

Optimal Threshold Based Brain Image Fusion for Brain Cancer Detection using Firefly algorithm



M. V. Srikanth, V. V. K. D. V. Prasad, K. Satya Prasad

Abstract: In this paper an attempt is made to diagnose brain disease like neoplastic disease, cerebrovascular disease, Alzheimer disease, fatal disease, Sarcoma disease by effective fusion of two images. Two images are fused in three steps: Step 1. Segmentation: The images are segmented on the basis of optimal thresholding; thresholds are optimized with natural inspired firefly algorithm by assuming fuzzy entropy as objective function. Image thresholding is one of the segmentation techniques which is flexible, simple and has less convergence time as compared to others. Step 2: the segmented features are extracted with Scale Invariant Feature Transform (SIFT) algorithm. The SIFT algorithm is good in extracting the features even after image rotation and scaling. Step 3: Finally fusion rules are made on the basis of interval type-2 fuzzy (IT2FL), where uncertainty effects are minimized unlike type-1. The novelty of the proposed work is tested on different benchmark Image fusion data set and proved better in all measuring parameters.

Index Terms: fuzzy entropy; Image Fusion; Firefly algorithm; Scale Invariant Feature Transform; interval type-2 fuzzy;

I. INTRODUCTION

Diagnosis of a disease is an important step to cure an illness. There are many diagnostic techniques and one of them is medical imaging. It is a technique to generate a visual representation of the desired part of the human body including tissues, bones and brain. Many multi-modal medical imaging techniques were introduced to achieve it. The main solution among them is Image fusion. Gathering required information from various images and fusing them together into a single image without any distortion and loss of information. Image fusion has many advantages, they include less ambiguity, improved reliability, image sharpening, feature enhancement, improved classification, diagnosing disease in early stages, easy to interpret, low in cost, reduces data transmission and fused image is true in color. Image fusion can be applied in medical diagnosis, satellite imaging, object detection and recognition, military, astronomy. Many techniques and classifications have been originated in image

fusion. The main techniques are spatial domain techniques [1], transform domain techniques [2], contrast pyramid technique, ratio pyramid technique, morphological pyramid technique [3], Laplacian pyramid technique, PCNN [4], pixel level image fusion technique [5], feature level image techniques [6], decision level image fusion techniques [7]. The spatial domain image fusion technique directly deals with the pixels of the input images. This technique can be analyzed in four ways namely, principal component analysis (PCA) [8], Intensity hue and saturation (IHS), Simple averaging, Simple maxima. Although they are very important techniques, they have certain limitations. Simple maxima produces highly focused images but it causes blurring [9]. Local contrast can be affected by blurring. Simple averaging cannot give clear images of the object but it is the simplest method for image fusion. Spectral degradation is produced due to principal component analysis technique. Intensity hue saturation is only suitable for color image fusion so it cannot be applied in medical imaging [10]. In transform domain techniques, initially the transform of the function is analyzed and the resultant coefficients of transforms are fused. Then, the inverse transform is estimated to get fused images. In this technique, images are converted into multi-resolution or multi-scale representations before fusion. This technique can be analyzed using discrete wavelet transform (DWT), DT-CWT, Curvelet transform [11], additive wavelet transforms, non-sub sampled Contourlet transform (NSCT). Contourlet transform is used for catching complex contours, edges and textures [12]. Few methods in the transform domain are far better than spatial domain methods in many aspects. Discrete wavelet transform cannot handle curved edges. Therefore it fails in fusing images of the brain in a required manner. It has poor directionality, shift sensitivity, destruction of phase information, less spatial resolution. It has Pseudo-Gibbs effect due to the down-sampling process. Curvelet transform is specially designed for curved edges and capturing curvilinear properties. Therefore it is beneficial in fusing the images of brain easily and clearly but this method is very complex and it takes very high processing time. DT-CWT technique has minor drawbacks as compared to spatial domain analysis and transforms domain analysis. DT-CWT technique has high directionality, better edge representation, approximate shift invariant property and takes less time for processing [13].

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* Correspondence Author

M.V.Srikanth, ECE, Gudlavalleru Engineering College, Gudlavalleru, A.P, India.

V.V.K.D.V.Prasad, ECE, Gudlavalleru Engineering College, Gudlavalleru , A.P, India.

K.Satya Prasad, RECTOR, Vignan University, Guntur, A.P, India.

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The Pyramid techniques in image fusion are suitable only for specific type of images. Therefore, only one bandpass image is generated by pyramid level image fusion techniques and they often cause blocking effects [3]. Apart from this, Contrast pyramid technique will lose much information while Morphological pyramid technique has bad edges.

The pulse coupled neural network (PCNN) technique is very useful for image segmentation, image enhancement and pattern recognition. It has an important biological background. PCNN is used to produce images with high contrast, clarity and information. M-PCNN is very useful when several images are fused at a time and depending upon the actual requirements, number of channels can be easily changed. Still it has drawbacks, it is very difficult and complex to set the design constraints, and they have to be adjusted manually or they can be estimated through large amount of training. But, every parameter is important. The performance of PCNN image fusion is completely dependent on those parameters. To overcome this drawback intelligent

implementation, low processing time, and high convergence speed. Soon after completion of image fusion techniques we have to face two main challenges image contrast and visual quality.

II. PROPOSED IMAGE FUSION

In this paper a region based feature level image fusion is proposed, the regions of both the images which are to be fused are obtained by perfect image segmentation. The images are segmented for extraction of similar regions or areas in both the images by optimal thresholds. The optimal thresholds are obtained using suitable optimization techniques by assuming fuzzy entropy as an objective function. The task of optimization technique is to maximize the objective function which leads to better threshold, henceforth improved segmentation of input images. The thresholds are optimized with the firefly algorithm and compared the results with some other state of art optimization techniques. After successful segmentation of both the

