Multimodal Medical Image Fusion Based on Sugeno's Intuitionistic Fuzzy Sets

Talari Tirupal, Bhuma Chandra Mohan, and Samayamantula Srinivas Kumar

Multimodal medical image fusion is the process of retrieving valuable information from medical images. The primary goal of medical image fusion is to combine several images obtained from various sources into a distinct image suitable for improved diagnosis. Complexity in medical images is higher, and many soft computing methods are applied by researchers to process them. Intuitionistic fuzzy sets are more appropriate for medical images because the images have many uncertainties. In this paper, a new method, based on Sugeno's intuitionistic fuzzy set (SIFS), is proposed. First, medical images are converted into Sugeno's intuitionistic fuzzy image (SIFI). An exponential intuitionistic fuzzy entropy calculates the optimum values of membership, non-membership, and hesitation degree functions. Then, the two SIFIs are disintegrated into image blocks for calculating the count of blackness and whiteness of the blocks. Finally, the fused image is rebuilt from the recombination of SIFI image blocks. The efficiency of the use of SIFS in multimodal medical image fusion is demonstrated on several pairs of images and the results are compared with existing studies in recent literature.

Keywords: Image fusion, Diagnosis, Uncertainties, SIFS, SIFI.

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I. Introduction

Image processing methods, such as image fusion, are increasing in importance in modern medicine and health care for fusing multimodal medical images, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), and positron emission tomography (PET) [1]–[3]. Currently, research in the handling and investigation of medical data has begun to flourish. The CT image provides solid structures, such as bones, and embeds with less distortion; however, it cannot identify physical changes, while the MRI provides normal and neurotic soft fleshy tissue information. Fusing the CT and MRI affords abundant information useful for diagnosis. In extracting the detail information from images, the advancement of developing new algorithms has provided a major impulse for new procedures in signal and image processing. The overall objective of the computer aided diagnostic system is to enable early diagnostics, disease monitoring, and better treatment. Medical images from diverse modalities offer complementary information, and this is integrated for superior examination. Fusion of multimodal medical images provides a single fused image, which is reliable for better and enhanced investigation and diagnosis.

In medical image processing, the most important research issue is to extract maximum information by fusing multimodal images. Existing research methods include the pixel averaging method [4], pyramid decomposition method [5], and discrete wavelet transform (DWT) method [6]–[8]. A detailed survey of medical image fusion techniques is referenced in [9]. The simplest method of image fusion is to yield a pixel-by-pixel average of dualistic images, which primes unwanted special effects such as contrast reduction. All pyramid based methods cause blocking effects and undesired edges within the fused image. The wavelet-based methods using DWT do not provide shift invariance, which causes a major variation in the wavelet coefficients of the image for slight changes in the input image. In medical imaging analysis, it is important to identify and preserve the precise location of this information and this happens with a wavelet called undecimated discrete wavelet transform [10].

Medical images are ill illumined, as several structures are not clearly visible and many areas are vague in nature. For a better visual analysis of these images, physicians should have a worthy understanding of patient images for superior diagnosis. Therefore, medical image enrichment is extremely important in increasing the quality of the image. There are many crisp methods for enhancing images like histogram equalization and grey-level transformation; however, these do not properly improve the image quality as medical images contain many uncertainties. To compress such images, a mathematical tool, such as the fuzzy set theory was proposed by Zadeh [11] in 1965. Fuzzy sets accomplish a significant role in image processing for eliminating the vagueness present in images. Fuzzy sets take uncertainty in the form of a membership function that lies in the interval [0, 1] where zero represents no membership and 1 represents full membership. Fuzzy sets for real time images do not provide reasonable results because they contemplate only one uncertainty, which is in the form of a membership function. The generalized advanced form of fuzzy set theory, introduced by Atanassov [12] in 1986, is an intuitionistic fuzzy set (IFS), which considers more uncertainty constraints – membership degree and non-membership degree (due to the hesitation degree). The non-membership degree gives vague knowledge and adequately solves real time problems. Many uncertainties exist in every phase of image processing, and in using IFSs these uncertainties can be removed, and better results obtained.

