Multi-Modality Medical Image Fusion Using Cross Bilateral Filter with Fuzzy Logic

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Abstract. The domain of Medical images is escalating with the trend of digital image based diagnosis and treatment. When talking about Tumors and Cancers, medical images play significant role to identify the affected area with maximum precision. In this paper, Cross Bilateral Filter is used to focus on retaining the edges. The Muti-Modality medical images are firstly decomposed using Cross Bilateral Filter and Wavelets (in parallel), followed by fusion of detailed parts by Fuzzy Logic Inference System having 25 set of rules and approximate parts are fused with average rule. Lastly, the reconstruction is done to obtain the final fused image. To compare the results quantitatively as well as qualitatively, MR-T1, MR-T2 images when fused with proposed method, attained higher values for Standard Deviation (SD), Fusion Symmetry (FS), Correlation Coefficient (CC) and $Q^{AB/F}$ and lower value of $N^{AB/F}$.

Keywords: Cross Bilateral Filter, Fuzzy Logic, Image Fusion, Wavelets

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1 Introduction

A numbers of techniques have been developed for Image Fusion. The basic idea behind Fusion is to merge images of different modalities into a single image with the aim of getting the best information from each modality into an output image (Fused image). The first step for fusion is to decompose the source images into sub-bands for which Wavelet Transform is implemented in this paper. From the family of Wavelets, Biorthogonal Wavelet (bior2.2) is used in combination with Cross Bilateral Filter. The main advantage of using Cross Bilateral Filter as discussed in [1], is that it does not smoothes the edges which is made possible by taking into account the gray level similarity as well as geometric closeness of neighboring pixels. After decomposition, the fusion is done for which J. Tenget.al. [5]has used Fuzzy Logic based on MIN-SUM-MOM algorithm and has achieved more texture features with enhanced information. H. Kaur et. al. in [2]has also used Fuzzy logic and compared the fusion results with the results obtained from fusion with Wavelets. An iterative Fusion Transform (FTR) is demonstrated in [9], where using the capabilities of FTR i.e edge preserving and smoothing abilities, error image is calculated on each iteration and compared with original image and this continues till negligible error is obtained. The authors have also tabulated the effect of stages on the metrics indicating the improvement in performance at each stage. In this paper, decomposition is performed using CBF and wavelets. For fusing the decomposed sub-images, Fuzzy Logic is applied with defined set of rules. The proposed method was applied on Harvard Database MR-T1 and MR-T2 dataset pairs and on comparison with latest methods, the proposed method outperformed (on maximum of datasets) with higher metric values for Edge Strength(Q), Standard Deviation (SD), Feature Mutual Information (FMI), Fusion Factor (FF), Structural similarity index measure (SSIM), Feature similarity index measure (FSIM).

The paper is organized into various sections. Section 2 gives the detailedLiterature Survey in medical image fusion field. Section 3 discusses the techniques used for decomposition, fusion and Reconstruction of medical images. The workflow of the proposed technique is given in Section 4. Implementation and Performance demonstration of the proposed technique is given in Section 5 and 6 respectively. Finally the conclusions are presented in section 7.

2 Related Work/Literature Survey

Medical images [19] are fused at the pixel level and in [17], Yu Liu et. al. proposed a new technique to fuse medical images at pixel level using Sparse Representation(SR) model which unlike other SR model, can concurrently achieve multi-component and global SR of input images. Results indicate better performance when compared with benchmarking as well as state of the art methods based on SR methods.Curvelet Transform is used in combination with Genetic Algorithm (GA) in [7] in which image fusion features are optimized by reducing suspicions and diffuse present in the source image. Low and high frequency coefficients obtained from Curvelet Transform is used for wrapping and GA optimizes the features. The proposed method is tested on brain images and has outperformed when compared to existing ones.Parul shah et. al. in [11] has proposed a fusion rule taking into consideration the weighted average of input pixels and has achieved 50% minimization in artifacts in the final image (fused). Visual evaluation was done by 50 persons and gave rating of 1 to 5 and hence proved that the fused image is more human acceptable by proposed method. Cross Bilateral Filter is used in[1] to get the detailed image and weighted average from the detailed images are used to create the fused image. The performance is superior in terms of visual inspection and finer /similar when calculated on quantitative parameters. The information in medical image is very much impacted by the statistical properties of neighboring pixels and in [10], covariance matrix is computed for each image block. The unbiased eigen value thus obtained from this matrix gives the idea of edge strength and hence more weights are given to pixels with stronger edge. Weighted average is calculated to compute the final fused image in wavelet domain. The work has achieved increased sharpness as well as minimum artifacts when applied on different image pairs. . Weighted average in wavelet domain is also experimented by Parul Shah et. al. [12] where the weights are computed using information available at finer resolution bands. The performance is verified on multi-focus images. Proposed method gives low artifact output and is the desired feature of fusion, defined as MSE (Mean Square Error).

