International Journal of Computer Science and Business Informatics

IJCSBI.ORG

Pixel Level Image Fusion: A Neuro-Fuzzy Approach

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ABSTRACT

Image fusion is done for integrating images obtained from different sensors, which outputs a single image containing all relevant data from the source images. Five different image fusion algorithms, SWT, fuzzy, Neuro-Fuzzy, Fuzzylet and Neuro-Fuzzylet algorithms has been discussed and tested with two datasets (mono-spectral and multi-spectral). The results are compared using fusion quality performance evaluation metrics. It was observed that Neuro-Fuzzy gives better results than Fuzzy and SWT. Fuzzylet and Neuro-Fuzzylet were obtained by combining Fuzzy and Neuro-Fuzzy respectively with SWT. It was observed that Fuzzylet gives better results for mono-spectral images and on the other hand, Neuro-Fuzzylet had given better results for multi-spectral images at the cost of execution time.

Keywords

Image fusion, Fuzzy logic, image processing, Nero-fuzzy.

1. INTRODUCTION

For Intelligent systems, integration of information from different sensors plays a great role. Image fusion is done for integrating images obtained from different sensors, which outputs a single image containing all relevant data from the source images and provides a human/machine perceivable result with more useful complete information. Image Fusion has got great importance in many applications such as object detection, automatic target recognition, remote sensing, computer vision, flight vision, robotics etc. This paper deals with a comparison of certain pixel level image fusion techniques based on SWT, Fuzzy and Neuro-Fuzzy.

Many methods have been proposed and implemented for image fusion [1]. Wavelet transform based image fusion has the merits of multi-scale and multi-resolution. In [2], an approach of multi-sensor image fusion using wavelet transform and principal component analysis (PCA) was proposed and comparison of image fusion with different techniques based on fusion quality performance metrics is done. Wavelets have a disadvantage of shift variance which results in loss of edge information in fused image [3]. Stationary Wavelet Transform (SWT) solves this problem which is shift invariant [4]. Since the concept of image fusion is not that certain and crisp, Fuzzy logic and Neuro- Fuzzy logic are implemented for image fusion in order to incorporate uncertainty to the images [5]. The help of Neuro-fuzzy of fuzzy systems can achieve sensor fusion. The major difference between neuro-fuzzy and fuzzy systems is that a neuro-fuzzy system can be trained using the input data obtained from the sensors. The basic concept is to associate the given sensory inputs with some decision outputs. After developing the system, another group of input data is used to evaluate the performance of the system. Algorithms for image fusion using Fuzzy and Neuro-Fuzzy approaches are introduced in [6]. In [7], SWT with higher level of decomposition is introduced and Fuzzy logic is incorporated into it to form a novel algorithm called Fuzzylet.

This work is done as an extension to the work done in [7]. In this paper Neuro-fuzzy based image fusion is tested and compared with SWT and Fuzzy logic. An algorithm is formed in which Neuro-fuzzy is incorporated into SWT which is named as Neuro-Fuzzylet and compared with Fuzzylet. All the comparisons are done by evaluating Fusion Quality Performance Metrics and results are verified with different sets of images. In this paper, it is assumed that images to be fused are already registered.

2. IMAGE FUSION TECHNIQUES

Pixel level image fusion technique using SWT, Fuzzy and Fuzzylet are explained in [7]. Matlab code for SWT based image fusion is given in [8]. In [7] it is proved that SWT with higher decomposition levels and Fuzzy logic with greater number of membership functions gives the better result. Fuzzylet algorithm is formed by combining SWT with 4 levels of decomposition and Fuzzy with 5 membership functions. In this paper, Neuro-Fuzzy logic is also tested and compared with the results obtained in [7].

2.1 Neuro-Fuzzy Approach to Image Fusion

Neural Network (NN) is a network which stores the experimental knowledge and uses it for test data. Neuro- Fuzzy is a combination of Artificial Neural Network (ANN) and Fuzzy logic. Using this method we can train the system with input dataset and desired output. After training the system, this system can be used for any other set of input data. A Neuro-fuzzy system is a fuzzy system which is trained by any of neural network learning algorithms and according to the training data system parameters are modified automatically. Implementation of Neuro-Fuzzy system is done using ANFIS. ANFIS stands for Adaptive Neural Fuzzy Inference System.

