets were demonstrated to be an efficient tool for representing one-dimensional signals but for images these are not able to represent the directions of the edges and contours accurately because of their limited directionality (Do and Vetterli, 2002). In the recent past, transforms such as like contourlets (Do and Vetterli, 2002) and curvelets (Candes *et al*., 2006) are introduced to overcome the problems associated with DWT and other multiscale transformations. The contourlet transform is a multiscale, multidirection image transformation appropriate for representing edges and object boundaries in images effectively. But the presence of decimators and interpolators in its construction makes the contourlet transform translation-variant. Consequently, Da Cunha *et al*. (2006) proposed a shift-invariant decomposition called the Non Sub-sampled Contourlet Transform (NSCT) which is effectively used in many image processing applications.

The sensor information are often uncertain due to ambiguity/vagueness in the image data. Fuzzy logic is a tool capable of dealing with uncertainty associated with vagueness and/or imprecision (Cheng and Xu, 2000). In fuzzy logic, the problems to be solved are described in linguistic terms, rather than in terms of quantitative values and it employ fuzzy if-then rules to describe the system's functioning (Nedeljkovic, 2004). In recent times, fuzzy logic is efficient in many imaging applications including image classification, pattern recognition, enhancement and noise removal. As every image bears some fuzziness due to the ambiguity/vagueness in defining the various image attributes, fuzzy logic is suitable for multisensor image fusion.

In the past, several pixel based image fusion schemes were proposed (Li *et al*., 1995; Mitianoudis and Stathaki, 2007; Chen *et al*., 2008). An image fusion scheme using NSCT is presented by Yang *et al*. (2007) in which the NSCT coefficients at different scales are combined using different fusion rules. Researchers demonstrated significant performance improvement of NSCT fusion over wavelet based fusion. Zhang and Guo (2009) applied NSCT for combining multifocus images using different selection schemes for the low and high frequency coefficients. Li and Yang (2010) presented a hybrid fusion scheme using the NSCT and Stationary Wavelet Transform (SWT). Researchers considered two pixel based schemes, Serial NSCT Aiding SWT (SNAS) and Serial SWT Aiding NSCT (SSAN) and these demonstrated better fusion performance over NSCT fusion. Qingqing *et al*. (2011) proposed a method using NSCT for the fusing IR and visible remote sensing images using region energy as activity indicator. In all these methods the simple mean or max fusion rules were applied to choose coefficients and these do not take into consideration multiple features of the coefficients in decision making.

A feature based scheme using Discrete Wavelet Frame Transform (DWFT) and fuzzy logic is proposed by Liu and Lu (2007). The low-frequency NSCT sub-band is divided into three groups of regions and fuzzy logic is applied to decide the relative significance of the various regions. Mean of the region coefficients is employed as the region feature and this determines the region's degree of membership in the DWFT domain. Experiments show that this method outperforms the DWFT based fusion method.

The existing Pixel Based Image Fusion Methods, transforms the source images into multiresolution decompositions, compute a coefficient based activity measure and make use of either weighted-average function or choose-max rule to select the low-frequency coefficients. Practically, the objects and features to be combined in multisensor images are not linearly weighted. The main difficulty in image fusion lies in assigning the weights to the transform coefficients of the images to be fused. These weights are calculated based on some relevant features measured using the transform coefficients (Saleem *et al*., 2012). In this study, a Fuzzy Logic Based Inference System is implemented to find the weights of the low-frequency NSCT coefficients using two important activity level measures entropy and spatial frequency. The high-frequency NSCT coefficients use the local energy feature computed as the activity level measure. The fused high frequency NSCT directional coefficients are obtained by choosing coefficients having maximum activity.

