Texture Based Multifocus Image Fusion Using Interval Type 2 Fuzzy Logic

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Abstract
Multifocus image fusion is a process of fusing two or more images where region of focus in each image is different. The objective is to obtain one image which contains the clear regions or in-focus regions of each image. Extracting the focused region in each image is a challenging task. Various techniques are available in literature to perform this task. Texture is one such feature which acts as a discriminating factor between focused and out-of-focus regions. Texture based image fusion has been used in our approach in combination with interval type 2 fuzzy logic and discrete wavelet transforms. Performance metrics obtained using this approach are better compared to other existing techniques. Gray Level Cooccurence Matrix (GLCM) method is used to extract the texture. Type 2 Sugeno fuzzy logic is used to combine the images. The fused image is compared with the reference image when it is available. It is also compared with the original images and performance metrics are computed and presented in this paper.
Keywords: Discrete Wavelet Transform, Gray Level Cooccurence Matrix, Image Fusion, Multifocus Image, Type 2 Fuzzy Logic, Mamdani FLS, Sugeno FLS

1. Introduction
Image fusion provides a technique for combining images obtained from various sources into a single image. The corresponding images must be aligned images of the same scene. The fused image is more informative and useful for further processing tasks. Uncertainty is reduced, redundancy is minimized but relevant information is maximized in the output image (Srinivas Rao et al., 2012). Hence the objective of image fusion is to obtain the optimum image containing the best information from each corresponding image and discarding the irrelevant information or noise. As a result, the quality of the fused image will be better than any of the individual images.
Image fusion plays a major role in various fields. Multifocus image fusion is one such application where images of the same scene but with different points of focus are fused together (Jamal Saeedi et al., 2009). Fusion of magnetic resonance imaging (MRI), computed tomography (CT), positron emission tomography (PET) and single photon-emission computer tomography (SPECT) images has widespread applications in the medical field. Each of these images contain relevant information of various tissues. For example, MRI images highlight soft tissues whereas CT images highlight bone tissues (Rajiv Singh et al., 2013). Fusion of image obtain from various sensors like visible range sensors, infrared sensors, thermal sensors etc. is called multisensor image fusion is yet another application areas of image fusion (Thomas J.Meitzler et al., 2002). In poor visibility conditions pilots use the fusion of visible band and infrared images to land aircraft (Eduardo Fernandez, 2002). Another important field of application of image fusion is the fusion of remotely sensed images obtained from different sources like satellites or remote cameras. Multitemporal images which are the images of the same scene obtained at different times can also be fused.

Depending on the stage at which the fusion occurs, image fusion is performed at three different processing levels, (i) Pixel-level (ii) Feature-level and (iii) Decision-level (C.Pohl, 1998). In pixel-level based methods, the coregistered pixels of the input images are fused by using combination operators like maximum, average, weighted average etc. Boolean or fuzzy operations are also used. Feature level fusion involves extraction of features from the source images, for example, using segmentation techniques. Texture is one such feature. The extracted features are compared and fused using statistical approaches. Decision level fusion processes the input images individually for extracting information. Objects are detected and classified. They are then given as input to the fusion algorithm (Kalyani B et al., 2007). The fusion is performed based on decision rules.

Multifocus image fusion is the main focus of this paper. It is difficult to obtain the entire information of a scene when the objects of interest are at different distances from the camera lens. When the camera focuses on certain objects they appear clearer but the other objects appear blurred. By changing the point of focus, various images of the same scene can be obtained where certain regions appear in-focus and others appear out of focus. The goal of multifocus image fusion is to use a set of such images, which contain mutually exclusive points of focus and fuse them together so that the fused image contains only the in-focus regions of all the images. The result is that the best clarity image of the whole scene is obtained and hence the quality of the resultant image is better than any of the individual images. Selecting the clear region or the in-focus region from each of the images is the challenging task. Researchers have used several techniques to perform multifocus image fusion. The methods differ in the way the clear parts are distinguished from the blurred parts. Some techniques compare pixels of the corresponding images to make the decision whereas others divide the images into regions and use a certain criterion to decide the focused region. These regions could be blocks of equal size where comparison is made between overlapping or non-overlapping blocks. The regions could also be segmented regions based on specific criterion like edge based segmentation, texture based segmentation, etc. These steps can be performed either in the spatial domain or in the frequency domain.