The Fuzzy Inference System (FIS) is a model that does the following mappings:

- A set of input characteristics to input membership functions
- Input membership functions to rules
- Rules to a set of output characteristics
- Output characteristics to output membership functions and
- The output membership function to a single-valued output

A FIS has the following limitations:

- Membership functions are fixed and somewhat arbitrarily chosen
- Fuzzy Inference is applied for modeling systems in which the rules are predetermined strictly based on the viewpoint of user to the model.

The shape of the membership functions can be changed by changing the membership function parameters as it is dependent on these parameters. In an ordinary FIS, these parameters are selected arbitrarily in a trial and error basis just looking into the available data. For applying fuzzy logic to a system in which a collection of input-output data is available, a predetermined parameter set will not be available. In some situations arbitrary selection of parameters will not be sufficient to model a system in a desired way. Instead of choosing member ship function parameters arbitrarily, it would be more effective if the parameters are adjusting themselves based upon the input data variation. In such cases, Neuro-adaptive learning techniques can be incorporated into the FIS.

Using the input-output data given, ANFIS constructs a FIS whose membership function parameters are tuned using any neural network algorithm. This allows the FIS to learn from the data that are given as the test data. There is an ANFIS editor toolbox in Matlab which does all this learning. A Neuro-Fuzzy system can be schematically represented as in Fig 1.

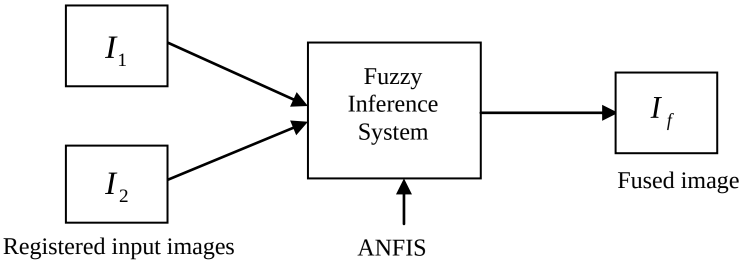

Figure 1. Schematic Diagram of Neuro-Fuzzy system

The ANFIS training structure obtained from Matlab ANFIS editor toolbox for two inputs and three membership functions is as shown in Fig. 2.

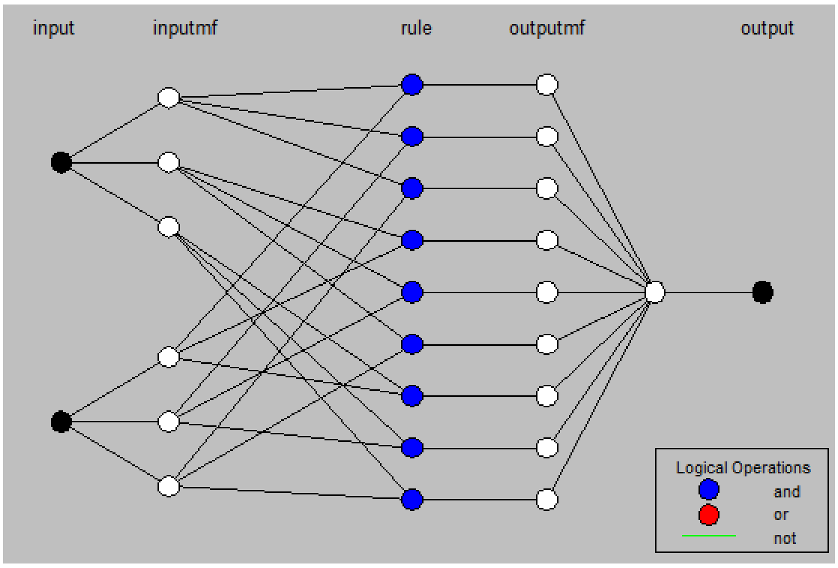

Figure 2. ANFIS training structure obtained for two inputs and three membership functions

In the ANFIS training structure shown in Fig.2. The leftmost nodes represent the inputs and the rightmost node represents the output. The branches are coded using different colors to indicate the logical operations used in rule formation, that is, it indicates whether *and*, *or* or *not* is used to combine antecedences to consequences.