This paper proposes a new technique for fusing two or more images using Sugeno's intuitionistic fuzzy sets (SIFS) to extract additional clinical information, which is complementary in nature and useful for better diagnosis. In the proposed method, initially, the registered [13] source images are fuzzified and then, the optimal value of the parameter is calculated for membership, non-membership, and hesitation degree, by means of exponential intuitionistic fuzzy entropy. Then, Sugeno's intuitionistic fuzzy image (SIFI) is generated for enhanced source images. Lastly, the fused image is obtained.

II. Preliminaries

1. Intuitionistic Fuzzy Set (IFS)

Image processing by IFSs primarily needs membership and non-membership functions. The construction of the IFS is briefly explained, initiating from fuzzy sets. A fuzzy set Z in a finite set $Y = \{y_1, y_2, y_3, \ldots, y_n\}$ is mathematically represented as:

$$Z = \{(y, \mu_z(y)) \mid y \in Y\}, \tag{1}$$

where the function $\mu_z(y){:}Y \to [0, 1]$ denotes the membership degree of an element y in the finite set Y. Then, the non-membership degree will be $1 - \mu_z(y)$.

Atanassov introduced a new fuzzy set called the IFS, which takes both membership $\mu_z(y)$ and non-membership $v_z(y)$ functions into consideration, holding $\mu_z(y) \to [0, 1]$, $v_z(y) \to [0, 1]$. An IFS Z in Y, is written as:

$$Z = \{(y, \mu_z(y), v_z(y)) \mid y \in Y\}, \tag{2}$$

which holds the condition $0 \le \mu_z(y) + v_z(y) \le 1$. A new parameter $\pi_z(y)$, called the hesitation degree and introduced by Szmidt and Kacpryzk [14], arises due to lack of knowledge while defining the membership degree, for each element y in Z and is given by:

$$\pi_z(y) = 1 - \mu_z(y) - v_z(y), \tag{3}$$

where $0 \le \pi_z(y) \le 1$. Based on the hesitation degree, the IFS is defined as

$$Z = \{(y, \mu_z(y), v_z(y), \pi_z(y)) \mid y \in Y\}. \tag{4}$$

2. Sugeno's Intuitionistic Fuzzy Set (SIFS)

A function $\phi(y)$:[0, 1], which is a continuous, increasing, and decreasing function, will be called an intuitionistic fuzzy generator [15], if $\phi(y) \le (1 - y)$ for all $y \in [0, 1]$ and $\phi(0) \le 1$, $\phi(1) \le 0$ from Sugeno's generating function [16] intuitionistic fuzzy generator, or a fuzzy complement is created and the fuzzy complemental function is defined as:

$$N(\mu_z(y)) = g^{-1}(g(1) - g(\mu_z(y))), \tag{5}$$

where $g(\cdot)$ is an increasing function, and g:[0, 1] $\to$ [0, 1]. Using the following function:

$$g(\mu_z(y)) = \frac{1}{\alpha}\log(1 + \alpha\mu_z(y)). \tag{6}$$

Sugeno's intuitionistic fuzzy generator is written as:

$$N(\mu_z(y)) = \frac{1 - \mu_z(y)}{1 + \alpha\mu_z(y)}, \quad \alpha > 0, \tag{7}$$

where $N(1) = 0$, $N(0) = 1$. From the function $N(\mu_z(y))$, non-membership values are calculated and with the help of a Sugeno type intuitionistic fuzzy generator, SIFS becomes:

$$Z_\alpha^{\mathrm{SIFS}} = \{y, \mu_z(y), (1 - \mu_z(y))/(1 + \alpha\mu_z(y)) \mid y \in Y\}, \tag{8}$$

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and the hesitation degree is given as:

$$\pi_z(y) = 1 - \mu_z(y) - \frac{1-\mu_z(y)}{1+\alpha\mu_z(y)}. \tag{9}$$

Equation (7), Sugeno's intuitionistic fuzzy generator, is chosen to convert a narrow range of dark pixels into a wider range of output pixels. Varying the value of α, changes not only the intensity of pixels, but also the ratios of red to green to blue in a color image. In certain multimodal medical images, where they are predominantly dark, an expansion of intensity levels and enhancement, in terms of contrast and discernable detail, is desirable, and this can be accomplished with Sugeno's equations.

