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# A SUGENO FUZZY LOGIC BASED CT AND MRI IMAGE FUSION TECHNIQUE WITH QUANTITATIVE ANALYSIS

**S Rajkumar[*1], Rishin Haldar[*2], Arvind Pillai[*3], Praneet Dutta[*4]**
[*1,2,3]School of Computing Science and Engineering, [*4]School of Electronics Engineering,
VIT University, Vellore, India.
Email: rajkumarsrajkumar@gmail.com

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**Abstract**

Medical images are available in different modalities, each with its own usage. For example, preferred use for CT scan is in imaging bone injuries, cardiothoracic imaging and cancer diagnosis. MRI is generally used for soft tissue imaging and brain tumour detection. Medical images from different modalities often yield pathological information and correspondingly physiological information as well. This has made the study of multimodal medical image fusion very attractive. There are many occasions which require the integration of such comprehensive information for clinical diagnosis. The system proposed contains a design for a multi-modality medical image fusion system using a Sugeno Fuzzy Logic (SFL) based fusion method.

The efficiency of the SFL based fusion method is established by comparing it with the existing methods, such as Principal Component Analysis (PCA), Laplacian Pyramid Approach(LPA), Discrete Wavelet Transform (DWT), Redundancy Discrete Wavelet Transform (RDWT) and Dual-Tree Complex Wavelet Transform (DTCWT) using quantitative metrics such as Entropy (EN), Signal to Noise Ratio (SNR) and Mutual Information (MI). The experimental results reveal that SFL based fusion method provides better quality of information in terms of Entropy, shows less noise ratio in terms of SNR and the higher value of MI indicate that more information from the original images are transferred to the fused image.

**Keywords**: Principal Component Analysis; Dual-Tree Complex Wavelet Transform; Fuzzy logic; Sugeno Fuzzy Logic; Entropy; Signal to Noise Ratio; Mutual Information.

## I. Introduction

An increasing number of medical examinations are completed using digital imaging in today's world, thus patients are exposed to a plethora of imaging modalities. Doctors need integrated information from such scans for accurate diagnosis, making Medical Image fusion a necessity. The different kinds of imaging techniques include CT, MRI, PET and SPECT, all of which retain unique applications. For example, PET and SPECT provide functional information which medically translates into information about visceral metabolism and blood circulation. CT scans and MRI provides structural/anatomical information.

Then again a CT scan is popular for recognizing the bone structure and MRI for soft tissue. Manual recombination of the images is possible, but it can be tedious and inconvenient. Additionally it can be imprecise, and different doctors often interpret the same images differently. This creates an urgent necessity to develop efficient automatic image fusion systems to improve the consistency of diagnoses and reduce some of the doctors' burdensome tasks. By image fusion, such systems would aim to better the image content so as to yield additional information to doctors and aid in the clinical treatment planning process. The fused images provide a comprehensive morphological and functional information set which reflects physiological and pathological changes. Image fusion combines multiple-source images using advanced image processing techniques [1]. It aims specifically to combine disparate and complementary data so as to improve the information obtained from the respective source images, and to bolster the precision of interpretation.

The actual fusion process is performed at three levels - pixel level, region level and decision level - the first being the simplest and the most common approach [2]. Pixel level fusion can be broadly classified into two categories: Spatial domain (for example, averaging and PCA methods) [3] and transform domain (LPA and DWT) [4]. A crucial disadvantage of spatial domain techniques is that they create spatial distortions. This provides an edge to techniques in the transform domain. Wavelet transforms are popular in image fusion because they give unique decomposition and reconstruction methods. DWT [5] is a widely used fusion method that allows image coefficient decomposition while still preserving the image information. But DWT suffers from shift sensitivity and poor directionality for complex value based transforms. DTCWT provides high directionality and shift invariance and thus overcomes the limitations of DWT, however DTCWT is quite time consuming.

In order to address the above mentioned problems, Fuzzy logic is used [6]. This paper proposes a fusion method using Sugeno Fuzzy Inference System instead of Mamdani type Fuzzy Inference System (FIS) used for image fusion. Though Mamdani type FIS is quite popular, the number of if-then-else rules increase rapidly with increase in the complexity of the system, which consequently increases the computational burden. The overall system structure of our effort is shown in Figure 1.