The brute force techniques used are maximum pixel selection, averaging and weighted averaging but the performance compared to the other techniques is not efficient. The other approaches used are based on principal component analysis (V.P.S.Naidu, 2008), Discrete Cosine Transform (V.P.S.Naidu, 2012). S.Li et al., 2001, divided the images into blocks and used spatial frequency as a measure of focused region in the image. I.De et al., 2006, use morphological filters and multi-scale top-hat transformation to detect focused region. S. Li et al., 2008, also use spatial frequency as a measure of clarity of the region. The regions are segmented using normalized cuts algorithm. V.Aslantas et al., 2010, used differential evolution algorithm to determine the optimal block size and then uses spatial frequency, variance and sum-modified-laplacian as the focus measure. Xi Bai et al., 2013, proposed weighted image fusion scheme based on multi-scale top-hat transform to extract bright and dim features. Ishita De et al., 2013, proposed a quad-tree based approach to select the block size and hence block size is not fixed. Energy of morphological gradients is used as the focus measure.

Multi-resolution based image fusion is used to speed up the process. Another advantage is that it separates the low frequency and high frequency components. Krista Amolins et al., 2007, provide an analysis of image fusion techniques based on Discrete Wavelet Transform. H. Zhao et al., 2013, uses multi-resolution based scheme where neighbour distance is used to measure a pixel's sharpness. Rajiv Singh and Ashish Khare, 2013, perform multiscale medical image fusion in wavelet domain. V.P.S.Naidu, 2011, perform multiresolution image fusion based on Fast Fourier Transform.

Fuzzy logic is a tool that is utilized when there is uncertainty (Harpreet Singh et al., 2004). Hence fuzzy logic is another tool used by researchers to fuse images. According to R.Maruthi et al., 2008, fuzzy logic based fusion techniques perform better than other techniques as they are basically developed handle uncertainties and imprecision. Fuzzy logic is the best tool to convert expert knowledge to mathematical form. Human experts are better at deciding the region of the image that should appear in the output image. This expertise is not easy to specify using crisp logic but fuzzy logic can solve this problem. Fuzzy sets, a set of membership functions and fuzzy rules are defined for this purpose. Srinivas Rao D et al., 2012, fuse images based on fuzzy logic. Thomas J.Meitzler et al, 2002, use neuro-fuzzy approach. Jamal Saeedi et al., 2009, use Fisher classifier to obtain a decision map and then fuzzy logic is used to define the rules based on the decision map. To improve the efficiency of fusion interval type-2 fuzzy logic is used recently by researchers. Fusion of Long Wave Infra Red and Electro Optical Images using Fuzzy Logic Type-1 and Type-2 is performed by Sudesh Kumar Kashyap, 2013. Swathy Nair et al., 2014, performed multifocus image fusion using type-2 fuzzy logic. Sudesh Kumar Kashyap, 2015, fused and IR and colour images using type-2 fuzzy logic. Analysis of their results proved that Sugeno Type-2 fuzzy logic outperforms the other techniques.

In this paper, we propose an algorithm to perform multifocus image fusion where texture is used as a focus measure. Interval Type II fuzzy logic (IT2FL) is used to specify the decision rules. To extract the texture, gray level cooccurence matrix method is used. The results obtained are compared with pixel level fusion using type-1 fuzzy and type-2 fuzzy logic.

1.1 Type 1 Fuzzy Logic System

L.Zadeh, 1965, proposed fuzzy sets and fuzzy logic. It is based on the membership functions represented by $\mu_A(x)$ which indicates the degree of membership of element x in fuzzy set A (Jaroslav Vlach et al., 2012). Type 1 Fuzzy Logic System (T1FLS) or simply fuzzy logic system consists of four components (i) Fuzzifier (ii) Rules (iii) Inference Engine (iv) Defuzzifier (J.M. Mendel, 1995). Fuzzifier converts crisp inputs into fuzzy sets. Fuzzy set is characterized by a membership function (MF). Figure 1 shows a triangular membership function. Fuzzy sets were introduced to model vagueness in a system (Srinivas Rao, 2012). Classical sets are special cases of member functions of fuzzy sets taking only values 0 or 1. The membership function values can be in the real unit interval [0 1]. Rules are a collection of if-then statements. They are provided by domain experts or can be extracted by numerical data. The inference engine combines the rules using inferential procedures. It actually maps input fuzzy sets into output fuzzy sets. The defuzzifier maps the output fuzzy sets of the inference engine to crisp values.