3. Intuitionistic Fuzzy Entropy (IFE)

Entropy plays an important role in image processing, and fuzzy entropy measures fuzziness in a fuzzy set. The idea of fuzzy entropy was first introduced by Zadeh in 1969, and the skeleton of non-probabilistic entropy was introduced first by De Luca and Termini [17]. Many authors [18]–[20] have since suggested different types of entropy measures using IFS theory. In this work, a new objective function called IFE is introduced, can be computed as in [21], and has been used to develop the proposed scheme, which is described as

$$IFE(z;\alpha) = \frac{1}{N}\sum_{i=1}^{n}\pi_z(y_i)\exp\left(1-\pi_z(y_i)\right), \tag{10}$$

where $\pi_z(y_i) = 1 - (\mu_z(y_i) + \nu_z(y_i))$ is the hesitation degree, $\mu_z(y_i)$ is the membership function, and $\nu_z(y_i)$ is the non-membership function.

Entropy (IFE) is calculated using (10) for α values ranging from [0.1–1], and is optimized by finding the maximum entropy value, that is

$$\alpha_{\text{opt}} = \max\left(IFE(z;\alpha)\right). \tag{11}$$

Using this known value of α, the membership degrees of the pixels in the SIFS are calculated, and finally, an SIFI is designed as below:

$$F^{\text{SIFI}} = \left\{\left(y, \mu_z(y;\alpha), \nu_z(y;\alpha), \pi_z(y;\alpha)\right) | y \in Y\right\}. \tag{12}$$

III. Proposed Method for Medical Image Fusion

This section addresses a proposed method for multimodal medical image fusion using SIFS, and the fusion procedure is accomplished by the subsequent steps and shown in Fig. 1.

1. Read the two input registered source images and denote as I_1 and I_2.

2. Images I_1 and I_2 of size $m \times n$ are fuzzified using the formulae

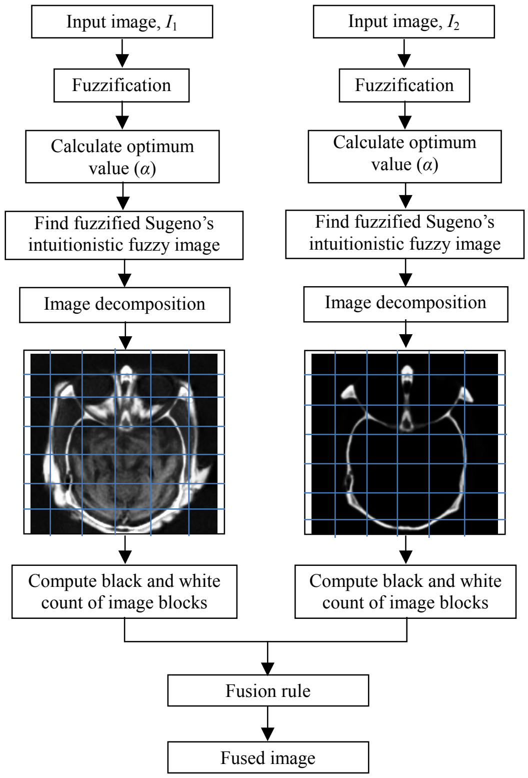

Fig. 1. Block diagram of the proposed medical image fusion.

$$\mu_1(I_{ij1}) = \frac{I_{ij1} - l_{\min 1}}{l_{\max 1} - l_{\min 1}}, \tag{13}$$

$$\mu_2(I_{ij2}) = \frac{I_{ij2} - l_{\min 2}}{l_{\max 2} - l_{\min 2}}, \tag{14}$$

where I_{ij1} and I_{ij2} defines the gray levels of the input images I_1 and I_2, respectively, and ranges from 0 to $L - 1$ (L is the maximum gray level in the image). $l_{\min 1}$, $l_{\max 1}$ and $l_{\min 2}$, $l_{\max 2}$ represents the minimum and maximum gray level values of the two input images, respectively.