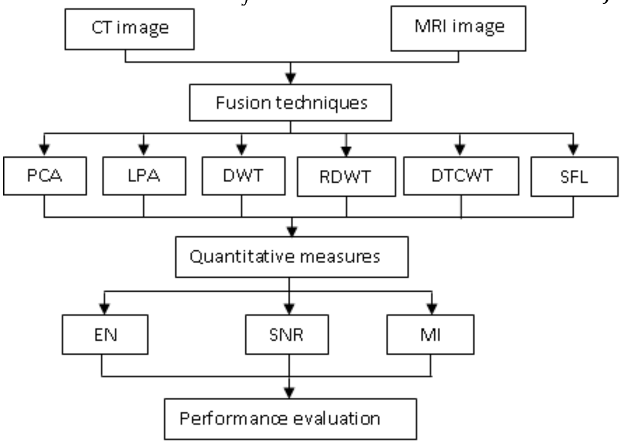



**Fig. 1: Overall system structure.**

The remaining part of this paper is organized as follows. Section II mentions our survey of the literature. Section III provides the details of the proposed method. Section IV describes the quantitative performance evaluation measures and compares the experimental results of the proposed method, both subjectively and objectively, with the other popular methods. Finally, we conclude in Section V.

## II. Literature Survey

Pixel level fusion can be categorized into Spatial and Transform domain techniques. Spatial domain techniques are a set of simple steps to obtain an image by direct application of fusion rules on pixel values of source images. We briefly point out two popular spatial domain techniques like Simple Averaging Method and Maximum Selection Scheme.

Simple Averaging Method is a linear spatial domain method applied at the pixel level [7]. The resultant coefficient for reconstruction of the fused image is calculated by an average of the two input images' coefficients. The value of the fused image is given in equation (1),

$$O(i, j) = (I_A(i, j) + I_B(i, j)) / 2 \qquad (1)$$

where O(i, j) is the fused image coefficient and $I_A$ (i, j), $I_B$(i, j) are input image coefficients.

Maximum selection is a non-linear spatial domain method which again operates on the pixel values [7]. The reasoning says that, the greater pixel value means that it is more in focus, thus choosing a greater value for each pixel results in highly focused images. This simple scheme simply selects the higher pixel value as the value for the fused image. The mathematical representation of maximum selection is given in equation (2).

$$O(i, j) = \max( I_A(i, j), I_B(i, j)) \qquad (2)$$

Spatial domain techniques often results in spatial distortions in the fused image without providing spectral information. Transform domain techniques overcome these limitations and provide a more sophisticated approach for image fusion. The basic idea behind these techniques is multi-resolution decomposition of the input images, integration of these decompositions and reconstruction by inverse transforms. Pyramid and wavelet transforms based techniques are commonly used transform domain image fusion techniques. The Laplacian algorithm, propounded by Burt and Adelson in 1983, works on a set of filtered and subsampled version of a predecessor image. The Laplacian pyramid consists of an ordered set of images, which are band pass copies of Gaussian pyramid. The lowest level for the construction of this pyramid is obtained from the source image and has the highest resolution. The higher levels are the scaled versions, constructed by recursively blurring (low-pass filtering), subsampling (decrease size), interpolating (expand) and differencing (subtracting two images pixel by pixel). The major disadvantage of Pyramid methods is the blocking effect, therefore, Wavelet transforms have become more popular in recent years. DWT [8] is an orthogonal wavelet (inverse of the wavelet is ad joint to the wavelet). It allows the decomposition of images into coefficients while preserving the content information. The object is to decompose the input images into wavelet transformed images using DWT and then performing fusion of transform coefficients of individual bands using some fusion rules. The output image is formed via an inverse discrete wavelet transform (IDWT). One of the major disadvantages of DWT is the shift invariance which can be eliminated by using Complex Wavelets. Complex Wavelet Transform [9] is a complex valued extension of DWT and can be mathematically expressed in equation (3),

$$\varphi_c(t) = \varphi_r(t) + j\varphi_i(t) \qquad (3)$$

where $\varphi_r(t)$ and $\varphi_i(t)$ are the real and imaginary parts. The Dual-Tree Complex Wavelet Transform (DTCWT) provides the complex transform of a signal by utilizing two distinct DWT decompositions (tree a and tree b). The DTCWT of a signal, say x, is obtained from two critically sampled DWTs implemented in parallel on the data. The filters are designed such that the sub band signals from the upper DWT may be taken as the real part and those from the lower DWT as the imaginary part. Let $h_0(n)$ and $h_1(n)$ be the low-pass/high-pass filter pair for the upper half of the tree and $g_0(n)$ and $g_1(n)$ be the low-pass/high-pass filter pair for the lower half. Equation (4) expresses how the complex wave is constructed from these two real waves.

