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Fine grained medical image fusion using type-2 fuzzy logic

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ABSTRACT

In recent years, many fast-growing technologies coupled with wide volume of medical data for the digitalization of that data. Thus, researchers have shown their immense interest on Multi-sensor image fusion technologies which convey image information based on data from various sensor modalities into a single image. The image fusion technique is a widespread technique for the diagnosis of medical instrumentation and measurement. Therefore, in this paper we have introduced a novel multimodal sensor medical image fusion method based on type-2 fuzzy logic is proposed using Sugeno model. Moreover, a Gaussian smoothen filter is introduced to extract the detailed information of an image using sharp feature points. Type-2 fuzzy algorithm is used to achieve highly efficient feature points from both the b images to provide high visually classified resultant image. The experimental results demonstrate that the proposed method can achieve better performance than the state-of-the- art methods in terms of visual quality and objective evaluation.

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1. INTRODUCTION

In last few decades, huge amount of data have been generated by various healthcare systems in real time. Therefore, for increasing the quality of healthcare data, various healthcare systems are moving from hardcopy towards digital ones with cost minimization [1]. These much bulky data from various healthcare systems has a potential to support extensive range of healthcare and medical applications. Moreover, in order to treat patients efficiently they have clinical decision support which can cure patients precisely. Certainly, the most essential aspects for diagnosis of patients are the assessment of medical data available from patients and the decisions to be sanctioned.

Recently, these bulky digital medical data have been associated with various rapid growing hi-tech innovations for the automation of digital data collection and storage and to develop more advanced techniques. Decision Support Systems (DSSs) helps the physicians in diagnosis of various patients by evaluating different type of diseases [2]. The use of DSS systems in association with numerous artificial intelligence techniques have helped for diagnosis and classify bulky and unmanageable amount of medical data which is gradually increasing all over world [3]. These type systems will help in evaluation of large medical data rapidly and more detailed manner [4].

Medical DSS more often obtain knowledge using real time data from various actual cases, whose training dataset (classification) is known. With the help of these training datasets, the novel models can be classified for the new incoming medical data. However, these decisions include various complex uncertainties related to medical diagnosis. Furthermore, different medical practitioners uses different decision making policies which may vary in nature. To reduce these type of complex model uncertainties and classification problems fuzzy logic has been widely adopt for several application fields. Specially, in medical applications several DSS examples can be found which rely upon fuzzy logics [5] and can help in medical diagnosis of patients.

Fuzzy logic is one among the most rapidly emerging technique in real time due to its effective handling capabilities in terms of uncertainty and demonstrating awareness in interpretable way. These can be attained with the help of approximate information and linguistic models using linguistic variables in numerical domain and correlations can be presented as logical guidelines. To develop fuzzy logics based DSSs, linguistic variables can be define to assemble huge informative knowledge, and fuzzy partitioning can be done to construct fuzzy rules.

Sensory measurements and mathematical prototypes based Non-linear organized mapping can be achieved using fuzzy logics. Mainly, fuzzy logics can be classified into two types as type 1 and type 2 fuzzy logics. However, type-1 fuzzy logics consists of several issues such as lesser stability, noise and poor handling of uncertainties etc. Conventional type-1 fuzzy logic system (FLS) can be used in decision making of highly nonlinear system with limited range of uncertainty. To improve decision making capabilities of FLS's presented in parameter uncertainties, adoption of type-2 FL is considered. Type-2 FL exhibit better capabilities in handling parameter uncertainties as it models vagueness and unreliability of information presented to it. Interval Type-2 fuzzy logic systems (IT2 FLSs) benefit from interval fuzzy membership functions which make them a preferable choice in the presence of uncertainties and/or appreciable level of noise in the system. Therefore, Type-2 fuzzy logics is preferred over type-1 of fuzzy logics. Type-2 sets and FLS's have been used in decision making [6], [7] solving fuzzy relation equations [8], survey processing [8], time-series forecasting [9], [10], function approximation [8], control of mobile robots [11], biometrics [12], and preprocessing of data [13]. IT2 FLSs can cover a wide range of uncertainties, like different meanings of words, noisy input data, different decisions made by different experts, etc.

In medical applications, fuzzy logics can be integrated with data fusion technique to fuse complementary information from two or more source images into a single image with more information and visually more attractive and can be process much efficiently. In various medical applications, both CT (Computed Tomography) and MRI (Magnetic Resonance Imaging) techniques disclose the structural and anatomical statistics, while both PET (Positron Emission Tomography) and SPECT (Single Photon Emission Computed Tomography) disclose the functional information. Therefore, multi-model medical image fusion technique can offer effective anatomical and physiological characteristics which will helps in image analysis, clinical diagnosis and effective treatment planning.

Therefore, this paper demonstrate a novel image fusion technique based on interval type-2 fuzzy logic system (IT2FLS) to handle non-linear uncertainties and achieve unbiased medical diagnose in medical image datasets. In particular, Type-2 logic system helps to model type-2 membership functions using type-2 membership variables. Here, type-2 fuzzy logics are used for higher degree stability and better management of uncertainty. The proposed fusion technique extract useful information from various CT, MRI, MR-T1 and MR-T2 images. First, we will take various combination of different input source images. Then, various patches extracted from both the images to detect essential feature points of both the images. These patches helps to extract image local features and helps to detect feature points which can integrated with type-2 fuzzy logics which evaluate weights for every image pixels present in various patches. In Next phase, the feature points are extracted. Feature points are used to determine the patterns of the different digital image as well as it helps to eliminate noise. It emphasizing pixels with gray tones and make them different than their neighbors. Feature point further passed to interval type-2 fuzzy logic system (IT2FLS). IT2FLS system used to determine an exact membership function, and also there is a measurement uncertainties. It also helps to set an enable modeling and minimizing the effects of uncertainties. Then using image fusion rule both images are fused together to integrate (complementary as well as redundant) information from multimodality in images to create a fused output image. It can be proved as significant technology for diagnostics and treatments in the field of medical instrumentation and measurement. It not only provides accurate description of the same object but also helps in required memory reduction by storing fused images instead of multiple source images. Simulation results shows that the superiority for our proposed scheme in terms of visual and quantitative analysis.

This paper is organize in following sections, which are as follows. In section 2, we describe about the image fusion issues and how they can be eliminated by using our proposed model. In section 3, we described our proposed methodology for image fusion of various image classes. In section 4, experimental results and evaluation shown, and section 5 concludes our paper.