3. Calculate optimum values of α_1 and α_2 for two input images individually using entropy (10) and (11).

4. With the optimum values of α_1 (0.7 is taken in this paper), find the fuzzified SIFI for the first input image by using below equations (15)–(17) and denote the fuzzified image as I_{Y1}.

$$\mu_1^{\text{SIFS}}(I_{ij1};\alpha_1) = \frac{(1+\alpha_1)\mu_1(I_{ij1})}{1+\alpha_1\mu_1(I_{ij1})}, \tag{15}$$

$$\nu_1^{\text{SIFS}}(I_{ij1};\alpha_1) = \frac{1-\mu_1(I_{ij1})}{1+3\alpha_1\mu_1(I_{ij1})+\alpha_1^2\mu_1(I_{ij1})+\mu_1(I_{ij1})}, \tag{16}$$

$$\pi_1^{\text{SIFS}}(I_{ij1};\alpha_1) = 1 - \mu_1^{\text{SIFS}}(I_{ij1};\alpha_1) - \nu_1^{\text{SIFS}}(I_{ij1};\alpha_1), \tag{17}$$

$$I_{Y1} = \left\{\left(I_{ij1}, \mu_1^{\text{SIFS}}(I_{ij1};\alpha_1), \nu_1^{\text{SIFS}}(I_{ij1};\alpha_1), \pi_1^{\text{SIFS}}(I_{ij1};\alpha_1)\right)\right\}. \tag{18}$$

Equations from (15)–(18) are repeated for optimum value α_2

(0.7 is taken in this paper) to find the fuzzified SIFI I_{Y2}.

5. Decompose the two enhanced images I_{Y1} and I_{Y2} into $m_1 \times n_1$ windows—the size of each is taken as 5 × 5 in this paper.

6. The black count and white count of each window of the images I_{Y1} and I_{Y2} are calculated and the fused image is obtained by using max, min operations given below:

$$F(i,j)=\begin{cases}\min\left\{I^{i}_{Y1}(i,j), I^{i}_{Y2}(i,j)\right\}, & \text{black count} > \text{white count},\\ \max\left\{I^{i}_{Y1}(i,j), I^{i}_{Y2}(i,j)\right\}, & \text{black count} < \text{white count},\\ \dfrac{I_{Y1}+I_{Y2}}{2}, & \text{otherwise},\end{cases} \tag{19}$$

where F, I^{i}_{Y1}, and I^{i}_{Y2} in the above equation represent the fused image, ith window of enhanced images I_{Y1} and I_{Y2}, respectively.

7. Finally, the fused image is defuzzified to obtain a crisp image using the defuzzification equation obtained by the inverse of (13)

$$I'(i,j)=(l_{\max}-l_{\min})*\mu_F(i,j)+l_{\min}, \tag{20}$$

where $\mu_F(i,j)$, $l_{\min}$, and $l_{\max}$ in the above equation represent the membership function, minimum, and maximum gray level values of the fused image F, respectively.

IV. Experimental Results

Based on the proposed algorithm, simulations are carried out in different sets of medical images, and the details are presented in this section. In this work, all the source images are assumed to be properly registered. Experiments on two different modality images are performed. The first example shown in Fig. 2, addresses CT and MRI images available at [22], which are complementary in nature, with a size of 256 × 256. Figures 2(c)–(h) are fused images of existing methods, such as the non-fuzzy [23], fuzzy method [24], Yager's IFS method [25], Chaira's IFS method [26], Bala's IFS method [27], and the proposed method (SIFS), respectively. Comparing all the fused images, the SIFS method provides a better-fused image than the other three, with high contrast and luminance, such that hard, soft tissue, and bone information can be seen in a single image.