$$\varphi_c(t) = \varphi_h(t) + j\varphi_g(t) \qquad (4)$$

Fusion rules can be then applied in the same way as DWT. The real and imaginary parts are then both inverted to obtain two real signals. The signals are averaged to obtain the final inverted transform.

DTCWT [10] fusion is carried out in three exhaustive steps: first, DTCWT is applied to both the input images to obtain the transformed coefficients. Next, the fusion of the coefficients is performed by applying maximum selection in lower sub band and entropy based selection in higher sub bands. Finally, inverse of DTCWT is applied to obtain the fused output image. The literature also points out the effective use of Mamdani type fuzzy logic for image fusion in pixel level [11]. First, the grey levels of input images are defined using fuzzy sets, which is the building block of the Fuzzy Inference System (FIS). This is called fuzzification of inputs. Next, these fuzzified inputs are evaluated according to predefined non-additive rules to calculate the membership degree of output. Finally, the defuzzification process is carried out to calculate the output grey level.

## III. Proposed System

This paper utilizes Sugeno Fuzzy inference method for the image fusion. Sugeno fuzzy model is also referred to as the TSK fuzzy model as it was first used by T. Takagi, M. Sugeno and K.T. Kang in 1984. Mamdani- type FIS entails substantial computation burden, to overcome this, Sugeno FIS is used which has a better processing time and also works well with optimization and adaptive techniques. The major difference between the two methods is that the Sugeno inference method's output membership function is either linear or constant. Sugeno method also provides increased flexibility and facilitates integration with Adaptive Neuro-Fuzzy Inference System (ANFIS) tool in MATLAB. Block diagram of Sugeno Fuzzy Logic based fusion method is shown in Figure 2.

The format of Sugeno type fuzzy model is

**If x is A AND y is B THEN z is f(x,y).**

where x, y, z are linguistic variables; A and B are fuzzy sets; f(x,y) is a mathematical function. Here Zero order Sugeno fuzzy model is used which applies fuzzy rules as follows:

**If x is A AND y is B THEN z is k.**

where k is a constant. In such a case, there is constant output from each fuzzy rule and singleton spikes represent all the membership functions.

Sugeno type fuzzy model for our experiments is carried out as follows:

1) Fuzzification of inputs and calculation of membership function: The input gray scale images contain pixel values ranging from 0-255 (256 gray values). These gray values are divided into a fuzzy set {B, C, G, I, W}, with five membership functions as follows: B- Black, C- Charcoal, G- Grey, I- Ivory and W- White. The output image uses the same fuzzy set and contains 256 gray levels as well. In the FIS construction, Triangular membership

function is chosen since it has less computational complexity than the other membership functions such as Gaussian, Trapezoidal etc.

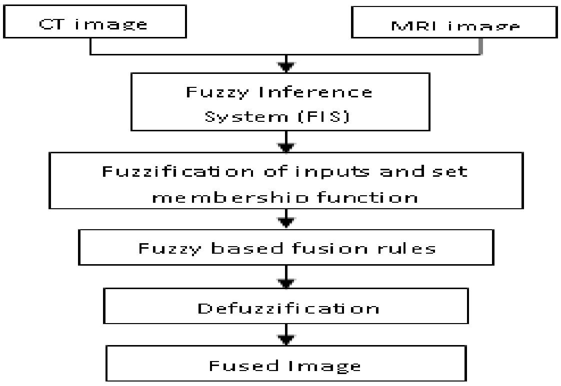



**Fig. 2: Block Diagram of Sugeno Fuzzy Logic.**

2) *Fuzzy rules*: Sugeno type fuzzy model rules are in the form of 'if-then'. W1 is the input image 1, W2 is the input image 2 and O is the output. There are a total of 25 rules, as tabulated in Table I.