For image fusion, the pixel values of input images and reference (desired) image are given to the ANFIS for training the FIS, so that the system will produce a fused image which is closer to the reference image from the input images. Algorithm for image fusion using Neuro-Fuzzy logic (abbreviated as $\boldsymbol{NF(I_1,I_2)}$) is as follows:

Step 1: Read the images (I_1 & I_2) to be fused into two variables

Step 2: Obtain a training data, which is a matrix with three columns (2 columns of input data and one column of output data)

Step3: Obtain a check data, which is a matrix of pixel values of two input images in column format

Step 4: Decide number and type of membership functions for both the input images

Step5: Generate a FIS structure from the train data and train the FIS

Step 6: Provide check data to the FIS structure for processing and obtain the output image in column format

Step 7: Convert the column form into matrix form to get the fused image I_f

In the case of dataset without a reference output, the 3rd column (output) of the training data is given as the maximum of absolute pixel values of the input images.

2.2 Neuro-Fuzzylet Algorithm for Image Fusion

In [7], Fuzzylet Image Fusion algorithm has been developed. In Fuzzylet algorithm, Fuzzy logic is used to find out the approximate and detail coefficients of SWT of input images. In Neuro-Fuzzylet, instead of Fuzzy Neuro-fuzzy algorithm discussed in section 2.A is used to calculate the SWT coefficients. The information flow diagram of image fusion using Fuzzylet is shown in Fig. 3.

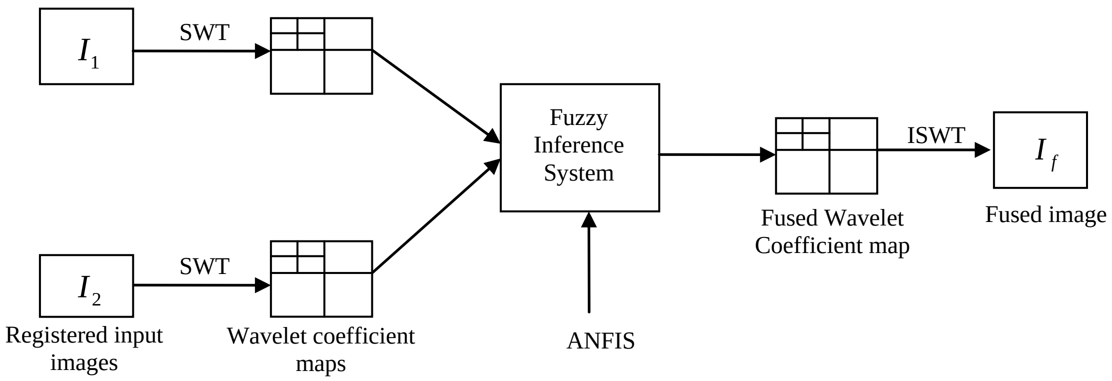

Figure 3. Schematic diagram of Neuro-Fuzzylet Image Fusion Algorithm

The images to be fused I_1 and I_2 are decomposed into $K(k = 1,2,...,K)$ levels using SWT. The resultant approximation and detail coefficients from I_1 are $I_1 \rightarrow \left\{ {}^1A_K, \left\{ {}^1H_k, {}^1V_k, {}^1D_k \right\}_{k=1,2,...,K} \right\}$. Similarly from I_2 the resultant approximation and detail coefficients are

$I_2 \rightarrow \left\{ {}^2A_K , \left\{ {}^2H_k , {}^2V_k , {}^2D_k \right\}_{k=1,2,\ldots,K} \right\}$. The fused image I_f can be obtained using SWT as:

$$I_f \leftarrow \left\{ {}^fA_K , \left\{ {}^fH_k , {}^fV_k , {}^fD_k \right\}_{k=1,2,\ldots,K} \right\} \quad (1)$$