The quality of the image is enhanced by considering the proposed method (7). This equation is chosen to convert a narrow range of dark pixels into a wider range of output pixels. Varying the value of 'α' changes not only the pixel intensity, but also the ratios of red to green to blue in a color image. In certain predominantly dark multimodal medical images, an expansion of intensity levels and enhancement, in terms of

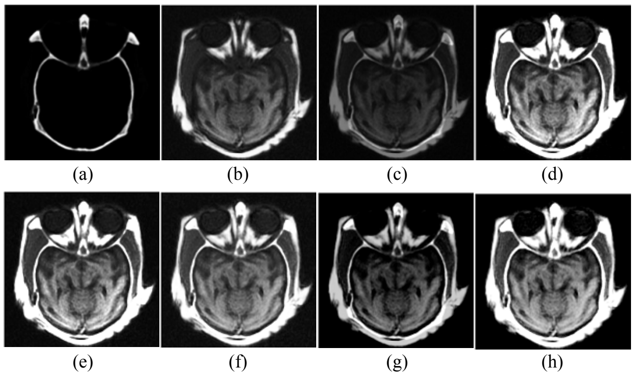

Fig. 2. Fusion results for CT and MRI images (a) CT image, (b) MRI image, (c) fused image using non-fuzzy, (d) fused image using fuzzy, (e) fused image using Yager's IFS, (f) fused image using Chaira's IFS, (g) fused image using Bala's IFS, and (h) fused image using proposed method (Sugeno's IFS).

contrast and discernable detail, is desirable and this can be accomplished with these types of equations. In fusing these enhanced multimodal medical images, additional clinical information can be extracted that is complementary in nature and the fused image quality can be improved. Therefore, we can say that a single image cannot provide all relevant information, and hence, multimodal medical image fusion is necessarily required to obtain all possible, complete information in a single composite image called a fused image.

For further evaluation of fusion results, different objective criteria are used. The first criterion is the feature mutual information (FMI) metric, proposed in [28]. The second criterion is the spatial frequency (SF) metric, proposed by Eskicioglu and Fisher in [29], which reflects the whole activity level, detailed differences, and texture changes of a fused image. Here, the activity level represents the amount of total energy present in the image, that is, the more the spatial frequency of an image, the more the energy content present in the image; and the part with the lesion will have more energy in the sense of more spatial frequency. Moreover, SF is denoted by a number. The third criterion is the edge based image fusion metric ($Q^{AB/F}$) metric, proposed by Xydeas and petrovic in [30]–[32], which considers the quantity of edge information transferred from the input images to the fused image. The fourth criterion is the quality index based on local variance (QILV) [33]. The last criterion is the modified spatial frequency (MSF) metric, proposed in [34], which provides an indication of how much of the relevant information enclosed in each of the input images has been transmitted into the composite image. The values of FMI, SF, $Q^{AB/F}$, QILV, and MSF of Fig. 2 are enumerated in Table 1.

The second example deals with T1 weighted MR and MRA images, with some illness as white structures, in the image

Table 1. Objective evaluation of different image fusion methods with proposed Sugeno's intuitionistic fuzzy set method for different pairs of multimodal medical images in Fig. 2.

Fusion method	FMI	SF	$Q^{AB/F}$	QILV	MSF
Non-fuzzy method [23]	0.81	4.869	0.426	0.334	10.92
Fuzzy method [24]	0.81	9.579	0.412	0.355	23.91
Yager's IFS [25]	0.84	10.41	0.501	0.360	25.34
Chaira's IFS [26]	0.83	11.87	0.747	0.351	26.53
Bala's IFS [27]	0.83	11.24	0.75	0.413	25.11
Proposed method (Sugeno's IFS)	0.93	17.29	0.859	0.639	38.52

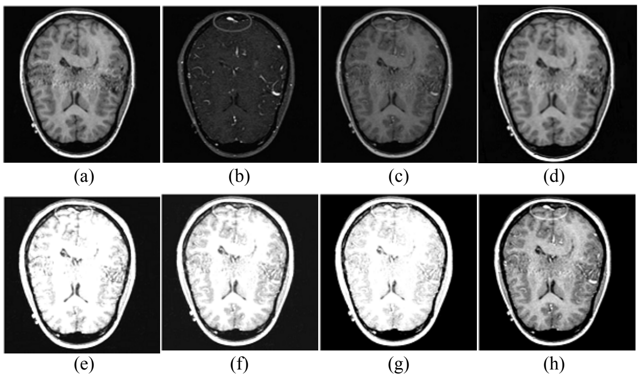

Fig. 3. Fusion results for T1-weighted MR and MRA images: (a) T1-MR image, (b) MRA image, (c) fused image using non-fuzzy, (d) fused image using fuzzy, (e) fused image using Yager's IFS, (f) fused image using Chaira's IFS, (g) fused image using Bala's IFS, and (h) fused image using proposed method (Sugeno's IFS).