There are two types of fuzzy inference methods, (i) Mamdani's Fuzzy Inference method introduced in 1975 and (ii) Takagi-Sugeno Fuzzy Inference method introduced in 1985. The output of Mamdani's Fuzzy Inference method is a fuzzy set which has to be defuzzified further. The output of Sugeno's method is a crisp value and hence does not require defuzzification. Sugeno's method is used to model inference systems in which the output membership functions are linear or constant. Fuzzy image processing consists of image fuzzification, fuzzy inference system and defuzzification (Eduardo Fernandez, 2002).

1.2 Type 2 Fuzzy Logic System

Type 2 Fuzzy sets were introduced by L.A.Zadeh in 1975. The fuzzy logic system that has atleast one type-2 fuzzy set (T2FS) is called a type-2 fuzzy logic system (T2FLS) (Sudesh Kumar Kashyap, 2013). Type-2 fuzzy sets are characterized by three-dimensional membership function. The third dimension gives additional degrees of freedom which helps in modeling uncertainties. Figure 2 depicts type-2 triangular membership function (J.M. Mendel et al., 2002).

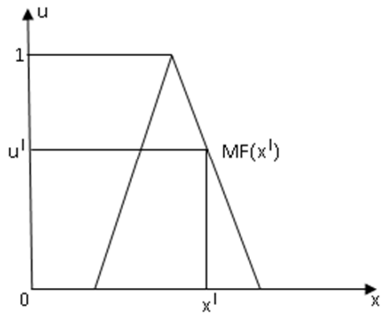


Figure 1 Type-1 Triangular MF

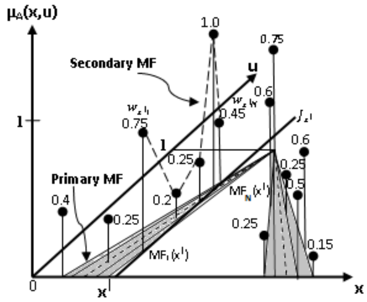


Figure 2 Type-2 Triangular MF

Type 2 Membership function (T2MF) is expressed as μ(x,u) where *x* is an element of X and *u* is an element of J_x. At each value of *x*, there are up to *N* membership function values, $MF_1(x)$, $MF_2(x)$,…..$MF_N(x)$ as shown in figure 4. Each membership function $MF_i(x)$ has a weight w_{xi} associated with it. In figure 2, these weights are represented as vertical lines with weight value on the top. In general T2FS *w* is defined over a range of values. If the weighting is uniform, this T2FS is called as interval type 2 fuzzy set (IT2FS) (J.M. Mendel, 2007). Interval type 2 triangular membership function is shown in figure 3. If all uncertainties in a T2FS disappears, T2FS reduces to T1FS.

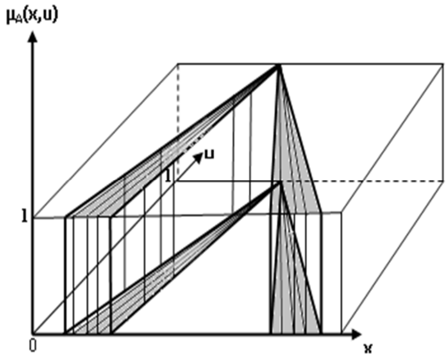


Figure 3 Interval Type 2 Triangular MF

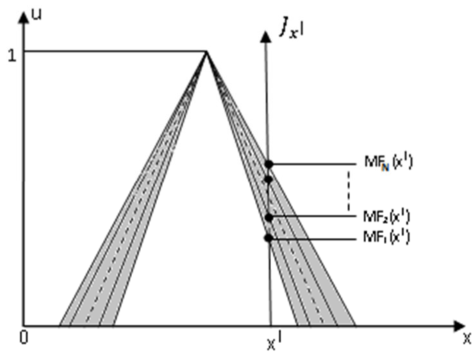


Figure 4FOU of Type 2 Triangular Membership Function

General type-2 fuzzy sets are characterized as shown in equation (1)