MATERIALS AND METHODS

NSCT: The Non-Subsampled Contourlet Transform (NSCT) is a multiscale, multidirection, shift-invariant image representation realized using Non-Subsampled multiscale Pyramids (NSP) and Non-Subsampled Directional Filter Banks (NSDFB) (Da Cunha *et al*., 2006). The multiscale property is accomplished by the NSP filters and the DFB provides the directionality. The schematic of the NSCT formed by combining the NSPs and the NSDFBs is depicted in Fig. 1. As shown, the NSP decomposes the input image into two subbands, a lowpass and a highpass. A NSDFB further splits the

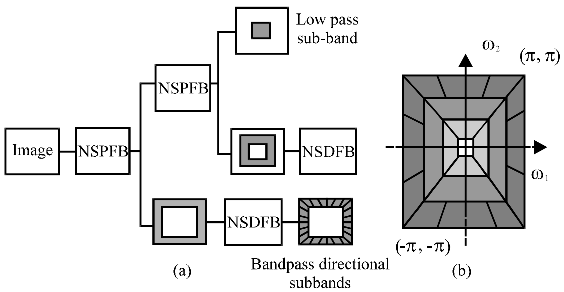

Fig. 1: Schematic structure of non-subsampled contourlet transform; a) block diagram representation and b) frequency division

high-pass subband into many directional subbands. This iterative procedure is repeats with the low-pass subband until the required NSCT scales and directions are obtained (Da Cunha *et al*., 2006).

Fuzzy logic: Fuzzy logic is an efficient means of modelling systems dealing with uncertainties. It represents human knowledge using fuzzy if-then rules. A fuzzy set is represented by a membership function that maps the elements of the set into real numbers in range [0, 1]. In general, the membership functions depict the fuzziness in a fuzzy set (Cheng and Xu, 2000). A Fuzzy Inference System (FIS) is a rule-base system that performs the mapping from the input space to an output using the knowledge base. The rule base is a set of linguistic rules that describe the relations between the different inputs to the system and the outputs.

Any image contains considerable fuzzy information (Ross, 1995) and hence an image or its transform can be considered as an array of fuzzy singletons (Cheng and Xu, 2000). Each element in the image or its transform has a membership value that denotes the degree belongingness. A fuzzy image processing system comprises of three stages: fuzzification of the input variables, the Rule-Based Inference System and defuzzification. Fuzzification is the process of converting a crisp quantity into fuzzy. The quantitative inputs are converted to linguistic variables by the fuzzifier using the membership functions. The knowledge base component stores particulars about the input, output fuzzy partitions, the corresponding membership functions and the if-then rules provided by the user. The Fuzzy Inference System uses this knowledge base to generate a fuzzy response. The FIS employs an Aggregation Method to combine all the fuzzy subsets of the output, in order to generate a single subset. The defuzzifier converts the fuzzy output of the inference system to a crisp value using the defined output membership functions.

Proposed fusion method: This study describes the proposed fusion method using fuzzy logic. Here, the fusion of two source images I_1 and I_2 is performed but this process can be extended to more inputs. The images to be fused are decomposed using NSCT into required number of levels as low-frequency coefficients $C^L(i, j)$ and high frequency coefficients $C^{s,d}(i, j)$ at scale s and direction d where s = 1, ..., S, d = 1, ..., D, S denotes the number of scales and D denotes the number of frequency orientations. The inputs to the fuzzy logic are the activity level indicators entropy and spatial frequency of the two source images computed using the NSCT low frequency coefficients. The entropy and spatial frequency of the transform coefficients is a good measure of their importance. The output of fuzzy logic is the weights to be assigned to each low frequency coefficient based on its importance. The low frequency coefficients are combined using these weights and these weights vary from pixel to pixel. For the high frequency NSCT coefficients of the source images, the coefficient based activity indicator energy is computed using a convolution kernel at all scales and directions. The fused high frequency sub-bands are generated by choosing the coefficients with maximum energy. Figure 2 depicts the block schematic of the proposed fusion scheme.