Table 2. Objective evaluation of different image fusion methods with proposed Sugeno's intuitionistic fuzzy set method for different pairs of multimodal medical images in Fig. 3.

Fusion method	FMI	SF	$Q^{AB/F}$	QILV	MSF
Non-fuzzy method [23]	0.81	6.149	0.498	0.414	13.57
Fuzzy method [24]	0.81	14.64	0.419	0.454	24.39
Yager's IFS [25]	0.81	23.01	0.526	0.526	30.84
Chaira's IFS [26]	0.83	25.01	0.552	0.674	33.07
Bala's IFS [27]	0.84	24.45	0.590	0.736	35.83
Proposed method (Sugeno's IFS)	0.92	31.99	0.651	0.857	48.31

shown in Fig. 3. Fusing these two images provides abnormalities in the soft tissues more clearly with high spatial resolution, and the exact location of lesion structure with soft tissues can be observed. Figure 3(h) gives the fused image for the proposed method. Table 2 gives further assessment of results in terms of objective criteria.

The third example deals with MRI and PET images shown in Fig. 4, and are downloaded from the Harvard university

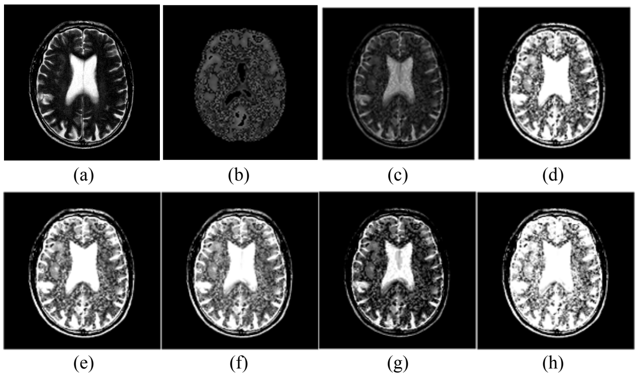

Fig. 4. Fusion results for MRI and PET images having Mild Alzheimer's disease: (a) MRI image, (b) PET image, (c) fused image using non-fuzzy, (d) fused image using fuzzy, (e) fused image using Yager's IFS, (f) fused image using Chaira's IFS, (g) fused image using Bala's IFS, and (h) fused image using proposed method (Sugeno's IFS).

Table 3. Objective evaluation of different image fusion methods with proposed Sugeno's intuitionistic fuzzy set method for different pairs of multimodal medical images in Fig. 4.

Fusion method	FMI	SF	$Q^{AB/F}$	QILV	MSF
Non-fuzzy method [23]	0.93	8.305	0.246	0.422	18.99
Fuzzy method [24]	0.93	23.22	0.247	0.273	15.97
Yager's IFS [25]	0.94	30.44	0.333	0.308	20.01
Chaira's IFS [26]	0.92	31.01	0.506	0.526	37.4
Bala's IFS [27]	0.93	39.41	0.54	0.605	44.0
Proposed method (Sugeno's IFS)	0.98	42.38	0.771	0.852	54.14

website [35]. Here, the MRI image is registered to the corresponding PET image, and both images are gray colored. Fusion of these two images gives both the anatomy of the brain tissue and functional information of the brain with high spatial resolution and no spatial distortion of the fused image. Figure 4(h) shows the fused image of the proposed method. Table 3 summarizes the objective criteria in comparing with all the fusion methods for the MRI and PET medical data set.

The fourth set of images are MRI and SPECT brain tumor images of size 256 × 256 taken from the Harvard university website [35], and are shown in Fig. 5 for evaluation of different fusion algorithms. Fusing the two images, we get anatomical information and functional knowledge of the human brain in a single image. Figure 5(h) shows the fused image of the proposed method, and the tumor is clearly enhanced when compared with other methods. It is also compared in terms of fusion metrics and proved that the suggested method is superior in terms of other methods and is represented in the Table 4.