Where

$${}^fA_K = \frac{{}^1A_K + {}^2A_K}{2} \quad (2)$$

$${}^fH_k = NF({}^1H_k , {}^2H_k), k = 1,2,\ldots,K \quad (3)$$

$${}^fV_k = NF({}^1V_k , {}^2V_k), k = 1,2,\ldots,K \quad (4)$$

$${}^fD_k = NF({}^1D_k , {}^2D_k), k = 1,2,\ldots,K \quad (5)$$

Where, the function $NF(a,b)$ is a Neuro-Fuzzy logic based image fusion algorithm described in section 2.A.

3. IMAGE FUSION QUALITY EVALUATION INDICES

The quality of fused images obtained from different algorithms (SWT, Fuzzy, Neuro-Fuzzy, Fuzzylet and Neuro-Fuzzylet) is compared using Fusion Quality Performance Evaluation Indices. In this paper, two datasets are used for the evaluation of algorithms. One among the datasets has a reference image to which the fused image is compared while the other is not having a reference image. So for the two datasets different evaluation indices are used. Evaluation indices are calculated for all algorithms and compared to find out the best algorithm.

A. With Reference Image

For datasets having reference image, fusion quality could be evaluated using the following evaluation indices:

1. *Root Mean Square Error(RMSE)*
   RMSE is computed as the root mean square error of the corresponding pixels in the reference image I_r and the fused image I_f. The RMSE between a reference image and the fused image is given by:

$$RMSE = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(I_r(i,j) - I_f(i,j) \right)} \quad (6)$$

   Where $I_f(i,j)$ and $I_r(i,j)$ are the gray value of fused image and reference image respectively at index (i, j). For better quality images, the root mean square error should be less.

2. *Peak Signal to Noise Ratio (PSNR)*
   Peak signal to noise ratio (PSNR) value will be high when the fused and the ground truth images are comparable. Higher value implies better fusion. PSNR can be calculated as:

$$PSNR = 20 log_{10}\left[\frac{L^2}{RMSE}\right] \tag{7}$$

   Where, $RMSE$ is the root mean square error and L is the number of gray levels in the image.

3. *Relative dimensionless global error in synthesis*(*ERGAS)*
   Relative dimensionless global error in synthesis (ERGAS) calculates the amount of spectral distortion in the image it is given by:

$$ERGAS = 100\frac{h}{l}\sqrt{\frac{1}{B}\sum_{b=1}^{B}\left(\frac{RMSE(b)}{m(b)}\right)^2} \tag{8}$$

   Where, $\frac{h}{l}$ is the resolution ratio, $m(b)$ is the mean of bth band and B is the number of bands.

4. *Structural Content (SC)*
   Structural content can be calculated by using the equation:

$$SC = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} I_r(i,j)} \tag{9}$$

   Structural content should be 1 for fused image identical to the reference image.

5. *Error Image (EI)*
   The error image is computed as the difference between corresponding pixels of reference and fused image. Image of better fusion quality would have less error and an ideal fusion results in a complete black error image.

$$EI = I_r - I_f \tag{10}$$

B. Without Reference Image

Evaluation indices that are used for datasets without reference image are:

1. *Entropy (H)*
   Entropy is used to measure the information content of an image. Entropy is sensitive to noise and other unwanted rapid fluctuations. An image with high information content would have high entropy. Entropy is defined as:
   $$\boldsymbol{H = -sum\left(p \times log_2(p)\right)} \quad (11)$$
   Where, p contains the histogram counts returned from the Matlab function 'imhist'.

2. *Mean (m)*
   Mean gives the mean pixel value, which is formulated as:
   $$\boldsymbol{m = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N} I_f(i,j)} \quad (12)$$
   Where, $I_f(i,j)$ is the gray value of fused image at index (i,j), MxN is the size of the image.

3. *Standard Deviation (SD)*
   It is known that standard deviation is composed of the signal and noise parts. This metric would be more efficient in the absence of noise. It measures the contrast in the fused image. An image with high contrast would have a high standard deviation. SD is given by:
   $$\boldsymbol{SD = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left(I_f(i,j) - m\right)}} \quad (13)$$
   Where, m is the mean pixel value of the fused image.