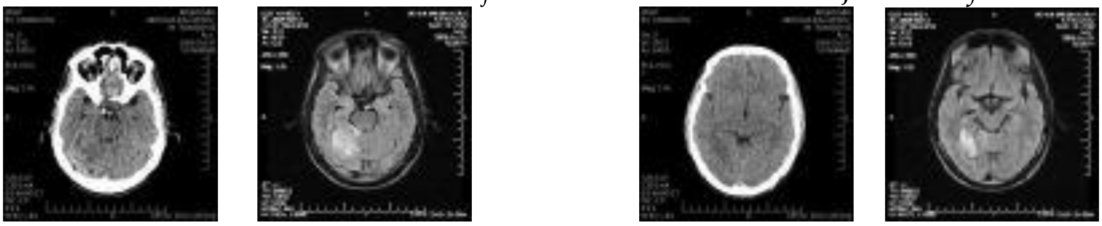
3) *Defuzzification*: Defuzzification is the process of transferring truth values into output. We use 'wtaver' (weighted average) for defuzzification. The output of fis file is in the form a single column matrix which is then converted into an image matrix to obtain the fused output image.

**Table-I: Fuzzy rules in matrix form.**

| W1 \ W2 | B | C | G | I | W |
|---|---|---|---|---|---|
| **B** | B | C | C | G | I |
| **C** | C | B | G | I | I |
| **G** | C | C | G | I | W |
| **I** | C | G | I | I | W |
| **W** | I | G | I | W | W |

## IV. Experimental Results and Performance Analysis.

The input images consist of six brain images taken each from CT and MRI (T2). Each input set consists of one CT image and one MRI (T2) image, and there are six such input sets. Each input set outputs one fused image. All images have the same size of 256 * 256 pixels, with 256-level gray scale. Some of the sample input images are shown in Figure 3.



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

Fig. 3: Sample input images: (a) dataset4 CT image, (b) dataset4 MRI-T2 image, (c) dataset 5 CT image, (d) dataset5 MRI-T2 image.

**Subjective Evaluation of Results:**

Subjective comparison can be done by visually analysing the images in Figure 4, which shows the resultant fused images from PCA method, LPA, DWT method, RDWT method [12], DTCWT method and finally, the proposed SFL based fusion method. From Figure 4, it is evident that the proposed SFL based fusion method generated results with good visualization (i.e. high luminance and contrast) than other existing methods.