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x\subseteq[0,1]} \mu_{\tilde{A}}(x,u)/(x,u) \quad (1)$$

where *x* is the primary variable and has domain X; *u* ∈ U is the secondary variable and as domain J_x at each x∈X; *J*x is the primary membership of x. The secondary grades $\mu_{\tilde{A}}(x,u)$ is set to 1 for interval type-2 fuzzy sets and hence interval type-2 fuzzy sets are characterized as shown in equation (2) (Jerry M Mendel et al., 2006)

$$\tilde{A} = \int_{x\in X}\int_{u\in J_x\subseteq[0,1]} 1/(x,u) = \int_{x\in X}\left[\int_{u\in J_x\subseteq[0,1]} 1/u\right]/x \quad (2)$$

The union of all the primary memberships is called footprint of uncertainty (FOU). An IT2FS is characterized by its 2-d FOU.

$$\mathrm{FOU}(\tilde{A}) = \bigcup_{\forall x\in X} J_x \quad (3)$$

In figure 4, the shaded region is called the FOU. Figure 5 shows the FOU of Gaussian primary membership function. It is bounded by a lower member function ($\underline{\mu}_{\tilde{A}}$(x)) and an upper membership function ($\overline{\mu}_{\tilde{A}}$(x)) which are two type-1 membership functions (Jerry Mendel, 2007).

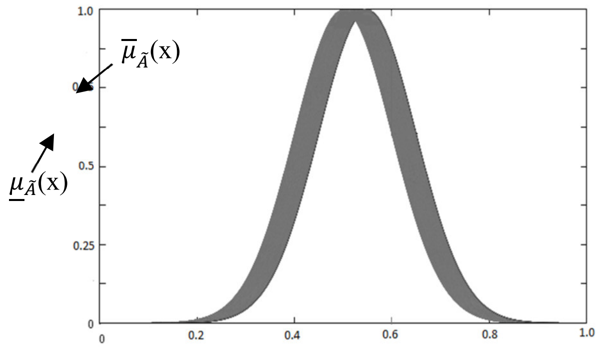


Figure 5FOU of the Gaussian primary membership function

The footprint of uncertainty is the area between $\underline{\mu}_{\tilde{A}}$(x) and $\overline{\mu}_{\tilde{A}}$(x). Using eq.(3),

$$\text{FOU}(\tilde{A})=\cup_{\forall x\in X}\left[\underline{\mu}_{\tilde{A}}(x),\overline{\mu}_{\tilde{A}}(x)\right] \quad (4)$$

The operations, such as union, intersection and complement operations can be performed on T2 fuzzy sets. Type-2 FLS has five components (i)Fuzzifier (ii) Rules (iii) Inference Engine (iv) Type Reducer (v) Defuzzifier. The type reducer is used to generate a type-1 fuzzy set output and then it is defuzzified to a crisp value.

The three fuzzifiers used in Mamdani T2FLS are singleton, non-singleton type 1 and non singleton type 2 (Sudesh Kumar Kashyap, 2015). Sugeno T2FLS uses only singleton fuzzifier. Singleton is the most commonly used fuzzifier but it is not suitable when noise is present. In that case nonsingleton fuzzifier is used (Liang, Qilian, 2000). Singleton fuzzifier is as illustrated in figure 6. The fuzzified inputs $\bar{f}$ and $\underline{f}$ are found at the intersection of singleton at 'x' with the lower membership and upper membership function. In non-singleton type 1 fuzzifier shown in figure 7, fuzzified inputs $\bar{f}$ and $\underline{f}$ are obtained at the intersection of Gaussian function whose mean is at 'x' with the lower membership and upper membership function. In non-singleton type 2 fuzzifier shown in figure 8, fuzzified inputs $\bar{f}$ and $\underline{f}$ are obtained at the intersection of set of Gaussian function whose centres are at 'x', with the lower membership and upper membership function.