Membership functions and fuzzy rules: In a typical fuzzy decision-making process, the main elements are the fuzzy sets, fuzzy membership functions and the fuzzy if-then rules. The performance of a Fuzzy Logic Based System depends on the choice of the membership function. The Gaussian membership function is used in this study to describe image's features as it is highly suitable for image processing applications with its smooth and concise representation. The Gaussian membership functions make a continuous transition from one interval to another and hence the input-output can be related more accurately (Hameed, 2011). The Gaussian membership function for the variable y is given by:

$$\text{Gauss}\left(y, \left[\sigma_i, \mu_i\right]\right) = e^{-(y-\mu_i)^2/2\sigma_i^2} \tag{1}$$

Where:

μ_i = The centre

σ_i = The width of the ith fuzzy set selected for the inputs and output

In order to realize a FIS for fusion it becomes essential to define the number of fuzzy subsets for all the inputs and output. The measured activity measures entropy and spatial frequency have different ranges and

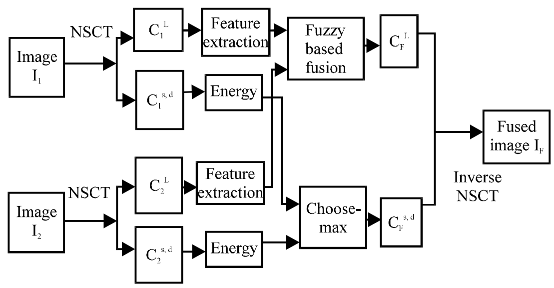

Fig. 2: Block schematic of the proposed Fusion Method

are first normalized to be in the range [0, 1]. These input variables spatial frequency S_1, spatial frequency S_2, entropy H_1 and entropy H_2 are then mapped to fuzzy domain. The universe of discourse for the input variables are divided into five regions, a linguistic label and membership function is assigned to each fuzzy subset. The fuzzy set related to the input parameters are considered as very low, low, medium, high and very high and fuzzy these values are overlapped within each universe of discourse. The number of subsets selected for the output variable W_1 is seven and are considered as very low, low, medium low, medium, medium high, high and very high. Figure 3 depicts the membership functions selected for the inputs and output.

Once the membership functions are defined, the next step is to define a set of fuzzy rules. The proposed fusion scheme uses Mamdani Type Inference System and the general fuzzy inference rules with four inputs and one output is given by:

$$\text{Rule j: (IF } S_1 \text{ is } A^j \text{ and } H_1 \text{ is } B^j \text{ and } S_2 \text{ is } C^j \text{ and } H_2 \text{ is } D^j \text{ THEN } W_1 \text{ is } E^j\text{)}$$

where, S_1, H_1, S_2 and H_2 are the measured input variables; A^j, B^j, C^j and D^j are the fuzzy sets representing the jth antecedents; W_1 is the linguistic output variable and E^j is the fuzzy set representing the jth consequent. A fuzzy rule base with 100 rules that describe the relation between the input and output fuzzy sets is formed. More number of rules will result in increased time complexity of the fusion process and hence only a set of selected rules that are just adequate to describe the input-output relation of the proposed system is used.

The next step in the process is to take crisp measured inputs S_1, S_2, H_1 and H_2 and determine the degree of belongingness to each of the corresponding fuzzy sets. These fuzzified inputs are then applied to the antecedents of the if-then rules. Then, the fuzzy output formed by each rule is aggregated. The output of the FIS is a fuzzy subset and the fuzzy centroid defuzzification method is used to generate a crisp output W_1.