S. Arivazhagan et. al.[13] has considered multi-focus and multi-spectral input images and modified the wavelet based region level method. Edge information of high frequency sub-bands is used to combine the low frequency sub-bands to eliminate the blur part. The results are verified using entropy, fusion symmetry and peak signal to noise ratio. Parallel saliency features in multi-scale domain is used in [3] to fuse the anatomical and functional information of MRI-CBV and SPECT-Tc , MRI-T1 and PET-FDG images. At first, Average filter is used to decompose images into smooth and detail layers. Edge saliency and color saliency weighted maps are used to extract the high spatial resolution structural information and high intensity color detail respectively. Weighted least squares filter is used in [15] to decompose into low-frequency (LF) and high-frequency (HF) layers. For fusion of LF layers, Laplacian pyramid in combination with sparse representation is used and for HF layers, max-absolute rule is used. The authors said that results are competitive to the state-of-the art methods and can be further improved using adaptive selection criteria and using other modalities. Intrinsic image decomposition (IID) is implemented in [4] to deal with colored PET images and MRI (in grey) images. Retinex method recovers reflectance from MRI and Grey world method extracts the high-intensity information with color constancy. Three methods are devised i.e. IID+PCA, IID+ICA and IID+HIS and stated that IID+PCA and IID_IIC are computationally fast and statistical evaluation is also done

3 Techniques and Methods

The presented paper has experimented with three techniques namely: Cross Bilateral Filter, Discrete Wavelet Transform and Fuzzy Logic. A brief description of the respective methods and implementation is given in the sections 3.1, 3.2 and 3.3.

3.1 Cross Bilateral Filter (CBF)

Also known as JointBilateralFilter has edge preserving and image smoothing features making it more suitable for medical images where edges are utmost important. CBF is a variant of Bilateral Filter, where one image is used to shape the kernel, then applying it on the other image and vice versa. The core idea behind the working of bilateral filter is calculation of weights based on Euclidean as well as color space distance. Mathematically, CBF is calculated as:

- **For image A,**

$$A_{CBF}(p) = \frac{1}{W} \sum_{q \epsilon s} G_{\sigma_s} (||p - q||) G\sigma_r (|B(p) - B(q)|)\, A(q)$$

Where, the Edge Stopping function is defined as:

$$G\sigma_r(|A(p) - A(q)|) = e^{\frac{-|A(p) - A(q)|^2}{2\sigma_r^2}}$$

And W is a constant with equation:

$$W = \sum_{q \epsilon s} G_{\sigma_s} (||p - q||) G\sigma_r (|B(p) - B(q)|)$$

- **For image B,**

$$B_{CBF}(p) = \frac{1}{W} \sum_{q \epsilon s} G_{\sigma_s} (||p - q||) G\sigma_r (|A(p) - A(q)|)\, B(q)$$

Where, the Edge Stopping function is defined as:

$$G\sigma_r(|B(p) - B(q)|) = e^{\frac{-|B(p) - B(q)|^2}{2\sigma_r^2}}$$

And W is a constant with equation:

$$W = \sum_{q \epsilon s} G_{\sigma_s} (||p - q||) G\sigma_r (|A(p) - A(q)|)$$

After computing CBF of each input i.e. A_{CBF} and B_{CBF}, it is subtracted from original image i.e. A, Brespectively to get the details A_{DETAIL}, B_{DETAIL} and likewise maximum details are fetched from each image by making filter kernel close to Gaussian.

A_{DETAIL}=A-A_{CBF}

B_{DETAIL}=B-B_{CBF}

The implementation of CBF is done using MATLAB 2015b, and the Fig.1 shows the CBF component and Detail components

3.2 Discrete Wavelet Transform (DWT)

When a discrete set of wavelet scales and translations with some defined rules are implemented, they can be referred to as Discrete Wavelet Transform. The wavelets are constructed using a scaling function having some specific scaling properties. The idea behind discrete wavelet transform is to decompose the image into different coefficients without the loss of information. After the fusion evaluation on sub-bands, the final fused output is a single image which is calculated by taking inverse of DWT. After experimenting with the various families of wavelet like Haar, Daubechies,Symlets, Biorthogonal and many more, Biorthogonal2.2 (bior2.2) is implemented in this paper.Yong Yang et. al. [18] used fusion scheme by combining the coefficients obtained from decomposition by the wavelet transform. The authors have used Daubechies db8 with decomposition level of 3. Visibility based selection method is used for low-frequency coefficients and maximum window based method for high frequency coefficients for fusion.