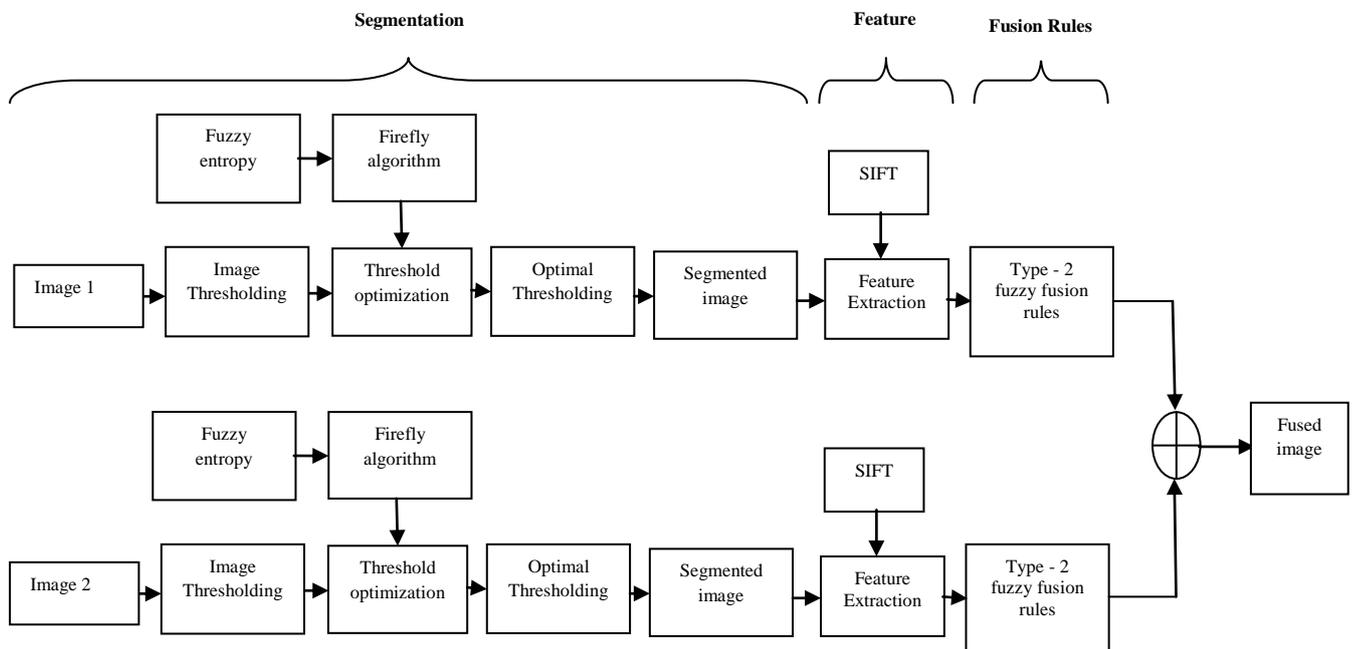


Fig.1 Block diagram of proposed technique

optimization algorithms are used. They are GA-PCCN, PSO-PCCN, QPSO-PCCN, MDE-PCNN and FOA-PCCN [14]. The pixel level can hold large amount of information and it also has high precision. The area may approach by which you can achieve pixel level image fusion. They are, intensity hue saturation, principal component analysis and multi-resolution analysis which is widely used. To decide a technique which is rightly suitable for our application we should consider certain parameters like strength, orientation, offset of the image edges, ridges and other singularities. After deciding the technique we move for global optimization techniques. To achieve our objective, global optimization is a task for finding the best set of admissible conditions. It is used to find the maxima and minima for continuous and differential functions. The techniques are firefly algorithm (FA), gray wolf optimization (GWO) [15], particle swarm optimization (PSO) [16], Honey bee mate optimization (HBMO) [17]. Among them, firefly algorithm is more advantageous like simple mathematics, ease of

images, the feature of the input images are extracted with a suitable feature extraction techniques. In general the features of an image are texture, edge and contour. In this paper, image features are extracted with Scale Invariant Feature Transform (SIFT) algorithm, it was invented by David Lowe in 1999 [18] and the working principal of the algorithm starts with random extraction of objects from reference image and new object from other image is recognized on the basis of minimum Euclidean distance between the reference and object which is to be detected. The detailed description about the algorithm is found in reference number [19]. The extracted features of both the images are fused based on type - 2 fuzzy fusion rules. Theory of fuzzy set was created in 1965 by Zadeh [20]. However, it is found that type-1 fuzzy set is not adaptive and flexible, therefore,

similarly proposed a type -2 fuzzy set, and in which membership function is uncertain because of uncertainty in membership relationship. So it is adaptable for both certain and uncertain problems. Figure 1 shows the block diagram of proposed algorithm.

Image thresholding: Image thresholding is one of the imagesclustering technique. It is used in many applications like image processing, data mining, data clustering etc., because of its simple and flexible nature. Image thresholding may be bi-level or multi-level, in first case two thresholds are used for segmentation of the given image into three regions. Whereas, in second case, number of thresholds are fixed by the user depending on his requirement. If number of thresholds are 'c' then the number of clusters or segments are 'c+1'. The segmented result depends on perfect placement of thresholds which segment the input image. Placing these thresholds is difficult task for different images. So in this, these thresholds are optimized with firefly algorithm by considering fuzzy entropy as objective function.

III. METHODS

In this section a brief review of fuzzy entropy, Firefly algorithm, Scale-Invariant Feature Transform, Type-2 Fuzzy Set and Fusion Rules are discussed.

3.1 Fuzzy entropy:

Fuzzy entropy is an extension of Claude Shannon entropy and is an entropy of a fuzzy set. The Shannon entropy $H(x)$ of an event 'x' with elements $\{x_1, x_2, x_3, \dots, x_N\}$ and respective probabilities $\{P_1, P_2, P_3, \dots, P_N\}$ is $-\sum_j^N P_j \log P_j$, then the fuzzy entropy of fuzzy subset B with finite fuzzy set $\{x_1, x_2, x_3, \dots, x_N\}$ and respective probabilities $\{P_1, P_2, P_3, \dots, P_N\}$ is

$$H_B^P = -\sum_j^N \mu_B(X_j) P_j \log (P_j) \quad (1)$$

Where μ_B is membership function of event B. above equation gives fuzzy entropy of a fuzzy event B with respect to the distribution P. The same concept can be extended to image thresholding. Let two thresholds T_1 and T_2 partition the image into three distinguished regions D_1, D_2 and D_3 and its corresponding probability distribution function P_1, P_2, P_3 membership function μ_1, μ_2, μ_3 and each region fuzzy entropy is H_1, H_2, H_3 respectively then the overall fuzzy entropy is

$$H_T^P = H_1 + H_2 + H_3 \quad (2)$$

After evaluation of overall fuzzy entropy, optimal thresholds are finding by using eq. (15) as in reference [21]