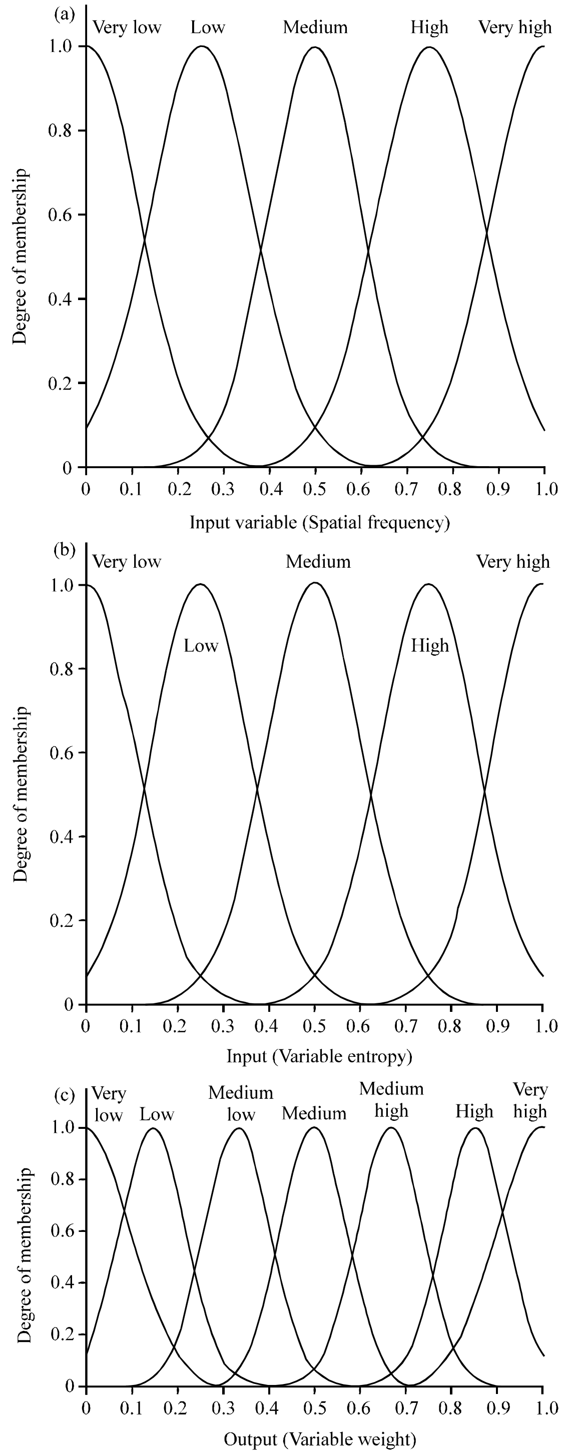

Fig. 3: Membership functions; a) membership function for inputs spatial frequency 1, spatial frequency 2; b) membership function for inputs entropy 1, entropy and c) membership function for output variable

Fusion of NSCT low-frequency subband: The NSCT low frequency coefficients corresponding to the input images

I_1 and I_2 are $C_1^L(i, j)$ and $C_2^L(i, j)$, respectively. The inputs to the fuzzy logic are the normalized spatial frequency measures S_1 and S_2, entropies H_1 and H_2 of the low frequency coefficients of the two source images. The spatial frequency measure signifies the overall activity level in any image (Li and Yang, 2008) and entropy is a measure of the information content of an image. Hence, these set of features are computed at each coefficient location using a m×n window centered on that coefficient. The spatial frequency and entropy of the NSCT low frequency coefficients $C^L(i, j)$ are defined by spatial frequency:

$$S^L = \sqrt{(R_F)^2 + (C_F)^2} \tag{2}$$

Where:
R_F = The row-frequency
C_F = The column frequency:

$$R_F = \sqrt{\sum_{i=1}^{m}\sum_{j=2}^{n}\left[C^L(i,j) - C^L(i,j-1)\right]^2} \tag{3}$$

$$C_F = \sqrt{\sum_{i=1}^{m}\sum_{j=2}^{n}\left[C^L(i,j) - C^L(i\text{-}1,j)\right]^2} \tag{4}$$

Entropy:

$$H^L = -\sum_{i=1}^{m}\sum_{j=1}^{n} C^L(i,j)\log_2 C^L(i,j) \tag{5}$$

where, m×n is the size of the window used. The features S^L and H^L are used to measure the overall activity level of the low frequency coefficients.