4. *Spatial Frequency (SF)*
   This frequency in spatial domain indicates the overall activity level in the image. Image with high spatial frequency offers better quality. It can be calculated as
   Row Frequency (RF):
   $$\boldsymbol{RF = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=1}^{N-1}\left(I_f(i,j) - I_f(i,j-1)^2\right)}} \quad (14)$$
   Column Frequency (CF):
   $$CF = \sqrt{\frac{1}{MN}\sum_{j=0}^{N-1}\sum_{i=1}^{M}\left(I_f(i,j) - I_f(i-1,j)^2\right)} \quad (15)$$
   Spatial Frequency (SF): $\boldsymbol{SF = \sqrt{RF^2 + CF^2}}$ (16)

5. *Cross Entropy (CE)*

Cross-entropy evaluates the similarity in information content between input images ($I_1 \& I_2$) and fused image. Better fusion result would have low cross entropy. Cross entropy can be calculated as:

$$CE(I_1, I_2; I_f) = \frac{CE(I_1; I_f) + CE(I_2; I_f)}{2} \tag{17}$$

Where, $CE(I_1; I_f) = sum\left(p_{i_1} \times log_2\left(\frac{p_{i_1}}{p_{i_f}}\right)\right)$

$$CE(I_2; I_f) = sum\left(p_{i_2} \times log_2\left(\frac{p_{i_2}}{p_{i_f}}\right)\right)$$

p_i is the normalized histogram of the image I.

6. *Fusion Factor(FF)*

Fusion factor of two input images ($I_1 \& I_2$) and fused image (I_f) is given by:

$$FF = I_{1f} + I_{2f} \tag{18}$$

Where, $I_{1f} = sum\left(P_{i_1 i_f}\ log\frac{P_{i_1 i_f}}{P_{i_1} P_{i_f}}\right)$

$$I_{2f} = sum\left(P_{i_2 i_f}\ log\frac{P_{i_2 i_f}}{P_{i_2} P_{i_f}}\right)$$

$P_{i_1} \& P_{i_f}$ are the probability density functions in the individual images and

$P_{i_1 i_f}$ is probability density function of both images together.

FF indicates the amount information present in fused image from both the images. Hence, higher value of FF indicates good fusion quality. But it does not give the indication that the information are fused symmetrically. For that another metrics called fusion symmetry is used.

7. *Fusion Symmetry(FS)*

Fusion symmetry indicates how symmetrically the information from input images is fused to obtain the fused image. It is given by:

$$FS = abs\left(\frac{I_{1f}}{I_{1f} + I_{2f}} - 0.5\right) \tag{19}$$

Since this metric is a symmetry factor, from the equation it is clear that its value should be as low as possible so that the fused image would contain the features of both input images. Fusion quality depends on degree of Fusion symmetry.

8. *Fusion Quality Index(FQI)*
Fusion Quality Index is given by:

$$FQI = sum\left(c(w)\left(\lambda(w)QI(I_1, I_f \mid w) + (1-\lambda(w))QI(I_1, I_f \mid w)\right)\right) \quad (20)$$

Where, $\lambda(w) = \frac{\sigma_{i_1}^2}{\sigma_{i_1}^2 + \sigma_{i_2}^2}$ computed over a window; $c(w) = max(\sigma_{i_1}^2, \sigma_{i_2}^2)$ over a window & $QI(I_1, I_f \mid w)$ is the quality index over a window for a given source image and fused image.
The range of this metric is 0 to 1. One indicates the fused image contains all the information from the source images. FQI of a better fusion would have maximum value in between 0 & 1.

9. *Execution Time (Et)*
It gives the time taken to execute the algorithm.