3.2 Firefly algorithm:

Firefly algorithm is nature inspired optimization algorithm developed and implemented by Xin She Yang in 2009 [15]. It is inspired by flashing pattern and natural behavior of fireflies. Fireflies always follow a specific strategy wherein a few brighter fireflies try to move towards brighter fireflies. Firefly Algorithm is developed using the flashing light and found in tropical and temperate regions. Most of the species became famous due to bioluminescence process, the process for the flashing light and attracting mating partners. The brighter firefly will attract other few brighter fireflies and consequently allows fireflies to explore the search space, i.e., update their positions. Light intensity (I) decreases with the increase in the distance (r). Air acts as barrier to become weaker intensity of light with the distance. In this connection, the brightness (fitness) of every firefly is calculated using the objective function. The primary parameter of the FA is the formulation of attractiveness and variation of light intensity.

The attractiveness varies with the distance r_{ij} between the i^{th} and j^{th} firefly. The distance between any two fireflies is calculated using the Cartesian distance method as per Eq. (3).

$$r_{ij} = |x_i - x_j| = \sqrt{\sum_{k=1}^d (x_{i,k} - x_{j,k})^2} \quad (3)$$

Firefly i is attracted to brighter firefly j and its movement is determined as per Eq. (4)

$$X_i = x_i + \beta_0 e^{-\gamma r_{ij}} (x_j - x_i) + \alpha(rand - 0.5) \quad (4)$$

The first term is the attraction (γ); the value of γ (zero to infinite). If γ is approaching zero, then the attractiveness and brightness become constant, ($\beta = \beta_0$). When the γ is equal to the infinity ($\gamma = 1$) the brightness and the attractiveness decreases. The second term is the randomization parameter and used for generating the random number in order to facilitate random movements. Initially, FA starts with the population of randomly positioned fireflies on the basis of brightness. The movement of the fireflies depends upon their amount of brightness emitted.

During the iterative process, the brightness of one firefly is compared with other in the population and move towards the brighter firefly. This movement depends upon the distance between the fireflies. During the iterative process, the best solution is continuously updated until the stopping conditions are satisfied.

The detailed FA algorithm is given below.

Step 1: Randomly selected fireflies (thresholds) and its corresponding parameters, population size, maximum iteration.

Step 2: Initialize α, β and γ parameters, and then initialize rest of thresholds with random numbers.

Step 3: Find fitness of all fireflies by giving to objective function i.e Eq. (2).

Step 4: Randomly selected a population and recorded fitness values. If there is a population with higher fitness value, then it moves towards the brighter fireflies (highest fitness value) based on the Eq. (5) - (7).

$$\text{Euclidean } r_{ij} = \|X_i - X_j\| = \sqrt{\sum_{k=1}^{N_c} \sum_{h=1}^L (X_{i,k}^h - X_{j,k}^h)^2} \quad (5)$$

Here X_i is randomly selected codebook, X_j is brighter threshold

$$\beta = \beta_0 e^{-\gamma_{i,j}} \quad (6)$$

$$X_{j,k}^h = (1 - \beta) X_{i,k}^h + \beta X_{j,k}^h + u_{j,k}^h \quad (7)$$

where u_{ij} is random number between 0 to 1, $k=1,2,\dots,N_c, h=1,2,\dots,L$.

Step 5: If selected firefly doesn't find brighter fireflies in search space, then it moves randomly with the following equation.

$$X_{i,k}^h = X_{i,k}^h + u_{j,k}^h \quad k=1, 2, \dots, N_c, h=1, 2, \dots, L \quad (8)$$

Step 6: repeat step (3) to (5) until one of the termination criteria is reached.

3.3 Scale-Invariant Feature Transform

Harris feature detectors are rotation invariant i.e same corners in images are detected even after image rotation and before rotation, but it fails to detect corners when image is scaled. After scaling the image, corners in an image may or may not be corners.

So this feature detector is scale variant [22]. To overcome this drawback, scale-invariant feature transform (SIFT) is introduced in the year 2004. The algorithm follows 4 steps:

A. Scale space peak selection: Potential locations for finding features

Different sizes of windows are used for different scaled images for detection of key points and this process is known as scale space filtering, difference of Laplacian of Gaussian (DoG) produce a windows of different sizes. Difference of Gaussian value is calculated by difference of two Gaussian images.

B. Key point localization:

Accurately locating the feature key points

After successful identification of key points in first stage, these points are further refined for accuracy by generating a different window sizes on basis of Taylor series and after doing this, if obtained extreme location intensity is greater than the user defined threshold (contrast threshold) then consider it or else discard. Similarly any unwanted edges found after difference of Gaussian function, those locations are removed by 2x2 Hessian matrixes as like in Harris corner detector. So only utmost edges and key points are obtained after set A and step B.

C. Orientation assignment:

Assigning orientation to the key points

In this step, orientation is traced between the key points based on their scale, gradient magnitude and direction. In this paper, around 36 bins are used to cover 360 degrees. From histogram of an image the highest intensity 'H' is calculated and if any Key point intensity is above 80% of H, then it will be considered in tracing.

D. Key point descriptor:

Describing the key point as a high dimensional vector

Key point descriptor is obtained by local gradient which is generated in above three steps. The obtained gradient information is rotated to line up with the orientation of the key point and then weighted by Gaussian with variance of 1.5 key point scales. With this data, a collection of histograms are generated which are at center of key point. A total of 16 histograms which are arranged in the form of 4x4 grids and each grid carry 8 orientation bins. This leads to a feature vector of size 128. These vectors are called SIFT keys and used for identification of nearest possible object in an image. If more than three keys support a specific feature that will be consider for further process.