The fifth example deals with X-ray and vibro-acoustography

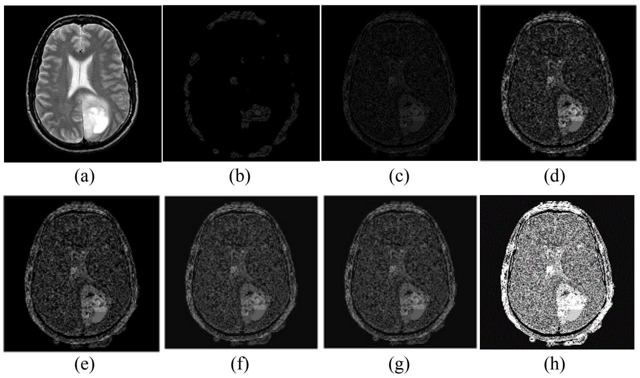

Fig. 5. Fusion results for MRI and SPECT images with Glioma brain tumor: (a) MRI image, (b) SPECT image, (c) fused image using non-fuzzy, (d) fused image using fuzzy, (e) fused image using Yager's IFS, (f) fused image using Chaira's IFS, (g) fused image using Bala's IFS, and (h) fused image using proposed method (Sugeno's IFS).

Table 4. Objective evaluation of different image fusion methods with proposed Sugeno's intuitionistic fuzzy set method for different pairs of multimodal medical images in Fig. 5.

Fusion method	FMI	SF	$Q^{AB/F}$	QILV	MSF
Non-fuzzy method [23]	0.93	8.606	0.542	0.868	17.86
Fuzzy method [24]	0.93	14.42	0.324	0.621	21.44
Yager's IFS [25]	0.94	28.4	0.556	0.243	29.92
Chaira's IFS [26]	0.95	25.44	0.65	0.192	31.44
Bala's IFS [27]	0.97	29.41	0.54	0.31	35.54
Proposed method (Sugeno's IFS)	0.99	30.61	0.713	0.917	39.86

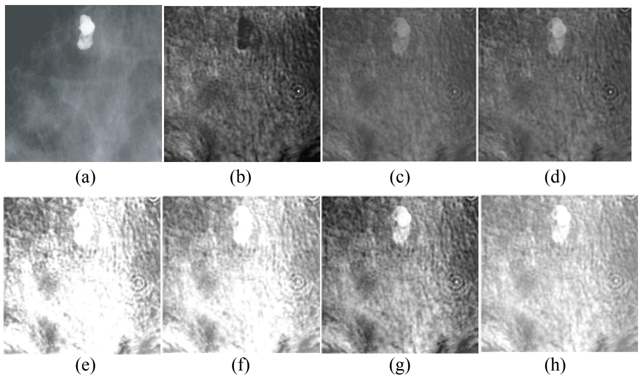

Fig. 6. Fusion results for X-ray and VA images: (a) X-ray image, (b) VA image, (c) fused image using non-fuzzy, (d) fused image using fuzzy, (e) fused image using Yager's IFS, (f) fused image using Chaira's IFS, (g) fused image using Bala's IFS, and (h) fused image using proposed method (Sugeno's IFS).

(VA) images as shown in Fig. 6. The registered X-ray and VA images provide complementary breast information. The X-ray image does not provide information about the depth or thickness of the disease object, whereas VA, on the other hand, is not hampered by tissue density. VA is a new imaging modality based on ultrasound stimulated acoustic emission, which can be fused with X-ray to enrich the breast cancer diagnosis [36]. The fused image of the proposed method can be seen in Fig. 6(h), which provides more information content than the other existing methods. Table 5 gives a comparison regarding the quality metrics.

Table 5. Objective evaluation of different image fusion methods with proposed Sugeno's intuitionistic fuzzy set method for different pairs of multimodal medical images in Fig. 6.