4. RESULTS AND DISCUSSIONS

The results obtained in [7] are taken and compared with Neuro-Fuzzy and Neuro-Fuzzylet fusion results. For experimentation, two datasets are taken. Dataset-1 is of CSIR- NAL indigenously developed SARAS images (mono-spectral), which consists of a reference image as shown in Fig. 2 and input images, which are obtained by blurring the reference image as shown in Fig. 3. The fusion techniques are further tested using another dataset; Dataset-2 which is a multispectral dataset consists of a Low Light TV (LLTV) image and a Forward Looking IR (FLIR) as inputs. Reference image is not available for this dataset. Different fusion techniques are compared using the fusion quality performance evaluation metrics described in section 3.

A. Dataset-1

As mentioned before, Dataset-1 consists of one reference image (I_r) and 2 input images (I_1 and I_2) of SARAS as shown in Fig. 4 and 5.

Fig. 4 Reference image of SARAS (I_r)

Fig. 5 Input images of SARAS (I_1 and I_2)

The fusion techniques are tested one by one on Dataset-1 in Matlab. In SWT algorithm, it is observed that fusion quality increases with the increase in levels of decomposition at the cost of execution time and it is found out that fusion results with 4 decomposition levels of SWT gives the better results [7]. In Fuzzy logic based algorithm, Sugeno FIS with 5 membership function had given better results. Fuzzylet algorithm is formed by combining SWT with 4 decomposition levels and Fuzzy with 5 membership functions [7]. ANFIS training is done to the FIS to get Neuro-fuzzy algorithm. Here also number of membership functions can be varied. Performance of image fusion using 3 and 5 membership functions with ANFIS is tabulated in Table-1. From the table, it is observed that there is no improvement in evaluation indices by increasing the number of membership function and execution time increases with increase in membership functions. So, ANFIS with 3 membership functions is selected for evaluation. For formulating Neuro-Fuzzylet, the fuzzy function is replaced with Neuro-fuzzy function in the Fuzzylet algorithm. The performance metrics obtained for different methods is tabulated in Table-2 for comparison.

Table-1 Comparison of the Performance metrics obtained using different membership functions of ANFIS

No:of MFs	Performance evaluation metrics											
	Entropy	RMSE	PSNR	SD	ERGAS	SF	SC	CE	FF	FQI	FS	Et(sec.)
3	3.578	0.016	66.542	0.199	1.828	0.067	1.003	4.682	3.377	0.816	0.018	**0.292**
5	3.548	0.016	65.993	0.198	1.844	0.062	0.986	4.714	3.376	0.814	0.012	0.473

Table-2 Comparison of the Performance metrics obtained from five image fusion techniques for Dataset-1

Algorithm	Performance evaluation metrics											
	Entropy	RMSE	PSNR	SD	ERGAS	SF	SC	CE	FF	FQI	FS	Et(sec.)
SWT	3.89	0.007	69.944	0.195	0.744	0.066	1.002	4.215	3.378	0.811	0.016	0.826
Fuzzy	3.578	0.031	63.142	0.195	3.560	0.046	0.981	5.228	3.358	0.771	**0.009**	0.455
Neurofuzzy	3.578	0.016	66.542	**0.199**	1.828	0.067	1.003	4.682	3.376	0.816	0.015	**0.292**
Fuzzylet	**4.061**	**0.005**	**71.062**	0.198	**0.224**	**0.068**	**1.000**	**3.255**	**3.389**	**0.882**	0.013	3.324
Neurofuzzylet	3.912	0.006	70.165	**0.199**	0.771	0.066	1.002	3.626	3.379	0.848	0.017	3.212

From the table it is clear that Neuro-Fuzzy gives better results than fuzzy (see values shown in red). But when it is combined with SWT, fuzzy gives better results. So out of the five algorithms, Fuzzylet gives best fusion results (see bold values) for Dataset-1. The fused and error images for all the algorithms are given from Fig. 6 and 7.