3.4 Type-2 Fuzzy Set

The theory called as fuzzy set created by Zadeh. Fuzzy set theory prominently solves the problems related to uncertainty. However, because type-1 conventional membership functions of fuzzy set are determined, the uncertainty effects minimization is difficult by using any kind of algorithm and membership function. In pragmatic applications, usually the membership function is based on intuition empirically with a high degree of subjectivity. A generalized fuzzy set proposed by Zadeh to deal with the problems mentioned above i.e., type 2 fuzzy set. In a second type Fuzzy set the relation between membership function and element is fuzzy and uncertain. Therefore a type-2 fuzzy set can describe the fuzzy membership function of uncertainty and the elements of uncertainty. Type-2 fuzzy set can be defined as

$$B = \{(y, u, \mu_B(y, u)) | \forall y \in Y, \forall u \in Ky \subseteq [0, 1]\} \quad (9)$$

Where B denotes the type-2 fuzzy set, $\mu_B(y, u)$ denotes its type type-2 membership function with $0 \leq \mu_B(y, u) \leq 1$. Ky denotes a primary membership function $\mu_B(y', u)$ denotes the secondary membership function when $y=y'$. However the complexity of type-2 fuzzy set is greater than that of type-1, in which more calculations are required. The problem exists while choosing secondary membership functions. In practical applications, a type-2 simplified fuzzy set often used, such as the interval type-2 fuzzy set [23]. The membership functions of the element in type-2 fuzzy set is defined as

$$B = \{(y, u, 1) | \forall y \in Y, \forall u \in Ky \subseteq [0, 1]\} \quad (10)$$

An alternative type-2 fuzzy set is defined as (with the help of membership functions of type-1)

$$B = (y, \mu_M(y), \mu_V(y)) | \forall y \in Y \quad (11)$$

$$\mu_M(y) \leq \mu(y) \leq \mu_V(y) | u \in [0, 1]$$

Where $\mu(y)$ denotes an initial membership function of thype-1, B is the interval type-2 fuzzy set, and $\mu_M(y)$ and $\mu_V(y)$ is the upper and lower membership functions with respect to upper and lower envelopes of the interval membership function (type-2) and fuzzy set type-1 membership function can be obtained. Practically a pair to characterize reciprocal parameters i.e.,

$$\mu_M(y) = [\mu(y)]\alpha, \mu_U(y) = [\mu(y)](1/\alpha) \quad (12)$$

Where α is a fuzzy linguistic hedge ($\alpha \geq 1$). Good output can be obtained when $\alpha \in [1, 2]$. Footprint of uncertainty (FOU) can be represented by relating both type-1 fuzzy set and type-2 fuzzy set [24]. The shape of type-2 fuzzy set is used in literature is represented by term FOU, therefore the distribution on the top of the shaded area is given by FOU.

3.5 Fusion Rule

Let's assume two images M and R which is to be fused. After successful segmentation of both the images its corresponding segmented regions are represented as $M: \{S_{p,q}^M\}$ and $R: \{S_{p,q}^R\}$ where p and q represents the segmented regions and its corresponding pixel positions respectively. The fusion rules play a significant role in performance of the proposed segmentation method. The earlier proposed image fusion rules are sensitivity to noise at high frequency i.e edges, region boundaries and textures [25] so in this paper, type 2 fuzzy logic is proposed which takes local and global information of the images. The shape of the membership function $\mu()$ is given as

$$\mu_{p,q}^I(i, j) = \frac{1}{1 + \left| \frac{s_{p,q}^I(i, j) - c}{a} \right|^2} \quad (13)$$

Where $I = (M, R)$ and (i, j) shows the spatial location of segmented images. Here, c is average of $(s_{p,q}^I)$ and 'a' is minimum of $(s_{p,q}^I)$. Next, at each position of the membership function, lower and upper membership functions $\mu_L(x)$ and $\mu_U(x)$ are calculated as follows:

$$\begin{cases} \mu_L^{I,p,q}(x, y) = [\mu_{p,q}^I(i, j)]^\alpha \\ \mu_U^{I,p,q}(x, y) = [\mu_{p,q}^I(i, j)]^{1/\alpha} \end{cases} \quad (14)$$

Fuzzy set performance is measured on the basis of fuzzy entropy, a high value of fuzzy entropy shows the best fuzzy set and low value of fuzzy entropy shows wicked fuzzy set [26]. Hence a higher value of fuzzy entropy leads to better image fusion rules. The detailed description about the fuzzy entropy already discussed in section 2.



IV. RESULTS AND DISCUSSION

The performance of proposed method is evaluated by performing experiments on five pairs of images related to different diseases of brain as shown in Figure. In Set-A, CT and T2- Weighted MR images of brain tumor related to neoplastic disease. In Set-B, CT, T2-Weighted MR images of brain stroke due to cerebrovascular disease. In Set-C, depicts the T1-Weighted MR and T2-Weighted MR images of brain related to Alzheimer disease. In Set-D, depicts the T1-Weighted MR and T2-Weighted MR images of brain related to fatal disease,

while in Set-E, represents the CT, T1-Weighted MR brain images due to sarcoma disease. The medical images used in the research were obtained from and <http://www.med.harvard.edu/aanlib/home.html>, <https://www.imagefusion.org/>. The images are segmented on the basis of image thresholding and optimal thresholds are obtained after fixing the tuning parameters (α , β_0 and γ) of the firefly algorithm. These values are fixed based on the occurrence of the maximum entropy. Table 1 shows the tuning parameters of firefly for different data set and number iterations, lower

Table 1: The parameters used in the FA algorithm

| Parameter | Value | Set-A | Set-B | Set-C | Set-D | Set-E |
|----------------------------|-------|-------|-------|-------|-------|-------|
| Population size (N) | 30 | | | | | |
| Iterations (itr) | 20 | | | | | |
| Lower bound (L_{UB}) | 0 | | | | | |
| Upper bound (L_{UB}) | 255 | | | | | |
| Alpha (α) | | 0.9 | 0.8 | 0.5 | 0.6 | 0.4 |
| beta minimum (β_0) | | 0.9 | 0.1 | 0.2 | 0.4 | 0.4 |
| gamma (γ) | | 0.7 | 0.6 | 0.6 | 0.3 | 0.1 |