Fusion method	FMI	SF	$Q^{AB/F}$	QILV	MSF
Non-fuzzy method [23]	0.85	4.7	0.385	0.249	9.823
Fuzzy method [24]	0.84	10.2	0.221	0.415	11.84
Yager's IFS [25]	0.84	19.76	0.276	0.549	20.69
Chaira's IFS [26]	0.85	14.23	0.414	0.674	23.15
Bala's IFS [27]	0.85	12.66	0.494	0.533	22.25
Proposed method (Sugeno's IFS)	0.94	23.43	0.672	0.692	27.21

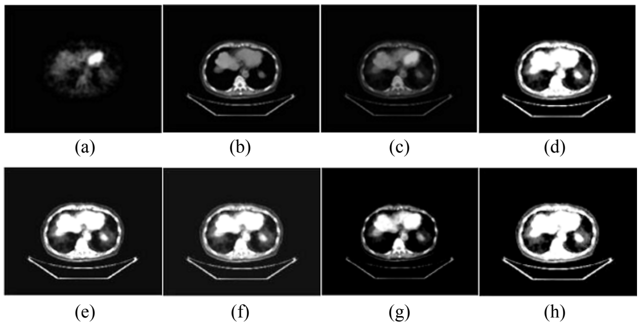

Fig. 7. Fusion results for Multimodality images (a) PET image, (b) CT image, (c) fused image using non-fuzzy, (d) fused image using fuzzy, (e) fused image using Yager's IFS, (f) fused image using Chaira's IFS, (g) fused image using Bala's IFS, and (h) fused image using proposed method (Sugeno's IFS).

Table 6. Objective evaluation of different image fusion methods with proposed Sugeno's intuitionistic fuzzy set method for different pairs of multimodal medical images in Fig. 7.

Fusion method	FMI	SF	$Q^{AB/F}$	QILV	MSF
Non-fuzzy method [23]	0.85	3.247	0.533	0.448	7.748
Fuzzy method [24]	0.84	12.96	0.274	0.481	10.93
Yager's IFS [25]	0.84	11.31	0.389	0.707	16.84
Chaira's IFS [26]	0.84	8.822	0.545	0.825	21.26
Bala's IFS [27]	0.85	7.758	0.592	0.530	18.74
Proposed method (Sugeno's IFS)	0.95	14.5	0.758	0.86	27.32

Figure 7 represents multimodality images, such as the CT and PET image. A CT image provides thick structures like bones and embeds with less distortion; however, it cannot identify functional changes. The PET image specifies the brain function and has a low spatial resolution. Fusing these two images, we obtain both functional information and extra spatial features without spatial distortion of the fused image, which can be seen in Fig. 7(h) for the proposed method. Table 6 gives objective information, which can readily ascertain that a fused image of the proposed method gives better results.

V. Conclusion

This paper presents a new method based on SIFS for fusing multimodal medical images. Large datasets are applied for each category, simulation results are found with superior visual quality compared to the other earlier-reported pixel, and fuzzy based image fusion methods. The basic idea of our proposed method includes three steps: In the first step, the images to be fused are initially registered and fuzzified. Then, the optimal value of the parameter is calculated for membership, non-membership, and hesitation degree using exponential intuitionistic fuzzy entropy. Finally, the fused image is obtained with the enhanced SIFIs.

Experimental results proved that the proposed method delivers better results visually and quantitatively with high contrast and luminance. In Fig. 2(h), it is observed that the edges of invisible soft tissue parts are clearly visible for better diagnosis and the quantitative value is high (0.859) from Table 1 when compared with other methods. Moreover, the detail differences and texture changes are reflected clearly in the fused image, and the quantitative value obtained is large (17.29) from Table 1. In the Fig. 5(h) geometric feature, the roundness of the tumor is clearly assessed visually to differentiate from blood vessels, and the quantitative results show that QILV is very high (0.917) from Table 4. Medical images, Xray-VA and PET-CT, usually have low contrast with vague regions and imprecise boundaries, which are common in medical images. Improvement in the quality of the fused image of Xray-VA and PET-CT may be attributed to the fuzziness of the membership function itself in SIFS and are well suited for such imprecise information.

For better fusion results, the proposed system can be prolonged further by applying it to different types of multimodal medical images using neuro fuzzy logic.

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