Fig. 6 Fused image using SWT, Fuzzy, Neuro-Fuzzy, Fuzzylet and Neuro-Fuzzylet respectively for Dataset-1

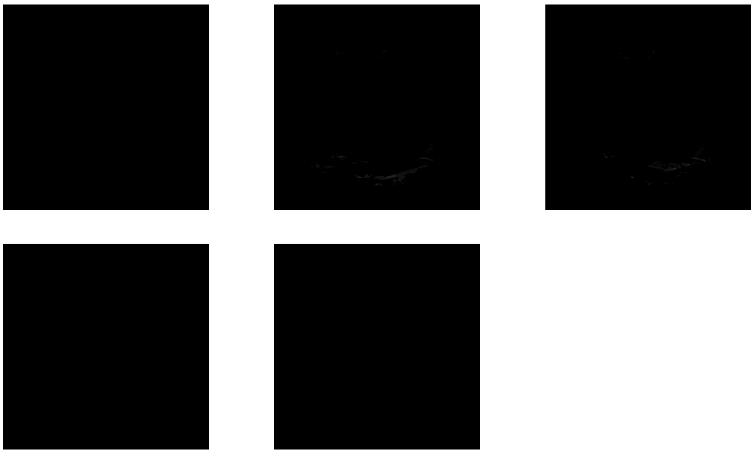

Fig. 7 Error image using SWT, Fuzzy, Neuro-Fuzzy, Fuzzylet and Neuro-Fuzzylet respectively for Dataset-1

B. Dataset-2

Dataset-2 is a multispectral data set consists of LLTV (I_1) and FLIR (I_2) images as inputs as shown in Fig. 8. Reference image is not available for this dataset, hence evaluation metrics explained in section 3.B is used for the comparison.

Human eye is sensitive to a limited range of the electromagnetic spectrum as well as to low light intensity. To obtain data that cannot be sensed by the eye, one can use sensor data such as IR sensors or image intensifier night time sensors. The human observer may use data from multiple sensors. For example, using the visual channel as well as the IR channel can substantially improve the ability to detect a target. This can be observed in the input images shown in Fig.8. In the LLTV image, the bushes, trees etc are more visible while in FLIR image, the roads are more visible. The fused image should render the necessary features of both images.

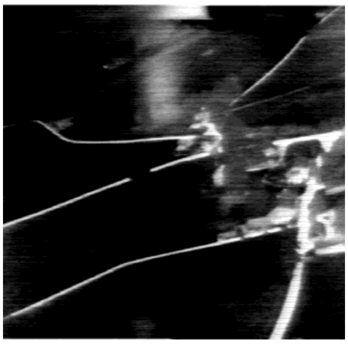

Fig. 8 Images to be fused (LLTV image and FLIR image)

Fused images using all the five algorithms are shown in Fig. 9. It is observed that in SWT result, all the features of both input images are visible but with poor clarity. Rendering of land texture, visual quality of image, etc are poor. In Fuzzy and Neuro-Fuzzy, it is observed that IR features are prominent. Its rendering quality is poor with dark texture and over enhanced view of elements like bushes, trees, etc.

The training data for ANFIS training is selected as mentioned in section 1.A. It is observed that, with the use of Fuzzylet and Neuro-Fuzzylet algorithm, both Visible and IR features are equally rendered maintaining the quality of both input image. So visually, Fuzzylet and Neuro-Fuzzylet provides better result. This can be further evaluated by evaluating fusion quality metrics tabulated in Table-3 for all the five algorithms.

Table-3 Comparison of the Performance metrics obtained from five image fusion techniques for Dataset-2

Agorithm	Performance evaluation metrics						
	Entropy	SD	CE	FF	FS	FQI	Et(sec.)
SWT	7.241	0.187	4.538	2.184	0.023	0.597	0.379
Fuzzy	7.095	0.217	**0.959**	2.185	0.023	0.496	0.428
Neuro-Fuzzy	7.301	0.283	2.308	2.228	0.033	0.437	**0.314**
Fuzzylet	7.296	0.288	4.535	2.346	0.043	**0.698**	1.225
Neuro-Fuzzylet	**7.321**	**0.296**	4.355	**2.419**	**0.045**	**0.698**	0.922

From the table it is clear that Neuro-Fuzzy gives better results than Fuzzy and SWT (see values shown in red).When it is combined with SWT, Neuro-Fuzzy gives better results. So out of the five algorithms, Neuro-Fuzzylet gives best fusion results (see bold values) for multispectral images.