Table 2: Set –A: Neoplastic disease

| Method | FSIM | ENTROPY | PSNR | SSIM | STD | $Q^{AB/F}$ | MI | CC |
|----------|----------|-----------|----------|----------|----------|------------|---------|---------|
| PSO | 0.893427 | 21.064733 | 34.32786 | 0.91319 | 0.189056 | 0.620952 | 3.23917 | 0.62095 |
| QPSO | 0.956501 | 21.109136 | 34.36472 | 0.914872 | 0.206056 | 0.663134 | 3.28259 | 0.66313 |
| HBMO | 0.958995 | 21.134748 | 34.38426 | 0.934355 | 0.234453 | 0.683590 | 3.28660 | 0.68359 |
| Proposed | 0.974199 | 21.422380 | 34.38873 | 0.968933 | 0.244550 | 0.697060 | 3.29482 | 0.69706 |

Table 3: Set –B: Cerebrovascular disease

| Method | FSIM | ENTROPY | PSNR | SSIM | STD | $Q^{AB/F}$ | MI | CC |
|----------|----------|-----------|----------|----------|----------|------------|---------|---------|
| PSO | 0.991425 | 22.640391 | 34.39331 | 0.94834 | 0.137244 | 0.594891 | 3.30639 | 0.59489 |
| QPSO | 0.960303 | 22.679535 | 34.58154 | 0.949456 | 0.152098 | 0.604217 | 3.34325 | 0.60422 |
| HBMO | 0.942479 | 22.689466 | 34.58518 | 0.953553 | 0.183669 | 0.683029 | 3.34592 | 0.68303 |
| Proposed | 0.9233 | 22.788329 | 34.61089 | 0.966054 | 0.197689 | 0.69309 | 3.35211 | 0.69309 |

Table 4: Set –C: Alzheimer disease

| Method | FSIM | ENTROPY | PSNR | SSIM | STD | $Q^{AB/F}$ | MI | CC |
|----------|----------|-----------|----------|----------|----------|------------|--------|---------|
| PSO | 0.336717 | 21.390594 | 32.82359 | 0.911531 | 0.777079 | 0.719411 | 3.1335 | 0.71941 |
| QPSO | 0.444859 | 21.405167 | 32.83409 | 0.93702 | 0.444859 | 0.720572 | 3.1335 | 0.72057 |
| HBMO | 0.66098 | 21.485016 | 32.85253 | 0.951837 | 0.66098 | 0.725686 | 3.1335 | 0.72569 |
| Proposed | 0.777079 | 21.491799 | 32.85539 | 0.951916 | 0.336717 | 0.746857 | 3.1335 | 0.74686 |

Table 5: Set –D : Fatal disease

| Method | FSIM | ENTROPY | PSNR | SSIM | STD | $Q^{AB/F}$ | MI | CC |
|----------|----------|-----------|----------|----------|----------|------------|---------|---------|
| PSO | 0.307900 | 22.177216 | 32.56973 | 0.897339 | 0.437479 | 0.742869 | 3.54065 | 0.74287 |
| QPSO | 0.437479 | 22.254970 | 32.63030 | 0.920576 | 0.833801 | 0.756198 | 3.54868 | 0.75620 |
| HBMO | 0.693950 | 22.278068 | 32.78759 | 0.924099 | 0.307951 | 0.768028 | 3.59584 | 0.76803 |
| Proposed | 0.833801 | 22.309109 | 32.81419 | 0.936259 | 0.693950 | 0.776092 | 3.62459 | 0.77609 |

Table 6: Set –E: Sarcoma disease

| Method | FSIM | ENTROPY | PSNR | SSIM | STD | Q ^{AB/F} | MI | CC |
|----------|---------|----------|--------|---------|---------|-------------------|--------|--------|
| PSO | 0.21906 | 21.23275 | 33.691 | 0.89593 | 0.24321 | 0.649 | 2.8722 | 0.649 |
| QPSO | 0.24321 | 21.25676 | 33.708 | 0.90873 | 0.32883 | 0.6583 | 2.8922 | 0.6583 |
| HBMO | 0.32883 | 21.39504 | 33.767 | 0.92194 | 0.21906 | 0.6615 | 2.8956 | 0.6615 |
| Proposed | 0.38262 | 21.51113 | 33.861 | 0.9251 | 0.38262 | 0.6793 | 2.9627 | 0.6793 |

bound, upper bound and population size. All the simulations are performed on HP Compaq LE1902X personal computer with Matlab version 2016a.

4.1. Measuring parameters

Structural similarity index (SSIM): Structural similarity index is used for the estimation of similarity or closeness between two images [27]. It is used to measure quality by comparing one image provided with the other image. It is

regarded as an excellent quality. It is the upgraded version of universal image quality index. Consider $D1=(m_1N)^2$ and $D2=(m_2N)^2$ are the two variables to make the division stable by making the denominator weak. N represents the dynamic range values of pixels. The general values for m_1 and m_2 are 0.01 and 0.03 respectively. If 'f' is the fused image and r is the reference image.

$$SSIM = \frac{(2r2f+D1)(2r2f+D2)}{(2r2f+D1)(2r+2f+D2)} \tag{15}$$

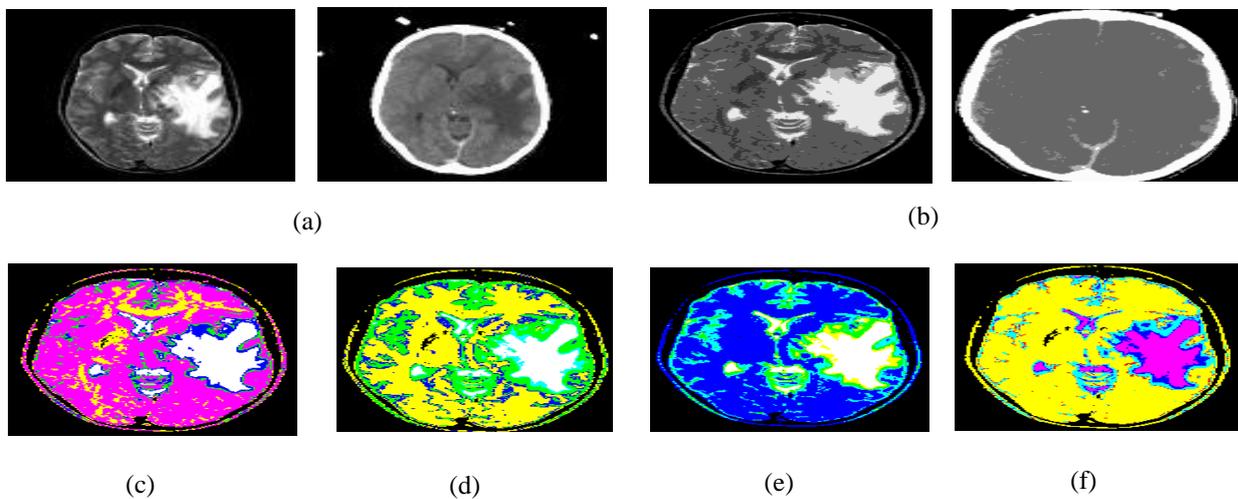


Fig. 2 a) input images b) Segmented images: Fused images c) with PSO d) with QPSO e) with HBMO f) with FA