2. LITERATURE SURVEY

In recent years, a healthy amount of research has been carried out in the field of electronic technologies to enhance the performance of image fusion techniques. Image fusion techniques can widely use in medical applications, image processing applications, remote sensing, satellite imaging, face recognition and security fields etc. To enhance further more image quality and visually more attractive fuzzy logics can be implemented with the use of data fusion technique in terms of fuse complementary information from two or more source images into a single image with more information. Type-2 sets and FLS's have been used in decision making [6], [7] solving fuzzy relation equations [8], survey processing [8], time-series forecasting [9], [10], function approximation [8], control of mobile robots [11], biometrics [13], and preprocessing of data [12].

In [14], a type-2 fuzzy set introduced using a Karnik-Mendel Algorithm which is an iterative and computationally intensive type reduction algorithm. This model efficiently eliminates the numerical problems and prevent infinite loops. This program demonstrates the superiority of type-2 fuzzy sets. In [15], a conditional fuzzy set which is similar to type-2 fuzzy set is proposed based on the product of primary and secondary variables. Difference of both variables are independent to each other whereas in type fuzzy systems secondary variables rely upon the primary variables which increases the complexities of fuzzy type-2 and make difficult for analyzing. In [16], an image fusion technique used to fuse two source images. The fused image can be evaluates in the basis of weighted sum information. The degree of focus is evaluated for various input images using fuzzy inference system. Finally, the fused image is evaluated using degree of focus map which is computed with the use of weight. In [17], an image fusion technique is presented for medical images using two cascaded algorithm such as Non sub-sampled Contourlet transform (NSCT) domains and discrete wavelet transform (DWT). Here, MRI (magnetic resonance imaging) and CT (Computed Tomography) images are used for training of the model. First, a DWT technique is employed to get principal component and then fusion rule is applied for NSCT domain to increase contrast of the features. In [18], the fusion technique employed to get contextual information for an effective measurements aggregation and also a time series estimated technique presented to process the aggregated values. A Type-2 fuzzy logic system is used for the precise identification in events due to thier reasoning abilities under uncertainty. Also verified type 2 fuzzy systems superiority over type-1 fuzzy systems. In [19], a fuzzy clustering technique is used to improve the quality of noisy images by eliminating noise based on Wavelet and Bi-dimensional Empirical Mode Decomposition (BEMD). In this paper a segmentation technique also adopted to provide SNR rates using FCM clustering dataset. In [20], a multi-modal medical fusion technique is used which rely upon 2-D PCA. Here, a brain image dataset is used for the fusion implementation. Image fusion outcomes are compared with PCA based fusion technique in terms of seven quality assessment parameters. Proposed algorithm result outperform the current PCA technique. In [21], a SIST technique is presented to get low-pass and band pass sub-band images of similar size as source images. Then, a fusion based PCNN technique is used to fuse the low frequency and band pass sub-band coefficients. Here, PCNN technique used in SIST domain to enhance spatial frequency and lastly, fused image can be attained with the help of ISIST (Inverse SIST).

In existing techniques, Noise and uncertainties of sensor data affect decision making capabilities. To negate effects of sensor data uncertainties on decision making, an interval type-2 based FLDS (IT2FLDS) system is introduced in their proposed paper for the fusion of medical images. Interval type-2 trapezoidal membership functions are used to handle uncertainties in input sensor data. Comprehensive details of type-2 fuzzy logic is available in [22] and is used to model IT2FLDS proposed. Matlab/Simulink and interval type-2 fuzzy logic system toolbox (IT2FLS) [23] is considered for building the IT2FLDS. Results obtained prove that type-2 FL based IT2FLDS system proposed handles sensor data uncertainties better compare to fuzzy type-1 counterpart [24].

3. MEDICAL IMAGE FUSION REPRESENTATION USING FUZZY LOGICS

Image fusion technique is used to retrieve complementary and redundant data from multiple source images to build a fused image [25]. This fused image provides detailed description of the same images and also provides accurate feature points. Fusion technique also reduces the storage capacities by loading fused image instead of multimodal input source images. In recent years, various image fusion techniques emerged for the medical images which usually consist pixel, feature and decision level fusion techniques. Image fusion can be widely used in various application such as in medical applications, image processing applications, remote sensing, satellite imaging, face recognition and security fields etc., However, existing fusion techniques consists of several issues such as high computational complexity, presence of uncertainties and noise, poor decision making and feature points of precision.

Therefore, a fusion technique for medical images using Type-2 fuzzy logic is presented. The proposed algorithm collects maximal information from both source images and fuse into a single image which high visual quality. Type-2 fuzzy logics is used to extract local features and evaluate weights of each pixels. Simulation outcomes shows the superiority of our proposed scheme based on visual and a quantitative analysis. The most essential advantages of Type-2 fuzzy logics works efficiently even in presence of noise and allow better management of uncertainty.

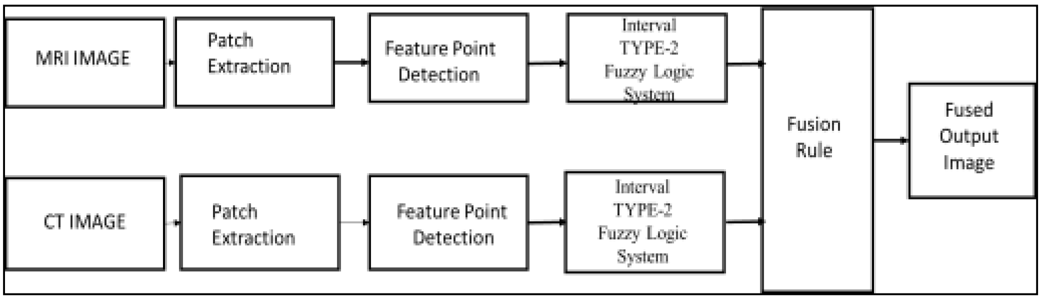

Figure 1. Block diagram of medical image fusion using type-2 fuzzy logic

Figure 1 demonstrates the block diagram of medical image fusion using type-2 fuzzy logic. Our proposed image fusion model used to reduce noise in multimodal medical images and provide high quality visually attractive image. First, we will take various combinations of different input source images. Then, various patches extracted from both the images to detect essential feature points of both the images. In Next phase, feature points are extracted and further passed to interval type-2 fuzzy logic system (IT2FLS). The IT2FLS system used to determine an exact membership function, and there exists measurement uncertainties. It also helps to enable the modeling and minimizing the effects of uncertainties. Then an image fusion technique is applied to fuse source images to get redundant and complementary information in an output fused image. This technique can be very helpful for the diagnosis of medical images. It also reduces memory by fusing multiple number of source images into single one.