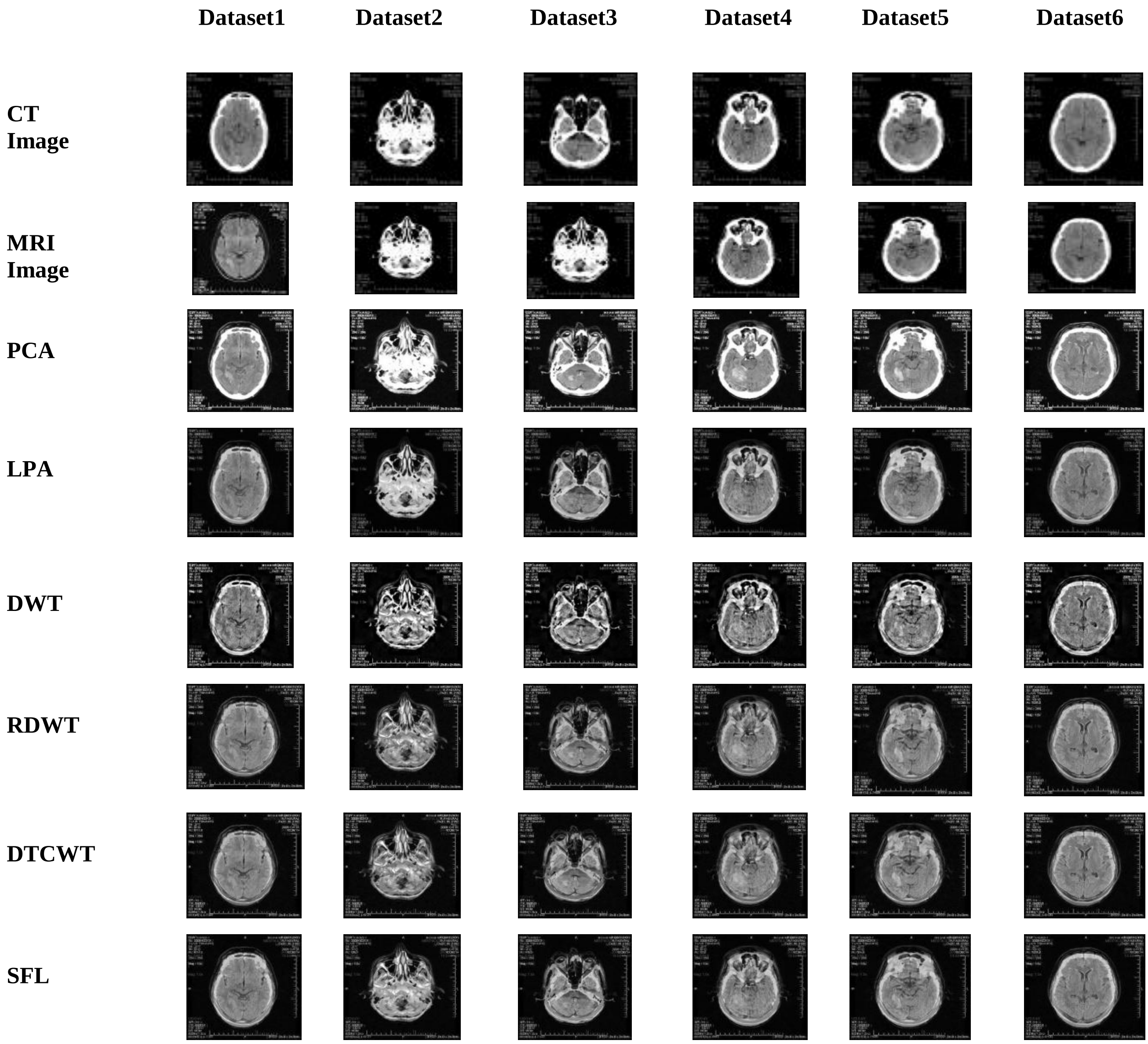



**Fig. 4: Subjective comparison of the fusion results over 6 images**

**Objective measures:**

Objective comparison, for better assessment of the required information from the images, is done by quantitative analysis of the fused images using well known metrics, namely Entropy (EN), Signal to Noise Ratio (SNR) and Mutual Information (MI).

*Entropy (EN):* Entropy reflects the magnitude of information. Higher entropy implies better fusion [13,14]. Entropy can be calculated as:

$$EN = -\sum_{i=0}^{L-1} P_F(i) \log_2 P_F(i) \qquad (5)$$

where $P_F$ is the normalized histogram of the fused image, L is the highest gray level for a pixel.

*Signal to Noise Ratio (SNR):* SNR [15] is expressed as the ratio of mean pixel value to the standard deviation of pixel values in an image being assessed,

$$SNR = Mean / SD \qquad (6)$$

where SD is standard deviation. SNR provides contrast information so the higher the value, the better is the fusion.

*Mutual Information (MI):* Mutual information [16] gives the mutual dependence between two variables. Supposing A and B are two such multimodal images, mutual information is given by:

$$M(A,B) = K(A) + K(B) - K(A,B) \qquad (7)$$

where K(A) represents the entropy of image A, K(B) represents entropy of image B and K(A,B) provides joint entropy. A higher value justifies a better fusion algorithm.

**Performance Analysis:**

For each of the above mentioned objective measures, the results generated from the proposed SFL based fusion method, as well as the PCA method, LPA, DWT method, RDWT method and DTCWT method are tabulated in Table- II, III and IV.

From the entropy values of fused images displayed in Table II, it is clear that the proposed SFL based fusion method not only outperforms the popular spatial domain techniques, it also fares better than DWT, RDWT and DTCWT for all the datasets.