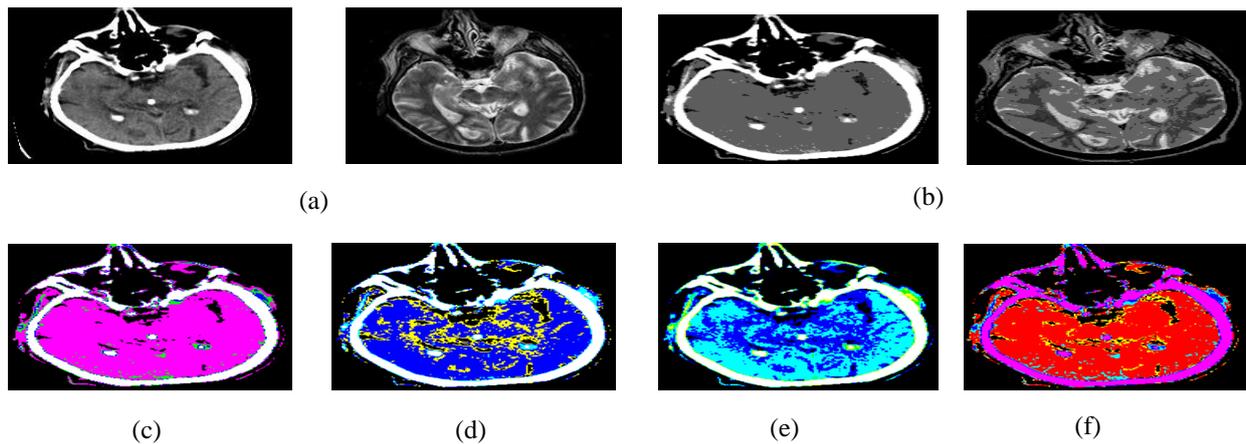


Fig. 3 a) input images b) Segmented images: Fused images c) with PSO d) with QPSO e) with HBMO f) with FA

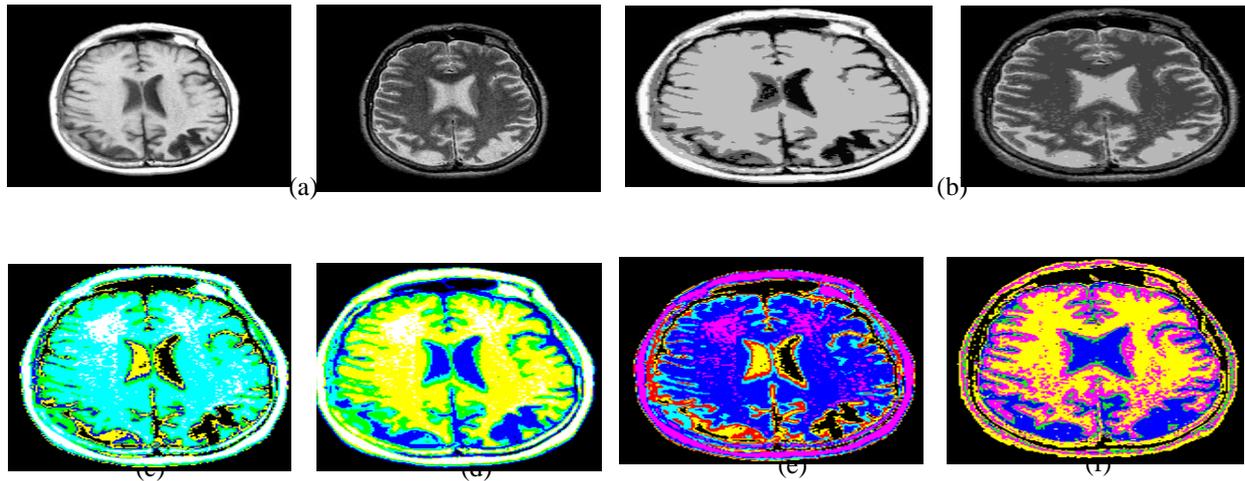


Fig. 4 a) input images b) Segmented images: Fused images c) with PSO d) with QPSO e) with HBMO f) with FA

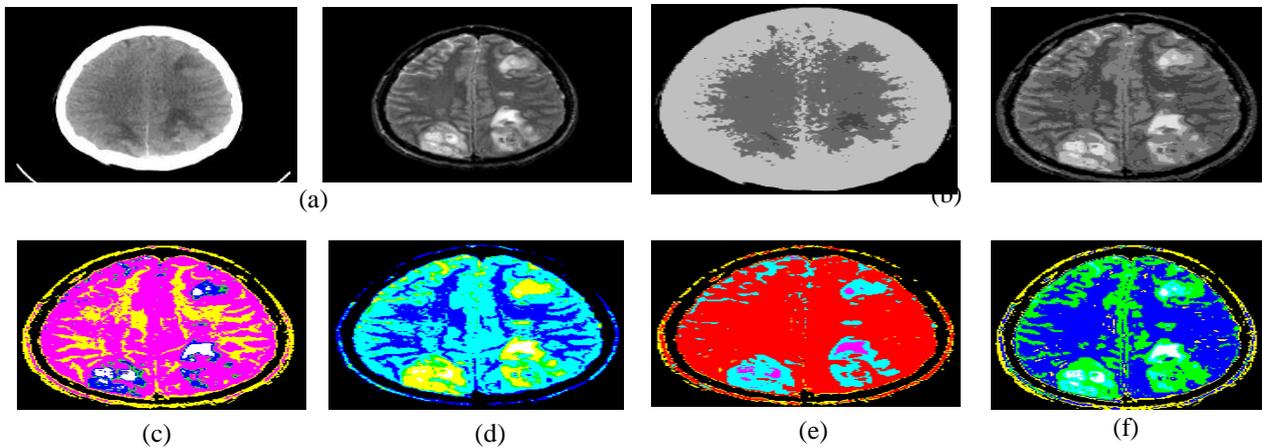


Fig. 5a) input images b) Segmented images: Fused images c) with PSO d) with QPSO e) with HBMO f) with FA