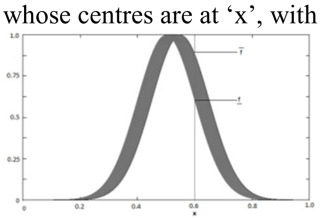


Figure 6 Singleton Fuzzifier

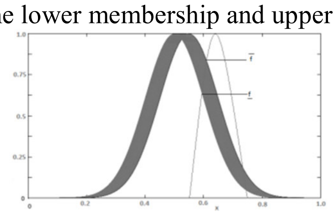


Figure 7 Non-Singleton Type 1 Fuzzifier

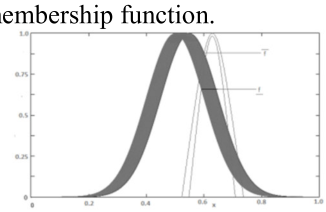


Figure 8 Non-Singleton Type 2 Fuzzifier

Fuzzy Logic consists of a set of IF and THEN rules. The IF part is called as the antecedent and the THEN part is called the consequent. These antecedent and consequent are modeled as fuzzy sets. Rules are described by the membership functions of these fuzzy sets. In T1FL, the antecedents and consequents are all described by the membership functions of T1 fuzzy sets. In T2FL, some or all of the antecedents and consequents are described by the membership functions of T2FS. Therefore the rules do not change from T1FL to T2FL.

Inference Engine converts the inputs fuzzy sets to output fuzzy sets. It uses the rule base. The antecedents of the fired rules are combined using the fuzzy operators. For each rule, the common implication methods used are *product* and *minimum*. Figure 9 illustrates the *minimum* implication method for a singleton fuzzifier.

Type reducer converts the type 2 fuzzy set into type 1 fuzzy set. The commonly used type reducers are centre of sets and centroid. Figure 10 shows the centre of sets type reducer.

The last step of a fuzzy logic system is defuzzification. In this step, the output fuzzy set is converted into a crisp number. There are various defuzzifiers like centroid, mean of maxima, maximum, etc.

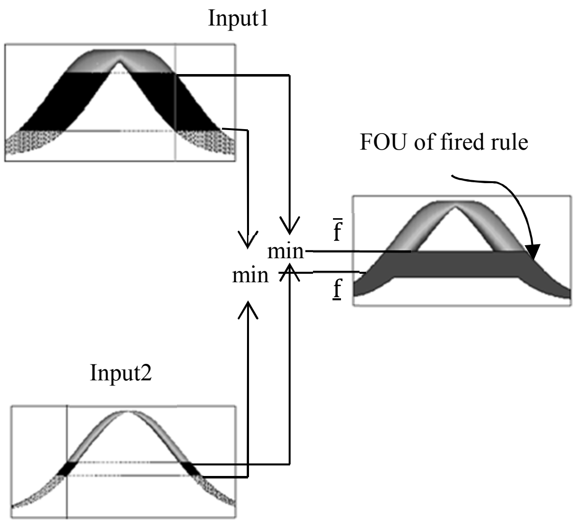


Figure 9 Fuzzy inference of a singleton fuzzifier

Figure 10 Type Reducer

1.3 Gray Level Co-occurence Matrix

Image textural properties carry useful information for discrimination purposes. Robert M. Haralick et al. (1973) provide a general procedure for extracting textural properties of blocks of image data. A set of textural features such as correlation, contrast, variance, entropy, angular second moment etc., are computed using Gray Tone Spatial Dependence Matrices also referred to a Gray Level Co-occurence Matrix (GLCM). Information about image textural characteristics such as homogeneity, contrast, number and nature of boundaries present, linear structure and the complexity of the image are contained in these features. In multifocus images, the in-focus regions have better contrast compared to the out of focus areas and hence this fact is utilized for their fusion. GLCM is a matrix which contains the number of times a specified pair of pixels occur in an image block. Contrast of an image block is computed using the spatial relationship of pixels in GLCM. Figure 11(a) and 11(b) represents the formation of the GLCM for 4 gray level image block where direction=0° and distance d = 1. GLCM can also be formed for the direction of 45º, 90º and 135º as shown in Figure 11(c). Contrast of an image block using GLCM is computed as shown in equation (5). G is the number of gray levels, P(i,j) is the (i,j)th entry in GLCM.