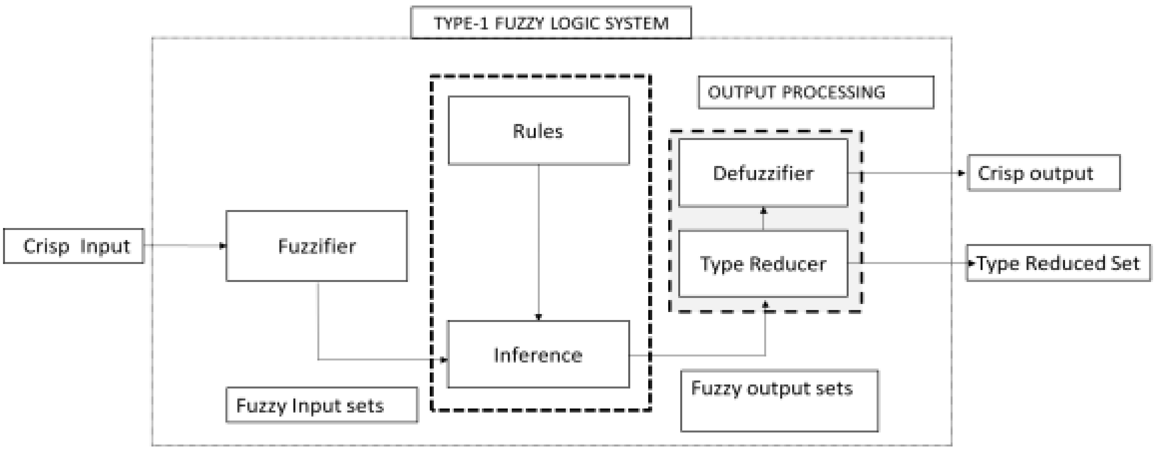

Figure 2. Architecture diagram of Interval type-2 fuzzy decision system (IT2FLDS)

Here, Figure 2 represents the Architecture diagram of Interval type-2 fuzzy decision system for medical image fusion. It consists of several blocks which are described below.

a. Crisp input

Crisp input is defined as the inputs which straightly measured by sensors and forwarded to fuzzy logic systems. The inputs which is forwarded to fuzzy logic through sensors, consists its own set of memberships function.

b. Interval Type-2 membership function

Type-2 fuzzy set is expressed using fuzzy membership functions. In our medical image fusion model a Gaussian memberships function is used. Expert opinions are used to implement an interval type-2 Gaussian Fuzzy membership functions to eliminate uncertainties. Moreover, these type-2 fuzzy set considered as an input for fuzzy inference engine which is link with rule base.

c. Fuzzifier

Crisp inputs obtained through sensors which is faded into fuzzifiers and then it will transform into Interval Type-2 Fuzzy Decision System which rely upon fuzzy memberships function. This procedure is known as Fuzzification. Type-2 membership functions are linked with fuzzifiers to form an Input Processing Unit which is demonstrated in Figure 1. This Input Processing Unit transform crisp inputs into type-2 fuzzy logic decision system.

d. Rules

Rules are described as "IF THEN "statements which is a group of linguistic variables. The linguistic variables linked with IF part termed as antecedent whereas the linguistic variables linked with THEN part is termed as consequent. AND operator can be utilized when model requires more than one rule.

e. Inference

Union and Intersection operators and rule base rules are utilized by Fuzzy Inference block to converts T2FLDS inputs into T2FLDS outputs. The Union and Intersection operators can be interchanged by Join ($\sqcup$) and Meet operators ($\sqcap$) IN type-2 fuzzy logic based decision system. Secondary membership functions can utilize these two operators.

f. Type-reduction

T1FLS can be obtained from the reduced sets of Type-2 fuzzy outputs through fuzzy inference engine which can be termed as type-reduced sets. In IT2FLDS, there are two type of approaches present in the type-reduction such as Karnik Mendel iteration approach and the Wu-Mendel uncertainty bounds approach. These two approaches rely upon centroid which is used in our model.

g. Defuzzification

Type-reduce sets output forwarded to defuzzificaton block. Left end point and right end point are utilized to compute type-reduced sets. Average value of the points defines the defuzzified value. This defuzzification values further it converts to the output crisp sets where it takes the decision whether image fusion is accomplished or not.

Initially, a medical image S is characterized in fuzzy domain with dimension $P \times Q$ with M levels is taken as a 2D array of fuzzy sets.

$$S = \{(s_{pq}, u_{pq}(s)) | (p,q) \in [(0,0),(P-1,Q-1)]\} \quad (1)$$

Here, s_{pq} represent the intensity value of every pixel and it consists of membership grade u_{pq} which ranges from 0 to $1 (0 \leq u_{pq} \leq 1)$. The range of every membership function with respect to image spatial intensity value is $[0, M-1]$.

3.1. Gaussian based Interval Type-2 Fuzzy Membership Function

Memberships function are used to characterize the properties of IT2FLDS sets. A medical image S with range $[0, M-1]$ can be transform into IT2FLDS property set which lies in the range of $[0,1]$ using a Gaussian membership function which are expressed [26] as,

$$u(s_{pq}) = e^{\left[-(s_{\uparrow}-s_{pq})^2/2\mathbb{F}_z^2\right]} \quad (2)$$

Here, $\mathbb{F}_z$ represents a type-2 singleton fuzzifier whereas $s_{\uparrow}$ and s_{pq} represents max. and $(p,q)th$ image scale values respectively.

Here, to characterize spatial domain pixels in fuzzy domain we have presented a histogram based interval type 2 membership function which is expressed as,

$$u_n = e^{[-(s_{\uparrow}-n)^2/2\mathbb{F}_z^2]} \quad (3)$$

Where, n represents a definite values which lies in the range of $[0, M-1]$ and fuzzifier matrices $\mathbb{F}_z$ can be represented as,

$$\mathbb{F}_z^2 = \sum_{n=0}^{M-1}(s_{\uparrow}-n)^4 f(n) \,.\, 2(\sum_{n=0}^{M-1}(s_{\uparrow}-n)^2 f(n))^{-1} \quad (4)$$

Where, n denotes the intensity level and $f(n)$ represents the frequency of occurrence of n intensity level in Histogram $\mathbb{H}_s$ and $f(n)$ can be expressed as,

$$f(n) = \mathbb{H}_s(n).[(P-1)(Q-1)]^{-1} \quad (5)$$

In a fuzzy domain, for a contrast-enhanced image, pixels can be of two types either dark (high) perception or light (low) perception which lies in the range from $u_l \in [l_{\downarrow}, l_{\uparrow}]$ and $u_u \in [u_{\downarrow}, u_{\uparrow}]$ respectively. The pixels at $u = l_{\uparrow}$ consist of highest ambiguity and do not lies in any of the perception. Let these pixels evaluates the fuzzy boundary then value at $u = u_{\uparrow}$ represent feature points.