**Table-II: Entropy Value Calculation of Fusion Images and Input Images.**

| | Dataset1 | | | | | Dataset6 |
|---|---|---|---|---|---|---|
| CT | **4.4107** | **3.726** | **4.073** | **4.386** | **4.4005** | **4.3064** |
| MRI | **6.2451** | **6.222** | **6.090** | **6.212** | **6.2666** | **6.1435** |
| PCA | **6.0341** | **5.808** | **5.846** | **6.007** | **6.0539** | **5.9395** |

| | | | | | | |
|---|---|---|---|---|---|---|
| LPA | **5.5349** | **5.298** | **5.325** | **5.359** | **5.5216** | **5.4378** |
| DWT | **6.2286** | **6.186** | **6.095** | **6.200** | **6.2721** | **6.1664** |
| RDW | **6.6690** | **6.657** | **6.576** | **6.667** | **6.7159** | **6.6363** |
| DTC | **6.6847** | **6.532** | **6.541** | **6.672** | **6.7276** | **6.6499** |
| SFL | **6.7039** | **6.674** | **6.584** | **6.688** | **6.7527** | **6.6625** |

The SNR results from Table III and Mutual Information results from Table IV are also quite positive for the proposed SFL based fusion method. It gives consistently superior results when compared to the popular spatial domain techniques as well as DWT, RDWT and DTCWT. It is very encouraging that the proposed SFL based fusion method, with its relatively simple approach, outperforms elaborate and computationally expensive methods like DWT, RDWT and DTCWT.

**Table-III: Signal to Noice Rasio Value Calculation of Fusion Images and Input Images.**

| | Dataset | Dataset | Dataset | Dataset | Dataset5 | Dataset6 |
|---|---|---|---|---|---|---|
| CT | **0.122** | **0.109** | **0.112** | **0.121** | **0.1228** | **0.1215** |
| MRI | **0.394** | **0.381** | **0.360** | **0.361** | **0.3870** | **0.3702** |
| PCA | **0.327** | **0.267** | **0.275** | **0.286** | **0.3006** | **0.3063** |
| LP | **0.182** | **0.172** | **0.171** | **0.164** | **0.1759** | **0.1747** |
| DWT | **0.374** | **0.355** | **0.345** | **0.352** | **0.3713** | **0.3593** |
| RDWT | **0.457** | **0.432** | **0.425** | **0.438** | **0.4540** | **0.4507** |
| DTCW | **0.547** | **0.612** | **0.620** | **0.564** | **0.5715** | **0.5663** |
| SFL | **0.574** | **0.651** | **0.636** | **0.639** | **0.6679** | **0.6523** |

**Table-IV: Mutual Information Value Calculation of Fusion Images.**

| | Dataset 1 | Dataset 2 | Dataset 3 | Dataset 4 | Dataset 5 | Dataset 6 |
|---|---|---|---|---|---|---|
| PCA | **5.9219** | **5.7149** | **5.7072** | **5.8872** | **5.9279** | **5.8297** |
| LP | **5.6683** | **5.5086** | **5.4571** | **5.5505** | **5.6627** | **5.5642** |
| DWT | **6.1656** | **6.1122** | **6.0085** | **6.1463** | **6.1973** | **6.0728** |
| RDWT | **6.0772** | **6.0050** | **6.0905** | **6.0566** | **6.0275** | **6.0861** |
| DT-CWT | **6.5470** | **6.5514** | **6.4597** | **6.5359** | **6.5846** | **6.4763** |
| SFL | **6.6311** | **6.5680** | **6.4861** | **6.5512** | **6.6076** | **6.4995** |

## V. Conclusion

This paper proposes a Sugeno Fuzzy Logic based method for image fusion. The proposed method is not only simpler than the exhaustive wavelet based image fusion methods like DWT, RDWT and DTCWT, it also has much less computational burden than popular fuzzy logic based image fusion methods like Mamdani FIS. Although the proposed method has been used to fuse gray scale CT and MRI images, the same techniques may also be used in the fusion of images of other modalities (PET, X-Ray, SPECT) with their true color.

The experimental results show that the proposed Sugeno Fuzzy Logic based method for image fusion generates visually better images, in terms of luminance and contrast, than popular methods like PCA method, LPA, DWT method, RDWT method and DTCWT method. The objective analysis, by using popular metrics like Entropy, SNR amd MI, also show that the proposed method gives better results than these popular image fusion techniques.

Experimental results reveal that the proposed SFL method is marginally better than DTCWT, in terms of SNR and MI. This gives us the motivation to improve our method further to obtain better results, which, in turn, will help with the accurate diagnosis of disease.

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**Corresponding Author:**
**S Rajkumar*,**
**Email:** rajkumarsrajkumar@gmail.com