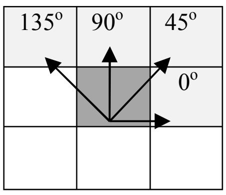
CONTRAST=$\sum_{n=0}^{G-1} n^2 \left(\sum_{i=1}^{G}\sum_{j=1}^{G} P(i,j)\right), |i-j| = n$ (5)

0	1	1	2	3
1	3	3	2	0
0	1	1	0	0
3	2	1	1	0
2	2	0	0	1

(a) Image Block

	0	1	2	3
0	2	3	0	0
1	2	3	1	1
2	2	1	1	1
3	0	0	2	1

(b) GLCM



(c) Orientations

Figure 11 Image block and its GLCM

2. Proposed Approach

The block diagram of the proposed approach is illustrated in Figure 12.

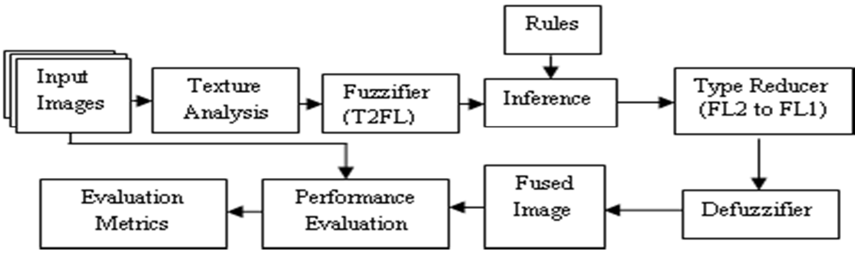


Figure 12 Block Diagram of the proposed approach

2.1 Algorithm of the proposed approach

Step 1: Input the images to be fused
Step 2: For each location of a sliding window, repeat step 3 to step
Step 3: Find the GLCM of the image block in all the eight directions at distance 1.
Step 4: Compute the contrast of the block using equation (5).
Step 5: Compute the average contrast value of all the eight GLCMs.
Step 6: Replace the centre pixel value with the average contrast value.
Step 7: Binarize the contrast image. The focused region will be white and defocussed region will appear black.
Step 8: Compute the centroid of the focused region in both the images.
Step 9: Find the euclidean distance between each point and the centroid in each image. Normalize these distances to lie in between 0 and 1.
Step 10: Extract and save the common regions of the images and copy to the output fused image
Step 11: Arrange the remaining area of the images into column vectors
Step 12 Set the fuzzy logic system as follows

a) Select the type of fuzzifier.
b) Select the number of membership functions for input and output.
c) Frame the rules for fusion of the images using the normalized distances.
d) Perform fuzzy inference. Two values $(\bar{f}, \underline{f})$ are obtained from antecedent operation. The fuzzified output is obtained by

$$\bar{\mu}_B^s = \bar{f} * \bar{\mu}_B$$
$$\underline{\mu}_B^s = \underline{f} * \underline{\mu}_B$$

where '*' represents T-norm operators

e) Apply 'Centre of sets' type reduction to convert the output into type 1 fuzzy set to obtain $\bar{y}$ *and* $\underline{y}$
f) The crisp output is obtained by defuzzification given by

$$Y = \frac{\bar{y} + \underline{y}}{2}$$

Step 13: Convert the output columns into image
Step 14: Merge the background and the foreground images to obtain the final fused image
Step 15: Compute the various performance metrics using the input images and output images.

Sugeno Type 2 fuzzy inference system is used in the proposed approach. The inputs to the fuzzy logic system are two arrays containing the normalized distances of the pixels from the centre of the focused region in the images. Two Gaussian membership functions are used for both the inputs as shown in Figure 14. The distances are divided into two membership classes as 'One' and 'Two'. 'One' indicates that lesser the distance from the focused centre in the first image, higher the probability that its value must be selected from the first image. 'Two' indicates that larger the distance, higher the probability that it is a focused value in the second image. The output is a matrix containing constant values 1 and 2 indicating whether the pixel value in the fused image is to be selected from the first or second input images respectively.