Standard deviation (STD): standard deviation is the estimation of gray contrast in the combined image. At the point when the estimated S is high, the fused image will have high contrast. When $p(k)$ is the probability of gray level k and k_m is the mean of k [27].

$$STD = \sqrt{\sum_{k=0}^{J-1} (k - k_m)^2 p(k)} \quad (16)$$

Mutual information (MI): Mutual information is utilized as a measure to know the performance in multimodal fusion [27]. If the value of MI is high then it suggests that the combined frame constraints more parental image information. $p(m)$, $p(n)$ are the marginal probability distribution functions of both the images, $p(m,n)$ is the joint probability distribution function.

Mutual information (MI): Mutual information is utilized as a measure to know the performance in multimodal fusion [27]. If the value of MI is high then it suggests that the combined frame constraints more parental image information. $p(m)$, $p(n)$ are the marginal probability distribution functions of both the images, $p(m,n)$ is the joint probability distribution function.

$$MI(m, n) = \sum_{m \in M} \sum_{n \in N} p(m, n) \log \left(\frac{p(m, n)}{p(m)p(n)} \right) \quad (17)$$

Where M and N are number of rows and columns of both the images.

Entropy: It is defined as the amount of information which the image contain. It can be used to measure the quality of the output fused image. The entropy can be known if probability density (p) of pixel levels is known. If the entropy is higher, then fusion is efficient [21].

$$Entropy = - \sum_{i=0}^{K-1} p(mi) \log p(mi) \quad (18)$$

Edge based similarity measure ($Q^{AB/F}$): It can be used to measure the edge details in a fused image. The value of Q is close to 1 for a high quality fused image. A number of ways are introduced to get the edge information of the image like simple edge detection algorithm, local gradients and many more [27]. It is calculated with below equation.

$$Q^{AB/F} = \frac{\sum_{i=1}^x \sum_{j=1}^y Qa(i, j)Wa(i, j) + Q(i, j)Wb(i, j)}{\sum_{i=1}^x \sum_{j=1}^y Wa(i, j) + Wb(i, j)} \quad (19)$$

$$Qa(i, j) = Qa_g(x, y)Qa_a(x, y), Qb(i, j) = Qb(x, y)Qb_a(x, y) \quad (20)$$

Correlation coefficient (CC): This parameter is used to measure the closeness between reference image and fused image. If the reference image and fused image are identical then the value of correlation coefficient is nearly equal to 1 [27]. If the difference between the fused image and reference image is additional, then the value of correlation coefficient will be less than 1.

$$C = \frac{\sum_{i=1}^J (m_i - M)}{\sqrt{\sum_{i=1}^J (m_i - M)^2 \sum_{i=1}^J (n_i - N)^2}} \quad (21)$$

Where M and N are mean values of corresponding images.

4.2 Experiments on CT/MRI Image Fusion

Neoplastic disease: Neoplastic diseases are conditions that cause tumor growth. It is the kind of tumor due to extreme development of cells in the brain. They can be benign and malignant. Benign tumors are non-cancerous and grow slowly and spread less to other organs. Malignant tumors are cancerous and can spread to other tissues or organs. If not detected in the early stage, it may be life threatening. Identifying such kind of growth at early stage, may not lead to cancer. If such kind of growth is malignant, it will spread to all other parts of brain at quick rate leads to cancer. From figure 2, such kind of tumor growth is identified better with the proposed algorithm as compared to others and table 2 shows the performance of the proposed algorithm in FSIM, SSIM, Entropy, PSNR, $Q^{AB/F}$ and MI.

Cerebrovascular disease: Cerebrovascular disease refers to conditions that affect the flow of blood through the brain and can lead to stroke. Hypertension (high blood pressure) is the most important risk factor for stroke and cerebrovascular disease. This disease, permanently or temporarily effected by some of the reasons like ischemia, area of brain, blood bleeding and in pathological process more than two blood vessels involvement. It includes aneurysms, vertebral stenosis, carotid stenosis and, stroke, vascular malformations and intracranial stenosis. These diseases can be prevented by medication and life style changes. Blood thinners and other modalities, including surgery are used to treat strokes. Figure 3 shows the effectiveness of proposed algorithm in visual quality and table 3 shows in all measured parameters proposed is better.

Alzheimer disease: Alzheimer's disease is an irreversible progressive brain disorder that slowly destroys memory and thinking skills eventually, the ability to carry out even simple tasks. It usually appears first in mid - 60s. There is no cure for this disease, but treatment can help slow the progression of the disease and improve quality of life. In general this disease is diagnosed by testing metal stability manually or eye tracing test or by MRI scan or by CT scan. A small structural difference in brain leads to disease, so identifying such kind of small difference is a big task for the researchers. In this paper, MRI and CT scan images are fused for better identification of small differences in brain which leads to early diagnosis of Alzheimer. T1-Weighted MR image of 70 years old man and T2-Weighted MR images of 73 years old man is considered for performance test of proposed method.

The qualitative result of the proposed algorithm is well explained in the figure 4. From the figure, the visual quality of Alzheimer disease is better with proposed as compared with other algorithms. The quantitative results of the proposed are as shown in table 4. It shows the superiority in all aspects.

Fatal disease: A fatal disease has no cure and ultimately results in death of the patient. Death can occur within a few hours to several years, depending upon the particular disease. Some examples of fatal diseases include cancer, severe heart disease, AIDS, dementia etc. As there is no cure, the patients can only be given supportive and palliative treatment. In this paper Pick's disease is consider as a fatal disease. Pick's disease is a rare disease which leads to loss of memory, reduction in thinking levels, remembering the language and abnormal behavior of human beings. The reason is some minor damage in brain tissues. This can be identified by fusing CT and MRI images and was successfully done with the proposed method and compared the results with other soft-computing techniques. Form table 5 and figure 5 it is observed the proposed method effectiveness in fusing the images.