The Fig.2, depicts the decompositionof MR-T1 image with Biorthogonal wavelet (bior2.2). The input image is decomposed into 7 sub-bands depicting approximate, vertical, horizontal and detail information. At level 1, the image produces four sub-bands and on requirement it can be further decomposed into more levels, in which the detail band is further decomposed to give coarse information. The Inverse Discrete Wavelet Transform (IDWT) combines the sub-bands to give us the single image by inversing the DWT.

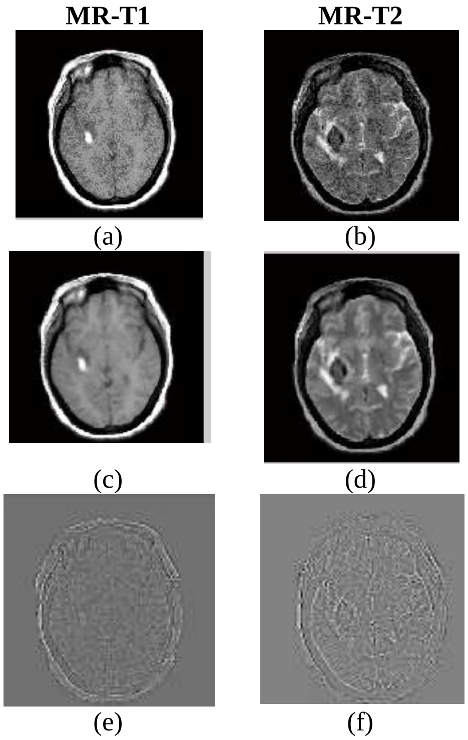


Fig.1 MR-T1 and MR-T2 images original images in (a) and (b), CBF output images in (c) and (d), and detail images in (e) and (f) respectively.

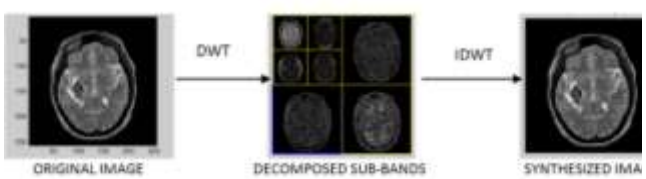


Fig.2 Decomposed sub-bands and synthesized images of source image using bior2.2.

3.3 Fuzzy Approach for Fusion

The human capacity of imprecise reasoning is formalized using Fuzzy Logic thus giving systems the capability to judge under uncertain conditions. Fuzzy logic deals with partial as well as approximate truths and is also termed as interpolative reasoning. Hybridization of binary crow search optimization is used to fuse medical images in [14] and evaluation shows better performance in terms of entropy, SSIM and FF.Nonsubsampled contourlet transform(NSCT) is used in combination with fusion entropy and presented in [2]. After application of NSCT, the low frequency components are used to calculate the membership degree, fuzzy entropy and used afterwards to conserve details. Regional energy maximization rule is applied on High-frequency components and the results indicate high average gradient, SD and edge preservation. Intensity-Hue-Saturation domains are individually fused using intuitionistic fuzzy logic andis implemented in [8], with suppression of noise followed by enhancement of image features and has overcome the problem of noise and low contrast in colored medical images. In this paper, Mamdani type FIS is constructed for fusion of detailed sub-bands with 25 rules, 2 inputs and 5 membership functions for each input. The membership functions are Gaussian in nature.

4 Research Methodology

The proposed technique consists of decomposing the input with two methods in parallel i.e. Cross Bilateral Filter (CBF) and Discrete Wavelet Transform (DWT). CBF has the ability of calculating vertical as well as horizontal edge strength which makes the final details obtained, more suitable to be fed to the Fuzzy Inference System (FIS).The proposed method is used with the setting of bilateral parameters as following:

Geometric Sigma=1.8

Radiometric Sigma=25

Kernel Size=5

Using the above parameter values, CBF is calculated and the respective detail is obtained by subtracting the CBF value from original image values. Now, the detailed image acts as an input for biorthogonal wavelet which gives approximate and detail sub-bands and the detail sub-bands of each image is fed to fuzzy inference system. The approximate sub-bands are fused using the average rule.