3.2. Medical Image Feature Preservation:

The Histogram Equalization Enlarging and Conversions techniques can be used to enhance the poor contrast of low quality images. In [27], an intensification operator is used to enhance contrast of the images which purely rely only upon membership function. The degradation of images are nonlinear and it performs uncertain activity in nature, thus, we introduce a modified non-linear contrast intensification operator $MNINT[u_n]$ which consists of three tunable factors such as intensification operator $\mathbb{I}$, fuzzier $\mathbb{F}_z$ and crossover point $s_{\mathbb{C}}$. This contrast intensification function can be expressed as,

$$u'(n) = MNINT[u(n)] = \left[1 + exp[-\mathbb{I}(u(n) - s_{\mathbb{C}})]\right]^{-1} \quad (6)$$

Where, $\mathbb{I}$ used to define the shape of sigmoid function. The fuzzifier parameter $\mathbb{F}_z$ and crossover point $s_{\mathbb{C}}$ can be fine-tuned through $u(n)$ whereas intensification operator $\mathbb{I}$ remains fixed to control the contrast in improvement levels of the image.

3.3. Fuzzy Type-2 Key Points Detection

The modified contrast intensification operator $MNINT[u_n]$ can be restate in terms of each $(p, q)th$ pixel,

$$u'(p, q) = MNINT\left[u_{pq}\right] = 1 + exp[-\mathbb{I}(u_{pq} - s_{\mathbb{C}})]^{-1} \quad (7)$$

Here, we have presented a fuzzy parameterized Gaussian-type feature point detector which can be expressed as,

$$K(p, q) = e^{-\sum_x \sum_y \left(\frac{[u(p+x,\ q+y) - u(p,q)]}{\mathbb{F}_{\mathbb{G}}}\right)^{\delta}} \quad (8)$$

Here, $x, y \in [-(m-1)/2, (m-1)/2]$, and the dimension of key feature point detector can be expressed as $m \times m$. The center pixels can be expressed by membership value as $u'(p, q)$ at the position of (p, q) whereas $K(p, q)$ is the output feature point pixels which replaces the prior central pixels. Gaussian function consists of two adaptable fuzzifiers such as δ and $\mathbb{F}_{\mathbb{G}}$.

Hypothetically, factors δ and $\mathbb{F}_{\mathbb{G}}$ describes Gaussian function which are more expressive than usual factors such as α and β as shown in [28]. A Gaussian membership function can be expressed as,

$$u_{GAUSS}(s; \varphi, \mathbb{C}) = exp\left[\frac{-(u-\mathbb{C})^2}{2\varphi^2}\right] \quad (9)$$

The Gaussian curve rely upon the factors φ and $\mathbb{C}$.Whereas the factor δ is expressed as the power of exponential term and a lone fuzzifier constant $\mathbb{F}_{\mathbb{G}}$ can be achieved by decreasing the denominator of exponential term,

$$u_{GAUSS} = exp\left[\left(\frac{-(s-\mathbb{C})}{2\varphi}\right)^{\delta}\right] \quad (10)$$

$$\Rightarrow 2\varphi \equiv \mathbb{F}_{\mathbb{G}} \quad (11)$$

Different type of Gaussian functions can be derived by applying the various combination of δ and $\mathbb{F}_{\mathbb{G}}$ which are Gaussian types. This results are visually very poor with unsmooth and dense feature points when experimenting with various fuzzifiers δ even values whereas odd integer values of fuzzifiers δ gives thinner and refined feature points. When the low odd values are used as feature points which are visually not clear as well as weak whereas high odd values gives visually clear feature points and also eliminates weak feature points.

Mathematically, the Gaussian function width can be expressed by the fuzzifier $\mathbb{F}_{\mathbb{G}}$. Thus, a thin Gaussian points can be achieved when low fuzzifer $\mathbb{F}_{\mathbb{G}}$ value elected which can decreases the distance into a crisp set approximately. To obtain detailed information from the feature points, the function need to be closer to crisp set and reverse for the high fuzzifier $\mathbb{F}_{\mathbb{G}}$ values. The factors δ and $\mathbb{F}_{\mathbb{G}}$ need to be pre-determined to ensure decent performance in a particular application which can be achieved using preliminary experiments and entropy optimization.

3.4. Feature and Key Points Refinement

Both strong feature points and impulse noise can be experienced when we have,

1) Larger values of $K, i.e. K(p,q) > 1$;
2) Lower values of $K, i.e. K(p,q) < 0$.

The feature points can be achieved between the ranges $[0,1]$ approximately, when a feature point attenuator pattern applied.

$$K'(p,q) = \downarrow [\{K(p,q) | p \in [0, P-1], q \in [0, Q-1]\}], \quad \forall K(p,q) > 1; \\ \text{And} \\ K'(p,q) = \uparrow [\{K(p,q) | p \in [0, P-1], q \in [0, Q-1]\}], \quad \forall K(p,q) < 0 \tag{12}$$

Finally, a Binarized Key Feature point based image can be developed by applying a simple thresholding method. Various experiments evaluate that the optimal threshold level Γ should lie in the range of $[\gamma_\downarrow, \gamma_\uparrow]$,

$$K''(p,q) = \begin{cases} 1, & for\ K'(p,q) \geq \Gamma \\ 0, & for\ K'(p,q) < \Gamma \end{cases} \tag{13}$$

Where, $\Gamma = [\gamma_\downarrow, \gamma_\uparrow], p \in [0, P-1]$ and $q \in [0, Q-1]$.The use of Image thresholding step rely upon the application relevance.

3.5. Optimization Adopted to Construct Weight Maps

To achieve four tunable factors such as $s_{\mathbb{C}}$, $\mathbb{F}_z$, δ *and* $\mathbb{F}_{\mathbb{G}}$ we require a fuzzy entropy optimization technique. The fuzziness degree of a set and image indefiniteness can be measured using entropy of a fuzzy set. Entropy I[29], can be expressed using Shannon's function $\mathbb{S}_i$, which is as follows,

$$I = (\log_e 2)^{-1} \sum_{n=0}^{M-1} \mathbb{S}_i f(n) \tag{14}$$

In fuzzy, we can express $\mathbb{S}_i$ as,

$$\mathbb{S}_i(u'(n)) = -u'(n) \log_e u'(n) - (1 - u'(n)) \log_e (1 - u'(n)) \tag{15}$$