Sarcoma disease: Sarcoma is a malignant tumor, a rare kind of cancer. Sarcomas grow in connective tissue cells, for example fat, blood vessels, nerves, bones, muscles and cartilage. They are treated by surgery to remove the tumor and radiotherapy and chemotherapy. Sarcomas are usually incurable and can be deadly. From figure 6, visual fused image quality obtained with firefly algorithm is far better than fused images obtained with PSO, QPSO and HBMO. The green color regions in figure 6(f) shows the tumor effected regions which is top highlighted with proposed firefly algorithm. The proposed method is better not only in visual quality but also in other fusion measuring parameters as shown in table 6. From the above discussions, results and experiments, it is found that proposed firefly algorithm gives advanced amount of mutual information (MI) by image thresholding and Scale-Invariant Feature Transform. The experimental results show that the proposed fusion technique has significant quantitative improvement than that of the existing fusion techniques. This fusion algorithm is tested for medical imaging applications and it is also well suited for other applications like remote sensing and developemnt of region of area. The proposed technique can be used for satellite imaging applications such as weather forecasting, forest degradation and object tracking applications. The proposed algorithm overcomes the limitations of PSO, QPSO and HBMO.

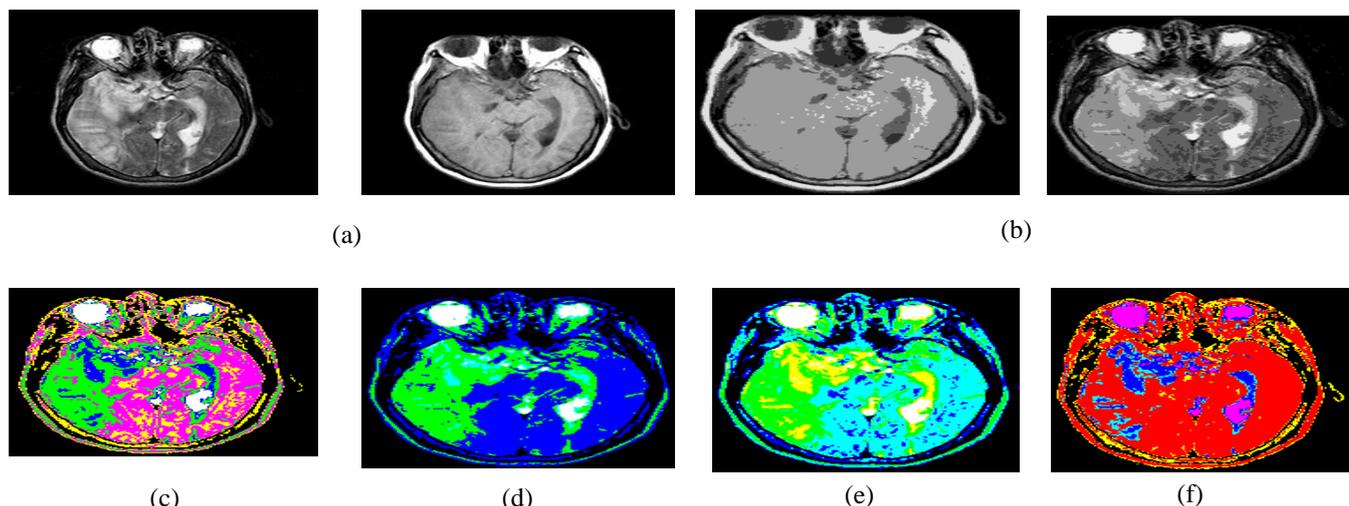


Fig. 6a) input images b) Segmented images: Fused images c) with PSO d) with QPSO e) with HBMO f) with FA

V. CONCLUSIONS

In this paper, two MRI images are fused for better diagnosis of diseases like neoplastic disease, cerebrovascular disease, Alzheimer disease, fatal disease, sarcoma disease. The two images are segmented first with firefly algorithm by assuming fuzzy entropy as objective function. Firefly algorithm is used to get optimal thresholds for better segmentation. The segmented regions of both the images are extracted with the Scale Invariant Feature Transform (SIFT) algorithm and on the basis of interval type-2 fuzzy set fusion rules both the images are fused. From the experiments, proposed algorithm is better in visual quality for diagnosing diseases and better in mutual information, Edge based similarity measure and correlation coefficient as compared to other algorithms.

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AUTHORS PROFILE



M. V. Srikanth, is a Research Scholar, pursuing Ph. D in the field of Image Processing from Jawaharlal Nehru Technological University, Kakinada, Andhra Pradesh, India. He has been working as an Academician in the capacity of an Assistant Professor in Electronics and Communication department of Gudlavalleru Engineering College, a reputed Autonomous Engineering College in Andhra Pradesh, India. Apart from regular Academia, the zeal to explore new technologies and a penchant towards pursuing research in the field of Image Processing has made him to do the research work in a governmental organization in Andhra Pradesh. His keen interests are inclined more towards Signal Processing and Embedded Systems.



Dr. V.V.K.D.V. Prasad, working as a Professor and Head of the Department of Electronics & Communication Engineering, in Gudlavalleru Engineering College, an Autonomous NBA accredited College in Andhra Pradesh, India. He received Ph. D for his work in Signal Processing in 2011 from Jawaharlal Nehru technological University, Kakinada, India. His areas of Interest include Signal Processing, Electrostatics, Electromagnetic fields and Transmission lines. He developed an abstract technical trait that addresses various other fields where digitalization can be achieved. His research findings are in the methodology used, problems encountered and the practical implications of composite features and filtering coefficients in advanced filters.



Dr. K. Satya Prasad received B.Tech. (ECE) degree from JNT University, Hyderabad, Andhra Pradesh, India in 1977, M.E. (Communication systems) from University of Madras, India in 1979, Ph.D. from IIT-Madras, India in 1989. He has more than 35 years of experience in teaching and 20 years in R&D. His current research interests include Signals & Systems, Communications, Digital signal processing, RADAR and Telemetry. He worked as Professor of Electronics & Communication Engineering & Former RECTOR, JNTUK and former Pro-Vice Chancellor, KLEF. At present he is professor of ECE and Rector, Vignan's Foundation for Science, Technology and Research (Deemed to be University), Vadlamudi, Andhra Pradesh. He received patent for his research work in 2015.