The output of the fuzzy system is the weight $W_1(i, j)$ to be assigned to the (i, j)th coefficient of the image I_1. The weight $W_2(i, j)$ for the corresponding low frequency coefficient in image I_2 is given by:

$$W_2(i, j) = 1\text{-}W_1(i, j) \tag{6}$$

Then, the low-frequency sub-band coefficients are merged using the fusion weights computed by fuzzy logic. The fusion rule formed for combining the low-frequency sub-band coefficients is given by:

$$C_F^L(i, j) = W_1(i, j) \times C_1^L(i, j) + W_2(i, j) \times C_2^L(i, j) \tag{7}$$

The schematic of the fusion of the low frequency coefficients is shown in Fig. 4.

Fusion of NSCT high frequency subbands: The high frequency directional coefficients, $C_1^{s,d}(i, j)$ and $C_2^{s,d}(i, j)$

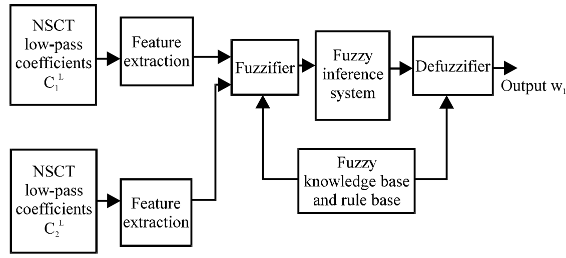

Fig. 4: Fusion of low-frequency NSCT coefficients using fuzzy logic

of the two input images are fused based on the activity measure local energy. The local energy characteristic of each coefficient is computed using an m×n window centered on that coefficient. The local energy feature of the high-frequency directional sub-bands is given by:

$$E^{s,d}(i, j) = \sqrt{\sum_{i'\in m}\sum_{j'\in n} P(i', j')\,[C^{s,d}(i+i', j+j')]} \tag{8}$$

Where:
$C^{s,d}$ = The decomposition coefficient at scale s and direction d
P = The convolution kernel

There, m×n is the size of the window function used. In this study, a 3×3 window is used and is given by:

$$P = \frac{1}{16}\begin{pmatrix} 1 & 1 & 1 \\ 1 & 8 & 1 \\ 1 & 1 & 1 \end{pmatrix} \tag{9}$$

The kernel P applied is a Gaussian filter that makes the proposed method robust to impulse noise. The fused NSCT high frequency directional coefficients are obtained using the fusion rule given by:

$$C_F^{s,d}(i, j) = \begin{cases} C_1^{s,d}(i,j) & \text{if } E_1^{s,d}(i,j) \geq E_2^{s,d} \\ C_2^{s,d}(i,j) & \text{otherwise} \end{cases} \tag{10}$$

The proposed fusion algorithm using NSCT and fuzzy logic is summarized as follows:

- Decompose the given input images to be fused using NSCT to N levels
- Compute the coefficient based activity measures spatial frequency and entropy for each low frequency coefficient in images I_1 and I_2 over a local neighbourhood of coefficients using a 3×3 window centered on each coefficient. The inputs to the fuzzy system are these activity measures S_1, S_2, H_1 and H_2. The output of the fuzzy logic is the weight $W_1(i, j)$ to be assigned to the coefficient (i, j) of the source image I_1

- For each of the input and output variables, divide the interval [0, 1] into the requisite number of fuzzy subsets, assign a linguistic label and a membership function
- Construct a rule-base with required number of fuzzy rules describing the relations between the input and output fuzzy sets
- Fuzzify the measured inputs and aggregate the fuzzy outputs produced by each rule. Apply the Fuzzy Centroid Defuzzification Method to generate a crisp output W_1
- Combine the low frequency subband NSCT coefficients using the weight W_1 computed as given by the rule in Eq. 6
- Fuse the high-frequency directional subbands of NSCT at all scales and directions using the fusion rule in Eq. 9
- Combine the fused low frequency and high frequency directional sub-bands and apply inverse NSCT to reconstruct the fused image I_F from the fused coefficients

RESULTS AND DISCUSSION

The input images for fusion were first decomposed to three scales by the NSCT with 2, 8, 8 directions from the coarser scale to the finer. This resulted in 11 sub-images of same size as the input images. Experimentation were carried out in an i3, 370 M processor with 4 GB RAM using MATLAB. The fuzzy logic toolbox in MATLAB is used for implementing the FIS and to define the fuzzy logic inference rules.