$where\ 0 \leq u' \leq 1$

Entropy optimization technique can only optimize $s_{\mathbb{C}}$ and $\mathbb{F}_z$ out of three tunable factors globally. Optimization process is not necessarily required in predetermined factor $\mathbb{I}$. The derivatives of I can be expressed in terms of $s_{\mathbb{C}}$ and $\mathbb{F}_z$,

$$\frac{dI}{ds_{\mathbb{C}}} = \frac{dI}{du'(n)} \cdot \frac{du'(n)}{ds_{\mathbb{C}}} = (\log_e 2)^{-1} \sum_{n=0}^{M-1} [\mathbb{I}^2 (u(n) - s_{\mathbb{C}}) \mathbb{G}(u')] f(n) \tag{16}$$

$$\frac{dI}{d\mathbb{F}_z} = \frac{dI}{du'(n)} \cdot \frac{du'(n)}{du(n)} \cdot \frac{du(n)}{d\mathbb{F}_z} = (\log_e 2)^{-1} \sum_{n=0}^{M-1} \left[\frac{[\mathbb{I}^2 u(n)(u(n) - s_{\mathbb{C}})(s_\uparrow - n)^2 \mathbb{G}(u')]}{\mathbb{F}_z^3} \right] f(n) \tag{17}$$

Where $\mathbb{G}(u')$can be expressed as,

$$\mathbb{G}(u') = u'(n)\,(1 - u'(n)) = \frac{e^{-\mathbb{I}(u(n) - s_{\mathbb{C}})}}{[1 + e^{-\mathbb{I}(u(n) - s_{\mathbb{C}})}]^2} \tag{18}$$

These derivatives can be used in recursive knowledge of the factors $s_{\mathbb{C}}$ and $\mathbb{F}_z$ by gradient descent scheme.

$$s'_{\mathbb{C}} = s_{\mathbb{C}} - \epsilon_1 \frac{dI}{ds_{\mathbb{C}}} \tag{19}$$

$$\mathbb{F}'_z = \mathbb{F}_z - \epsilon_2 \frac{dI}{d\mathbb{F}_z} \tag{20}$$

Where ϵ_1 and ϵ_2 are learning degrees for both factors $s_{\mathbb{C}}$ and $\mathbb{F}_z$ respectively. The adjacent optimization point in both positive and negative directions is used.

Optimization technique can also be applied on δ and $\mathbb{F}_{\mathbb{G}}$ to get its optimized values and as these factors are very much essential in extracting feature points. By considering Fuzzy entropy function locally, we can alter equation (15) by changing $u'(n)$ to the local feature point pixel $K(p,q)$,

$$\mathbb{S}_i\big(K(p,q)\big) = -\big[K(p,q)\, log_e\, K(p,q) + \big(1 - K(p,q)\big)\, log_e\big(1 - K(p,q)\big)\big] \tag{21}$$

The derivatives of I in terms of δ and $\mathbb{F}_{\mathbb{G}}$ can be expressed as,

$$\frac{dI}{d\delta} = \frac{dI}{dK(p,q)} \cdot \frac{dK(p,q)}{d\delta} = K \log_e\{K.(1-K)^{-1}\} \textstyle\sum_x \sum_y \left[\left(\frac{\mathbb{N}}{\mathbb{F}_{\mathbb{G}}}\right)^{\delta} \log_e\left(\frac{\mathbb{N}}{\mathbb{F}_{\mathbb{G}}}\right)\right] \tag{22}$$

$$\frac{dI}{d\,\mathbb{F}_{\mathbb{G}}} = \frac{dI}{dK(p,q)} \cdot \frac{dK(p,q)}{d\,\mathbb{F}_{\mathbb{G}}} = \frac{K\delta \sum_x \sum_y \mathbb{N}^{\delta}}{\mathbb{F}_{\mathbb{G}}^{\delta+1}} . \log_e\left\{\frac{K}{1-K}\right\} \tag{23}$$

Where $\mathbb{N} = [u'(p+x, q+y) - u'(s,h)]$. Above derivatives can be used for recursively learning several factors using gradient descent scheme,

$$\delta' = \delta - \epsilon_3 \frac{dI}{d\delta} \tag{24}$$

$$\mathbb{F}'_{\mathbb{G}} = \mathbb{F}_{\mathbb{G}} - \epsilon_4 \frac{dI}{d\,\mathbb{F}_{\mathbb{G}}} \tag{25}$$

Where ϵ_3 and ϵ_4 are the learning degrees for both factors δ and $\mathbb{F}_{\mathbb{G}}$ respectively. Here, we also applied gradient domain guided filtering uF_b to evaluate every decision map such as $\mathbb{D}_{1,j,} \mathbb{D}_{2,j,} and\ \mathbb{D}_{3,j,}$ which rely upon feature points with the respective source image S with its j^{th} component. Source image S is treated as a guidance image to produce the ultimate weight maps,

$$\mathbb{X}_{i,j}^{a} = uF_{b1}\big(\mathbb{D}_{i,j,} S_j\big) \tag{26}$$

$$\mathbb{X}_{i,j}^{d} = uF_{b2}\big(\mathbb{D}_{i,j,} S_j\big) \tag{27}$$

Where, $b1$ and $b2$ are the factors of gradient domain guided filtering and $i = 1,2,3,..i_{\uparrow}$ and $\mathbb{X}$ represents weights to be evaluated. Here, $\mathbb{X}^a$ represents the approximate value of weights and $\mathbb{X}^d$ represents the detailed value of weights. By combining all above calculations we can evaluate exact weight maps with respect to corresponding source image S_j with its j^{th} component which is expressed as,

$$\mathbb{X}_j^a = \textstyle\prod_{i=1}^{i_{\uparrow}} \mathbb{X}_{i,j}^a \tag{28}$$

$$\mathbb{X}_j^d = \textstyle\prod_{i=1}^{i_{\uparrow}} \mathbb{X}_{i,j}^d \tag{29}$$

Where, $\mathbb{X}_j^a$ and $\mathbb{X}_j^d$ are resultant weight maps of low and high frequency components. Here, the L represents the number of source images and finally, to sum every pixels into one all the values of L image weights maps are normalized.