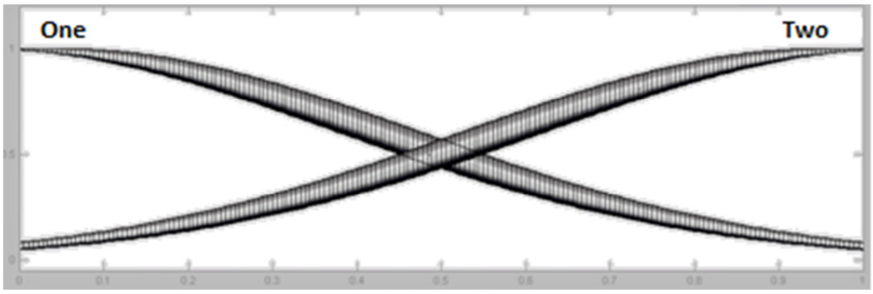


Figure 14 Gaussian Membership functions

Four rules are used for this purpose:
Rule 1: If input1is 'One' and input2 is 'One' then output is 1
Rule 2: input1is 'One' and input2 is not 'Two' then output is 1
Rule 3: If input1is 'Two' and input2 is 'Two' then output is 2
Rule 4: input1is 'Two' and input2 is not 'One' then output is 2

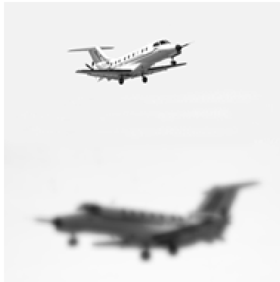
3. Experimental Results

Performance metrics used to measure the quality of the fused image are divided into two sets. One set of metrics which are computed when ground truth image is not available are Entropy, Standard Deviation (SD), Cross Entropy (CE), Spatial Frequency (SF), Fusion Factor (FF), Fusion Quality Index (FQI), Fusion Similarity Metric (FSM) and Fusion Symmetry (FS). Among these, Cross Entropy and Fusion Symmetry must be low and the other metrics must be high to indicate better fusion.

The set of metrics used when ground truth image is available are Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Percentage Fit Error (PFE), Signal to Noise Ratio (SNR), Peak Signal to Noise Ratio (PSNR, Correlation (CORR), Mutual Information measure (MI), Universal Quality Index (QI) and Structural Similarity Measure (SSM). Low values for RMSE, MAE and PFE, higher values for the remaining metrics indicate better fusion. The details of these metrics are given in V.P.S.Naidu et al, 2008.

The proposed approach is demonstrated using remotely sensed multifocus images and conventional multifocus images. Images of aircraft 'SARAS' are used as image set 1. In this set, one reference image and two complementary multifocus images are used. The details of this image are explained in V.P.S.Naidu, 2011. Figure 15 shows input images and results obtained after applying the proposed approach. The performance metrics of image set 1 are given in table 1 and table 2. Table 1 shows the results by comparing the input images with the output fused image. Table 2 contains the metrics by comparing the fused image with the ground truth reference image.

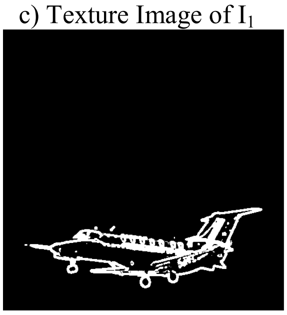
a) First Source Image I_1



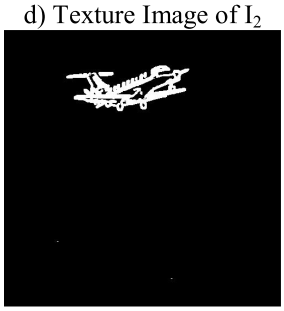
b) Second Source Image I_2

c) Texture Image of I_1

d) Texture Image of I_2



e) Binarized Texture Image of I_1



f) Binarized Texture Image of I_2

g) Fused Image

Figure 15 Experimental results of Image Set 1

Table 1 Evaluation Metrics without using reference image

METRIC	FL TYPE 1	T2M	T1NST2M	T2NST2M	T2S	T2S+TEXTURE
ENTROPY	3.9074	4.0471	4.0407	4.0370	4.0556	**4.0633**
SD	0.1957	0.1941	0.1955	0.1949	0.1987	**0.1997**
CE	2.5070	2.5071	2.5536	2.5616	2.7226	**0.0349**
SF	0.0582	0.0499	0.0479	0.0469	0.0592	**0.0710**
FF	0.34002	3.3983	3.3848	3.3695	**3.4066**	3.3797
FQI	0.8543	0.8545	0.8501	0.8476	0.8540	**0.8580**
FSM	0.7868	**0.7931**	0.7847	0.7815	0.7908	0.7872
FS	**0.000853**	0.0025	0.0022	0.0021	0.0023	0.0121