The multisensor images used in this study are: medical images consisting of Computerized Tomography (CT) image and a Magnetic Resonance Image (MRI) of a person, multimodal OCTVBS images consisting of visual and IR images and a pair of remote sensing images from two hyper-spectral airborne scanners. The amount of information in each pair of source images differs as they were acquired using different instrument modalities.

The fusion results of the proposed fuzzy based technique were compared with standard fusion schemes such as DWT, NSCT and hybrid NSCT (SSAN). In the experiments conducted for DWT two levels of decomposition were used. For NSCT and hybrid NSCT the number of decomposition scales and directions selected were the same as the proposed scheme. The performance of the various methods are evaluated using the objective evaluation measures entropy, Standard Deviation (SD), Mutual Information (MI), Petrovic metric Q^f_{AB} (Xydeas and Petrovic, 2000) and Piella quality index Q_{Piella} (Piella and Heijmans, 2003). The metrics MI, Q^f_{AB} and Q_{Piella} are measures based on the amount of information conveyed to the fused image from the inputs and larger these values better the quality.

Figure 5a and b shows two medical images a Computerized Tomography (CT) image and a Magnetic Resonance Image (MRI) of a person. The fused images are shown in Fig. 5c-f. The edges in the fused image in Fig. 5f are much clearer and have more edge information when compared with other fused images. It is clearly seen that the fused image obtained by the proposed fuzzy based scheme contain more details than all the other methods tested. The fused image with the proposed scheme has extracted all important information from the source images and scores higher in terms of the evaluation metrics as depicted in Table 1. It shows that the fuzzy based method has resulted in a fused image with the largest value of Q^f_{AB} and Q_{Piella}. Even a small difference of 0.01 is considered significant in assessing the quality as per the definition of these metrics (Wan *et al*., 2009).

Figure 6a and b show a pair of multimodal OTCBVS visible and IR source images, Fig. 6c-f show the fused images of the methods tested. It is observed from Fig. 6c that the DWT Method has taken most of the information only from the visible image. But in the proposed fuzzy based scheme in Fig. 6f, all the salient details from the IR and visible source images such as the lawn, street lamps were transferred to the fused image. Moreover, the objects in the fuzzy based scheme are visually more pleasing than NSCT and hybrid NSCT (Li and Yang, 2010) Methods. Table 2 lists the performance comparison results for the multimodal OTCBVS images. It demonstrates that the NSCT-Fuzzy Fusion Method proposed is than the Individual Multiresolution Methods (Li *et al*., 1995; Yang *et al*., 2007) and hybrid NSCT.

A pair of remote sensing source images is depicted in Fig. 7a and b. This pair of images was obtained by two hyperspectral airborne scanners and contains copious natural scenes and urban structures. The fused images of different methods were given in Fig. 7c-f. Table 3 presents the performance comparison results based on the fusion metrics. Fusion metrics show that the proposed NSCT Fuzzy and the DWT Methods are comparable in performance. But the NSCT (Yang *et al*., 2007) and Hybrid NSCT (Li and Yang, 2010) score lesser than the proposed Fuzzy Based Method.