3.6. Medical Image Fusion Considering Feature and Weight Maps:

The weighted averaging technique can be used to fuse approximate and detailed components of various source,

$$S_F^a = \textstyle\sum_j^L \mathbb{X}_j^a S_j^a \tag{30}$$

$$S_F^d = \textstyle\sum_j^L \mathbb{X}_j^d S_j^d \tag{31}$$

In last, the fused image $\mathcal{F}$ can be represented in terms of fused approximate S_F^a and detailed components S_F^d as,

$$\mathcal{F} = S_F^a + S_F^d \tag{32}$$

4. PERFORMANCE EVALUATION:

To determine the performance of our proposed image fusion model using type-2 fuzzy logics decision system T2FLDS five different set of medical images is considered. Matlab and Simulink are mainly used to carry out all the experiment. Type-2 of fuzzy toolbox [30], [31] is used to implement IT2FLDS. The performance of the image fusion model is determined using suitable fuzzy rules, membership function and Fuzzy Inference Engine (FIE).The experimental outcome clears that the IT2FLDS can handle better uncertainties in contrast to type-1 FLDS. Moreover, the primary experiment are further extended for handling the medical image fusion processing through the sensor data. The proposed image fusion model is implemented on clinically acquired various multi-modal medical images. The medical image dataset used in our experiments are taken from http://www.imagefusion.org/ and http://www.med.harvard.edu /aanlib/home.html which is an open source. The performance of proposed method can be evaluated based on the experiments carried on various medical images with different modalities.

4.1. Evaluation Criteria

This section describes the objective analysis of our proposed model using certain quantitative measures. There are various image quality measures to determine the visual quality of medical images in various aspects. Here, in this paper, we have considered both quantitative analysis and visual representation of the fused medical images. To evaluate the performance of proposed medical image fusion technique we have taken three distinct fusion performance metrics which are expressed as,

4.1.1. Feature Point Similarity Measure ($Q^{AB/f}$)

To evaluate the similarity between the feature points which are moved from base images to the fused image we have used Gradient based index ($\mathbb{Q}^{\mathbb{X}\mathbb{Y}/\mathcal{F}}$) [32] quality assessment matric which can be expressed as:

$$\mathbb{Q}^{\mathbb{X}\mathbb{Y}/\mathcal{F}} = \frac{\sum_{\mathbb{a}=1}^{p}\sum_{\mathbb{a}=1}^{q}[\mathbb{Q}^{\mathbb{X}\mathcal{F}}(\mathbb{a},\mathbb{b})g^{\mathbb{X}}(\mathbb{a},\mathbb{b})+\mathbb{Q}^{\mathbb{Y}\mathcal{F}}(\mathbb{a},\mathbb{b})g^{\mathbb{Y}}(\mathbb{a},\mathbb{b})}{\sum_{\mathbb{a}=1}^{p}\sum_{\mathbb{a}=1}^{q}[g^{\mathbb{X}}(\mathbb{a},\mathbb{b})+g^{\mathbb{Y}}(\mathbb{a},\mathbb{b})]} \tag{33}$$

Where,

$$\mathbb{Q}^{\mathbb{X}\mathcal{F}}(\mathbb{a},\mathbb{b}) = \mathbb{Q}_c^{\mathbb{X}\mathbb{F}}(\mathbb{a},\mathbb{b})\mathbb{Q}_r^{\mathbb{Y}\mathbb{F}}(\mathbb{a},\mathbb{b}) \tag{34}$$

$$\mathbb{Q}^{\mathbb{Y}\mathcal{F}}(\mathbb{a},\mathbb{b}) = \mathbb{Q}_c^{\mathbb{B}\mathcal{F}}(\mathbb{a},\mathbb{b})\mathbb{Q}_r^{\mathbb{Y}\mathcal{F}}(\mathbb{a},\mathbb{b}) \tag{35}$$

Where, the gradient strengths of two different medical images $\mathbb{X}$ and $\mathbb{Y}$ can be presented as $g^{\mathbb{X}}(\mathbb{a},\mathbb{b})$ and $g^{\mathbb{Y}}(\mathbb{a},\mathbb{b})$, respectively. The image width and image height can be expressed as P and Q whereas $\mathbb{Q}_r^{\mathbb{X}\mathcal{F}}(\mathbb{a},\mathbb{b})$ *and* $\mathbb{Q}_r^{\mathbb{Y}\mathcal{F}}(\mathbb{a},\mathbb{b})$ represents the strength of feature points for image $\mathbb{X}$ and $\mathbb{Y}$ respectively and for every base image orientation preservation values at place $(\mathbb{a},\mathbb{b})$.To evaluate the quantity of gradient information inserted into the fused image from the base images we have used a popular fusion metric $\mathbb{Q}^{\mathbb{X}\mathbb{Y}/\mathcal{F}}$.

4.1.2. Mutual Information

To specify amount of information of the fused image which conveys information about the base image, we present a Mutual information (MI) [33] quality metric. The mutual information between the fused and base image can be expressed as,

$$\mathbb{MI} = \mathbb{MI}^{\mathbb{X}\mathcal{F}} + \mathbb{MI}^{\mathbb{Y}\mathcal{F}} \tag{36}$$

Where,

$$\mathbb{MI}^{\mathbb{X}\mathcal{F}} = \sum_{\mathbb{w}=0}^{\mathbb{L}}\sum_{c=0}^{\mathbb{L}} \mathbb{H}^{\mathbb{X}\mathcal{F}}(c,\mathbb{w})\log_2\left(\frac{\mathbb{H}^{\mathbb{X}\mathcal{F}}(c,\mathbb{w})}{\mathbb{H}^{\mathbb{X}}(c)\mathbb{H}^{\mathcal{F}}(\mathbb{w})}\right) \tag{37}$$

$$\mathbb{MI}^{\mathbb{Y}\mathcal{F}} = \sum_{\mathbb{w}=0}^{\mathbb{L}}\sum_{\mathbb{h}=0}^{\mathbb{L}} \mathbb{H}^{\mathbb{Y}\mathcal{F}}(\mathbb{h},\mathbb{w})\log_2\left(\frac{\mathbb{H}^{\mathbb{Y}\mathcal{F}}(\mathbb{h},\mathbb{w})}{\mathbb{H}^{\mathbb{Y}}(\mathbb{h})\mathbb{H}^{\mathcal{F}}(\mathbb{w})}\right) \tag{38}$$

Where, the normalized mutual information between fused and base images $\mathbb{X}$ and $\mathbb{Y}$ can be expressed by $\mathbb{MI}^{\mathbb{X}\mathcal{F}}$and $\mathbb{MI}^{\mathbb{Y}\mathcal{F}}$, respectively where $c, \mathbb{h}, and\ \mathbb{w} \in [0, \mathbb{L}]$. The normalized histograms of the base and fused image can be denoted as $\mathbb{H}^{\mathbb{X}}(c)$,$\mathbb{H}^{\mathbb{Y}}(\mathbb{h})$), and $\mathbb{H}^{\mathcal{F}}(\mathbb{w})$.The joint histograms between the fused and base images $\mathbb{X}$ and $\mathbb{Y}$ can be denoted as $\mathbb{H}^{\mathbb{X}\mathcal{F}}(c,\mathbb{w})$ and $\mathbb{H}^{\mathbb{Y}\mathcal{F}}(\mathbb{h},\mathbb{w})$. High $\mathbb{MI}$ value shows the superiority of proposed fusion model.