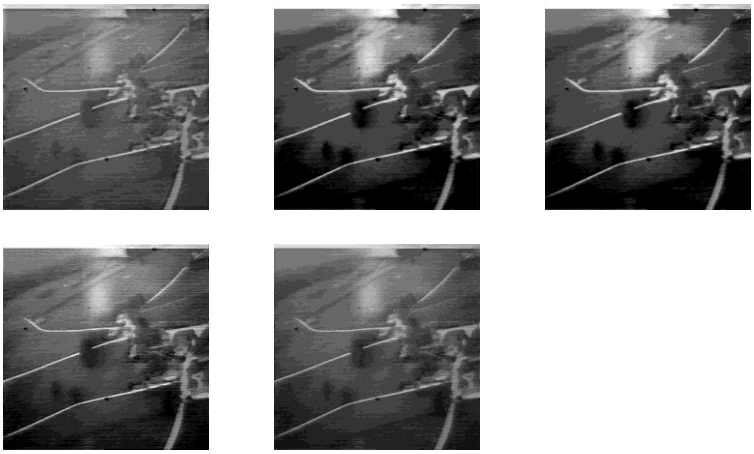

Fig. 9 Fused image using SWT, Fuzzy, Neuro-Fuzzy, Fuzzylet and Neuro-Fuzzylet respectively for Dataset-2

5. CONCLUSION

Five different image fusion algorithms, SWT, fuzzy, Neuro-Fuzzy, Fuzzylet and Neuro-Fuzzylet algorithms were discussed and tested with two datasets (monospectral and multispectral). The results were compared using fusion quality performance evaluation metrics. It was observed that Neuro-Fuzzy gives better results than Fuzzy and SWT. Fuzzylet and Neuro-Fuzzylet were obtained by combining Fuzzy and Neuro-Fuzzy respectively with SWT. It was observed that Fuzzylet gives better results for monospectral images and on the other hand, Neuro-Fuzzylet had given better results for multispectral images at the cost of execution time. It is hoped that the proposed algorithm can be extended for real time and color images.

6. REFERENCES

[1] Yanfen Guo, Mingyuan Xie, Ling Yang, “An Adaptive Image Fusion Method Based on Local Statistical Feature of Wavelet Coefficients” 978-1-4244-5273-6/9 2009 IEEE.

[2] VPS Naidu and J.R. Raol, “ Pixel-level Image Fusion using Wavelets and Principal Component Analysis,” *In defence journal*, Vol. 58, No.3, May 2008, pp. 338-352.

[3] Andrew. P. Bradley, “Shift-invariance in the Discrete Wavelet Transform”, in *Proc. VIIth Digital Image Computing: Techniques and Applications*, Dec. 2003, Sydney.

[4] Pusit Borwonwatanadelok, Wirat Rattanapitakand Somkait Udomhunsakul, “Multi-Focus Image Fusion based on Stationary Wavelet Transform and extended Spatial Frequency Measurement”, *International Conference on Electronic Computer Technology*, 2009, pp. 77-81.

[5] R. Maruthi and K. Sankarasubramanian, “Pixel Level Multifocus Image Fusion Based on Fuzzy Logic Approach”, *Asian Journal of Information Technology* 7(4): 168-171, 2008 ISSN: 1682-3915.

[6] Harpreet Singh, Jyoti Raj and Gulsheen Kaur, "Image Fusion using Fuzzy Logic and Applications", *Budapest Hungary*, 25-29 July. 2004.

[7] Swathy Nair, Bindu Elias, VPS Naidu, "Pixel Level Image Fusion using Fuzzylet Fusion Algorithm", in *International Journal Of Advanced Research in Electrical Electronics And Instrumentation Engineering*, ISSN 2278-8875, Dec 2013.

[8] www.mathworks.in/matlabcentral/fileexchange/authors/104729. Accessed on 21/2/2014.

This paper may be cited as:

Nair, S., Elias, B. and Naidu V., 2014. Pixel Level Image Fusion: A Neuro-Fuzzy Approach. *International Journal of Computer Science and Business Informatics, Vol. 12, No. 1, pp. 71-86.*