Table 4 provides the computational time in seconds of the three NSCT based methods tested. For these methods, three decomposition levels with 2, 8, 8 directions were used. It is seen that the time cost of the proposed

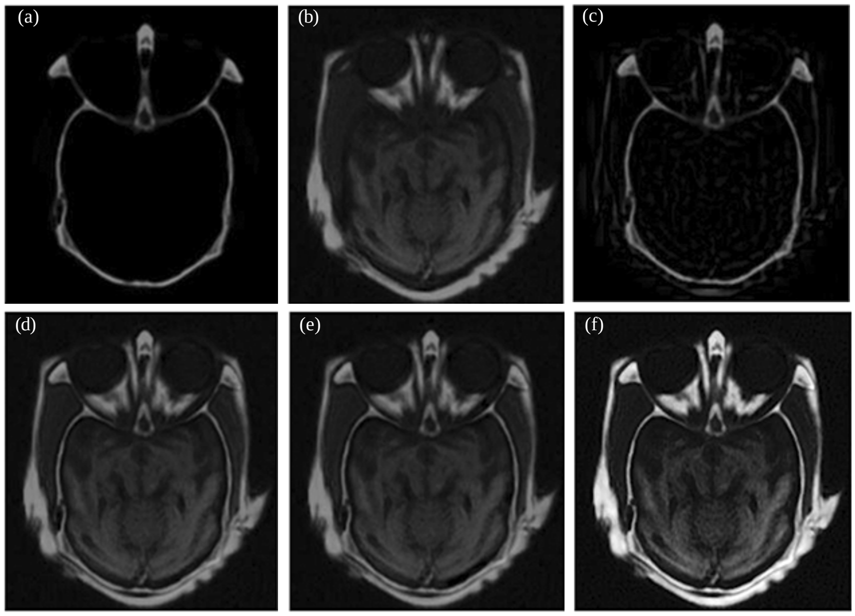

Fig. 5: Medical source images and fusion results (256 levels, size of 256×256); a) MRI; b) CT image and c-f) the fused images of DWT, NSCT, Hybrid NSCT and NSCT-Fuzzy (proposed) Methods

Fig. 6: OCTVBS source images (270×360, 256 levels) and fusion results; a) visible image; b) IR image and c-f) the fusion results of DWT, NSCT, Hybrid NSCT and NSCT-Fuzzy (proposed) Methods

Table 1: Performance evaluation metrics for medical images

	Performance metrics				
Fusion method	Entropy	MI	SD	Q^f_{AB}	Q_{Piella}
DWT	3.35	4.36	22.10	0.41	0.59
NSCT	5.91	4.81	31.11	0.55	0.62
Hybrid NSCT	5.94	4.90	31.40	0.57	0.62
NSCT-FUZZY	6.18	4.97	33.34	0.59	0.68

DWT: Discrete Wavelet Transform; NSCT: Non-Subsampled Contourlet Transform; SD: Standard Deviation; MI: Mutual Information; Q^f_{AB}: Petrovic metric; Q_{piella}: Piella metric

Table 2: Performance evaluation metrics for OTCBVS images

	Performance metrics				
Fusion method	Entropy	SD	MI	Q^f_{AB}	Q_{Piella}
DWT	7.49	66.19	4.50	0.59	0.79
NSCT	7.63	62.86	3.99	0.63	0.80
Hybrid NSCT	7.64	62.89	3.93	0.62	0.79
NSCT-FUZZY	7.85	67.30	5.03	0.67	0.81

DWT: Discrete Wavelet Transform; NSCT: Non-Subsampled Contourlet Transform; SD: Standard Deviation; MI: Mutual Information; Q^f_{AB}: Petrovic metric; Q_{piella}: Piella metric