4.1.3. Standard Deviation (STD)

To evaluate the amount of widening of grey values in a medical image, here we introduce a standard deviation metric. More the standard deviation, better the fusion results. The Standard Deviation (STD) can be expressed as,

$$STD = \left(\frac{1}{p\times q}\sum_{a=1}^{p}\sum_{b=1}^{q}(\mathcal{F}(a,b)-\hat{\mu})^2\right)^{1/2} \quad (39)$$

Where, $\mathcal{F}(a,b)$ represents the pixel values of fused image at the location (a,b) and $\hat{\mu}$ represents the mean value of that image.

4.2. Experiments and Discussions

We implemented a comprehensive objective analysis on the experimental outcomes by our proposed image fusion technique with Type-2 fuzzy logics. Here, Table 1 represents the quantitative performance comparisons of proposed technique in contrast with the conventional state-of-art-techniques for five different group of medical images. In Table 1, three quality analysis matrices are presented in which $\mathbb{MI}$ and STD are largest objective matrices and $\mathbb{Q}^{\mathbb{XY}/\mathcal{F}}$ lies in the range of 0 to 1. The larger $\mathbb{MI}$ value shows the superiority of our proposed fusion technique. Table 1 quantitative outcomes shows the robustness of our proposed technique in terms of spatial consistency as well as significant extracted information of our proposed method performs better than the conventional state-of-art fusion techniques. The better results of quality assessment matrices represents that the fused image carried out using our proposed technique can hold much more detailed information can attain a larger similarity and correlation to the base image when compared to other state-of-art fusion techniques.

We have performed our experiments on different multimodal medical image over the standard medical test images to validate the feasibility of our proposed image fusion technique. There are five different medical image group of each type are available and the two base images are perfectly pre-registered for every group pair as presented in Figure 3.

The proposed image fusion technique compared to seven other state-of-the-art image fusion techniques which rely upon the methods like GP, DWT, CT, NSCT, Scheme-1 [34], Scheme-2 [35] and NSCT + T2FLDS methods as presented in Figure 4. The proposed image fusion model with IT2FLDS technique outperforms all the other state-of-art-techniques in terms of Mutual Information ($\mathbb{MI}$), Standard Deviation (STD) and Feature Point Similarity Measure ($\mathbb{Q}^{\mathbb{XY}/\mathcal{F}}$) as presented in Table 1. The visual quality of medical images is much better using our proposed model in contrast to other state-of-art-techniques.

Table 1. Evaluation Indices for Fused Medical Images

Group	Indices	GP	DWT	DTCWT	CT	NSCT	Scheme-1[34]	Scheme-2[35]	NSCT T2FLDS	PROPOSED
Group1	MI	2.9816	2.3709	2.3663	2.1769	2.5573	2.6506	4.3924	4.5619	5.7741
CT/MRI	AB/F	0.652	0.618	0.6464	0.5763	0.6913	0.7014	0.7889	0.7859	0.6218
	STD	38.782	41.159	39.791	40.318	41.248	59.188	58.257	60.871	92.50
Group2	MI	3.3544	3.1367	3.2059	3.1086	3.2943	3.2339	3.0614	3.9635	3.837508
MR-	AB/F	0.5867	0.567	0.5998	0.5541	0.6287	0.5942	0.5802	0.6412	0.585129
T1/MRA	STD	68.3325	72.2603	70.9012	71.3378	72.219	82.6464	72.1308	90.1086	90.48137
Group3	MI	3.8479	3.1827	3.3156	3.1689	3.4469	2.8063	4.5088	4.6146	6.782690
CT/MRI	AB/F	0.5665	0.5299	0.5631	0.5297	0.5926	0.5206	0.6268	0.6469	0.656692
	STD	46.2356	50.8396	50.067	50.4575	50.9719	57.601	69.1269	69.1941	68.47939
Group4	MI	3.5102	3.2095	3.298	3.1454	3.4207	3.5195	3.5107	4.0579	4.294069
MR-	AB/F	0.6632	0.6347	0.6742	0.6333	0.6862	0.6862	0.6641	0.7154	0.677208
T1/T2	STD	34.585	37.3586	36.9695	37.3167	37.37	40.4041	38.4298	43.2922	53.3414
Group5	MI	3.3656	3.1878	3.2148	3.1445	3.2716	3.3301	3.3819	3.6634	5.086480
MR-	AB/F	0.5579	0.5266	0.5692	0.519	0.5848	0.5755	0.5631	0.6197	0.621281
GAD/T2	STD	62.5626	65.6693	64.7158	65.1074	65.4498	68.8262	70.1364	80.0055	85.94753

5. CONCLUSION

The growth of information processing technologies and frequent development of medical imaging have given rise to challenge of clinical assessment of medical images. Thus, Multimodal medical image fusion technique can prove a vital asset for the various clinical imaging sensor applications. Therefore, in this paper, a novel multimodal sensor medical image fusion technique based on type-2 fuzzy logics is presented.

To enhance the visual quality of reconstructed medical images and eliminate the drawbacks of existing state-of-art-techniques a Type-2 fuzzy logics based on Sugeno model is presented to carried out more detailed information, comprehensive objective analysis, spatial consistency, attain larger similarity and correlation. Experimental outcomes clearly demonstrates that our proposed technique can provide detailed fused image information and also enhance visual quality of medical images and increases similarity between base and fused image using type-2 Fuzzy logics. Moreover, our experimental results outperforms all the other existing state-of-art-techniques in terms of mutual information, standard deviation and Feature Point Similarity Measure which highlights the robustness and high efficiency of our proposed method. In future work, we will demonstrate our results on PET/MRI and SPECT/MRI colored images and compared with other state-of-art methods.