Table 2 Evaluation Metrics using reference image

METRIC	FL TYPE 1	T2M	T1NST2M	T2NST2M	T2S	T2S+TEXTURE
RMSE	0.0244	0.0360	0.0484	0.0520	**0.0237**	0.0272
PFE	2.6735	1.82	5.2891	5.6842	1.7845	**1.0085**
MAE	0.0074	0.0104	0.0132	0.0143	0.0062	**0.0061**
CORR	0.9994	0.9992	0.9986	0.9984	0.9988	**0.9995**
SNR	31.4583	28.0877	25.5324	24.9067	**36.4033**	34.4330
PSNR	64.2834	62.5981	61.3205	61.0076	**65.7560**	63.7708
MI	1.839	1.8271	1.8076	1.7966	1.8238	**1.9324**
QI	0.8321	0.8203	0.8111	0.8077	0.8375	**0.8456**
SSIM	**1.0**	0.9999	0.9998	0.9998	0.9998	0.9999

The second image set consists of two complementary conventional multifocus images of clocks. Here reference image is not available. Figure 16 shows the input images and results obtained after applying the proposed algorithm. Table 3 shows the evaluation metrics of image set 2.

The results obtained using the proposed approach is compared with type 1 fuzzy logic and direct type 2 fuzzy logic using various fuzzifiers. The best value for each metric is highlighted in the tables.

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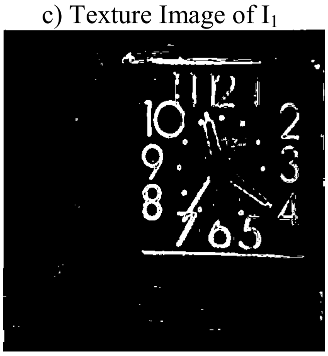
a) First Source Image I_1

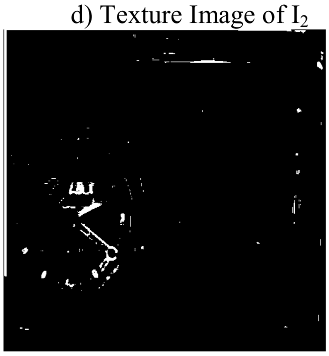
b) Second Source Image I_2

c) Texture Image of I_1

d) Texture Image of I_2



e) Binarized Texture Image of I_1



f) Binarized Texture Image of I_2

g) Fused Image

Figure 16 Experimental results of Image Set 2

Table 3 Evaluation Metrics without using reference image

METRIC	FL TYPE 1	T2M	T1NST2M	T2NST2M	T2S	T2S+TEXTURE
ENTROPY	7.2949	7.3317	7.3260	7.3269	**7.3386**	**7.2397**
SD	0.1954	0.1943	0.1937	0.1932	**1.1958**	**0.1961**
CE	**0.1288**	0.1354	0.1394	0.1383	0.1457	0.1089
SF	0.0347	0.0337	0.0344	0.0342	**0.0357**	**0.0398**
FF	3.2712	3.2713	3.2624	3.2569	**3.2718**	**3.3133**
FQI	0.8470	0.8465	0.8445	0.8438	**0.8475**	**0.7899**
FSM	0.8279	**0.8291**	0.8267	0.8261	0.8262	0.7150
FS	0.0073	0.0075	0.0071	**0.007**	0.0071	0.0388

4 .Conclusion

A feature level multifocus image fusion has been performed using interval type 2 fuzzy logic. Sugeno Type fuzzy logic systems has been tested. The quality of the resultant fused image has been tested using fusion performance metrics. Our previous work had shown that type 2 type 2 fuzzy logic performs better that other commonly used approaches like averaging, principal component analysis, multiresolution and type 1 fuzzy logic approaches. But in this work it is shown that when type 2 fuzzy logic is combined with texture features, the results obtained outperform all the other approaches. Further we want to use this technique to fuse medical images and test the performance.

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