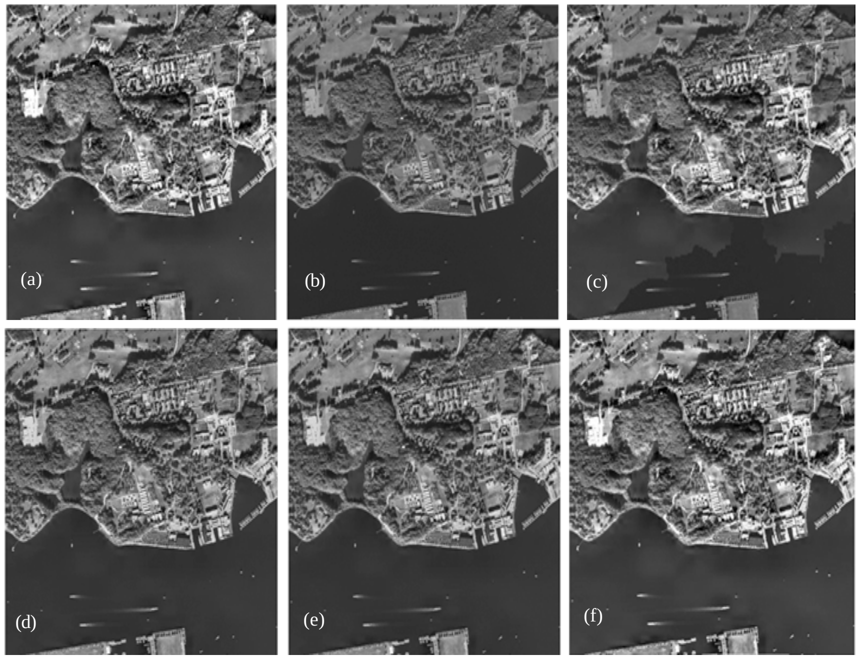

Fig. 7: Remote sensing source images and fusion results (256 levels, size of 512×512); a) Image I_1; b) Image I2 and c-f) the fusion results of DWT, NSCT, Hybrid NSCT and NSCT-Fuzzy (proposed) Methods

Table 3: Performance evaluation metrics for remote sensing images

	Performance metrics				
Fusion method	Entropy	SD	MI	Q^f_{AB}	Q_{Piella}
DWT	6.83	53.60	6.82	0.80	0.88
NSCT	7.10	53.36	6.79	0.78	0.84
Hybrid NSCT	7.12	53.52	6.81	0.79	0.83
NSCT-Fuzzy	7.27	55.70	7.97	0.81	0.90

DWT: Discrete Wavelet Transform; NSCT: Non-Subsampled Contourlet Transform; SD: Standard Deviation; MI: Mutual Information; Q^f_{AB}: Petrovic metric; Q_{piella}: Piella metric

Table 4: Time complexity of NSCT based fusion schemes

	Fusion scheme		
Images	NSCT	Hybrid-NSCT	NSCT-Fuzzy
Figure 5	69.36	112.40	104.20
Figure 6	85.30	148.46	132.46
Figure 7	220.16	408.36	401.06

NSCT: Non-Subsampled Contourlet Transform

fuzzy based scheme is higher than NSCT but slightly lesser than hybrid NSCT. Though the proposed scheme consumes more time than standard NSCT, it produces fused images with best visual quality.

Experimental studies reveal that the proposed fuzzy based fusion appreciably outperforms the individual multiresolution transform fusion methods, based on the fusion metrics. Results produced make obvious that the proposed method is able to capture important details from the sources and thus the fused image contains more accurate information of the scene. Further, analysis and processing with these highly informative fused images is expected to generate improved results. NSCT, an efficient image representation scheme combined with fuzzy is proved effective for fusing images of different kinds including medical, multimodal and remote sensing images.

CONCLUSION

In this study, researchers have applied a Rule Based Fuzzy System for pixel level fusion of multisensor images. This methodology uses NSCT for multiscale decomposition and fuzzy logic to determine the weights of the NSCT low frequency coefficients of source images based on their importance. Experiments conducted with images of different instrument modalities such as medical, multimodal and remote sensing images demonstrate that the proposed fuzzy based system has better performance than the DWT, NSCT and hybrid NSCT Methods visually and objectively. Experimental results confirm that the combination of NSCT and fuzzy logic is very effective in creating fused images with accurate information. However, further improvement in performance can be accomplished with more NSCT decomposition scales and directions at an increased computational cost.

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