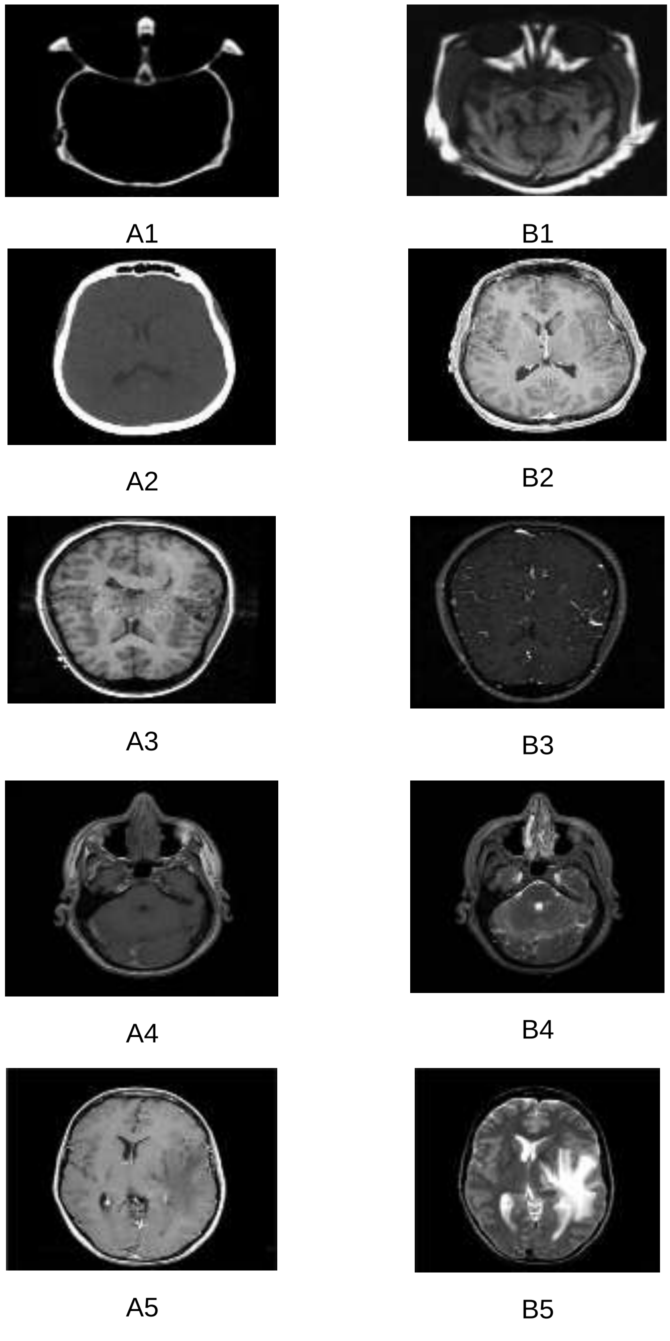

Figure 3. Source multimodal medical images: (a1), (b1) image group 1 (CT and MRI); (a2), (b2) image group 2 (CT and MRI); (a3), (b3) image group 3 (MR-T1 and MRA); (a4), (b4) image group 4 (MR-T1 and MR-T2); (a5), (b5) image group 5 (MR-Gad and MR-T2)

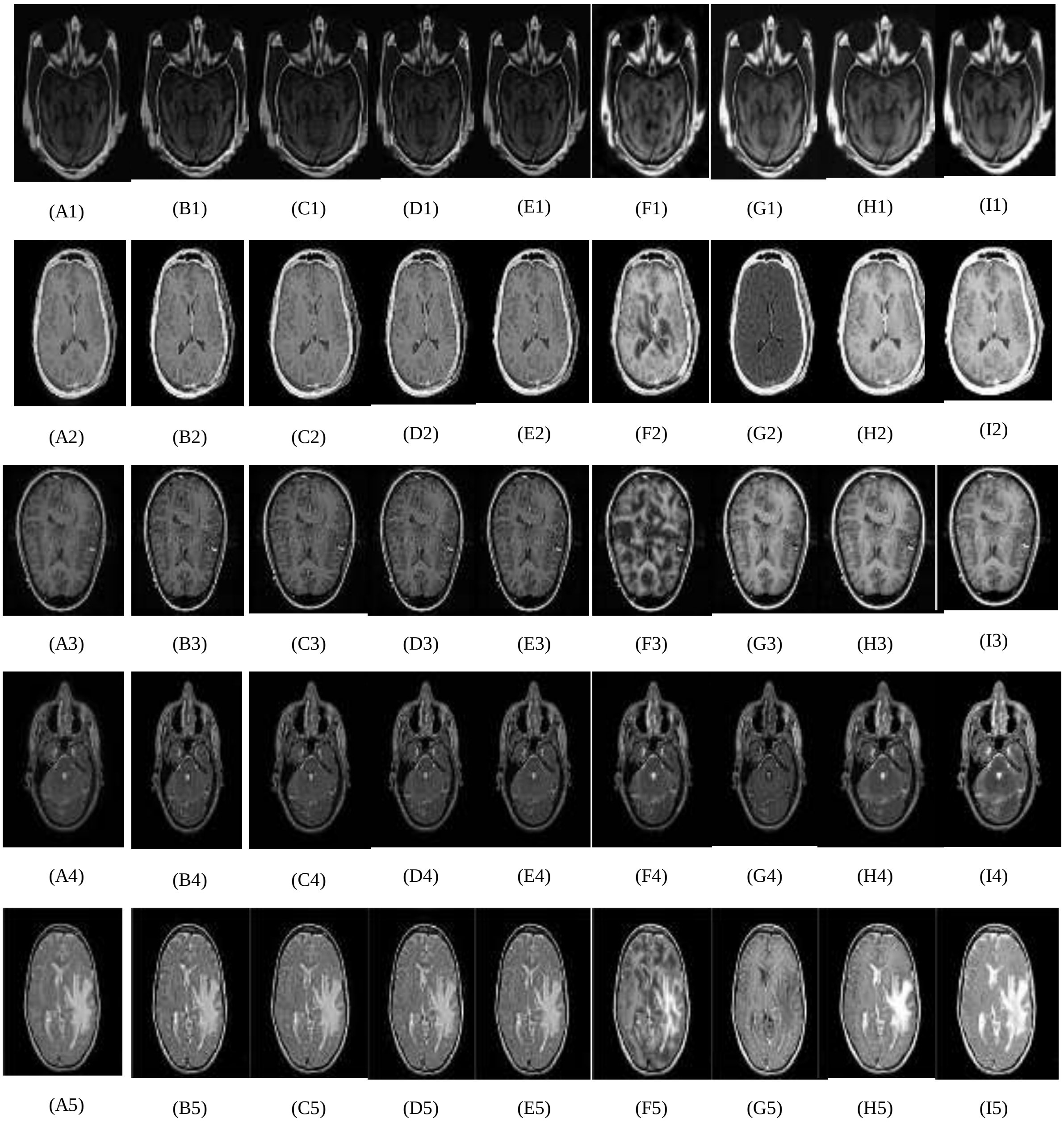

Figure 4. Visual results for the five pairs of CT/MRI images. Fused images from (a1)–(a5) GP based method; (b1)–(b5) DWT based method; (c1)–(c5) DTCWT based method; (d1)–(d5) CT based method; (e1)–(e5) NSCT based method; (f1)–(f5) scheme [38] method; (g1)–(g5) scheme [40] method; (h1)–(h5)NSCT + T2FL; (I1) - (I5)proposed method

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