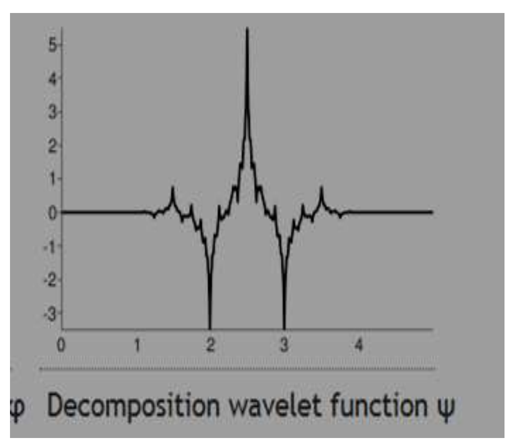


Fig.3 Decomposition wavelet function Ψ of Biorthogonal Wavelet

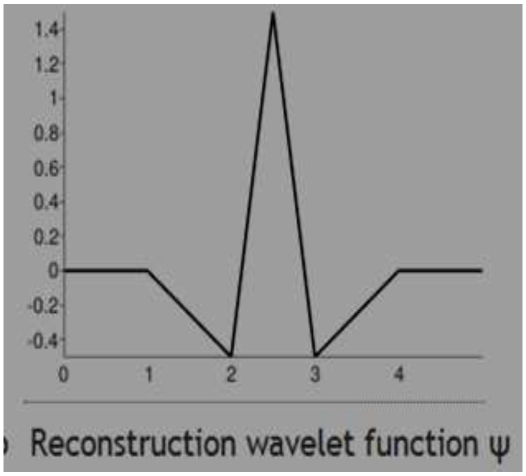


Fig.4 Reconstruction wavelet function Ψ of Biorthogonal Wavelet

The Biorthogonal wavelet family with bior1.5, bior2.2, bior4.4 and bior6.8 were tested and after comparison, bior2.2 was used to decompose input images symmetrically and biorthogonallywith decomposition and reconstruction wavelet function as depicted in the figure 3 and 4respectively.

To deal with the approximate components, average rule is followed.Fuzzy Logic fuses the detailed part obtained from CBF and is capable of handling the areas where there is imprecision. A Fuzzy Inference System(FIS) with 25 set of rules and 5 membership functions of Gaussian nature are used. The output membership functions are also taken to be Gaussian in nature. Reconstruction of the fused sub-bands is done to obtain a single fused image.The whole fusion process starting from decomposition and ending at reconstruction is given in figure 5.

5 Implementation

The implementation algorithm is divided into 6 steps and the steps are as follows:

- **Input:** A (MR-T1) , B (MR-T2)
- **Decomposition:** Deducing kernel weights from one image and applying it on the second image and hence A_{CBF}, B_{CBF} are produced.
- **Fetching the detailed image:** For this, output obtained from the above step is subtracted from original image to get the details A_{DETAIL}, B_{DETAIL}.
- **Wavelet Selection:** From the family of wavelets, Biorthogonal wavelet (bior 2.2) transform is applied on the source images A, B.
- **Fusion Strategy:**Fuzzy inference system and average rule is performed on the decomposed parts. Fuzzy Logic is applied on the detailed components. To deal with the approximate components, the average rule is followed to fuse the low-low, high-low and low-high sub-bands. The details obtained from the CBF is fed to the Fuzzy Inference system of Mamdani type for fusion with two input variables and one output variable with Gauss membership function for each input and output is defined. 25 Fuzzy rules are defined to fuse the pixels with min as AndMethod, max as OrMethod. For implication, min is used, max rule is used for aggregation and centroid for defuzzification.
- Reconstruction: This is the last step in which inverse wavelet transform is performed to reconstruct the final fused image. Fused sub-components are combined into a single image which is expected to be more informative for radiotherapy treatment planning.

6 Experimental Results

6.1 Evaluation and Result Analysis

Implementation of the proposed scheme is carried out on MR-T1 and MR-T2 pair taken from Harvard Database. Fused image obtained by proposed method is compared with different methods discussed in [1,11,12,7,10]. The parameters of bilateral filter used for the proposed method are - Geometric Sigma (σ_s)=1.8, Radiometric Sigma (σ_r) =25, Kernel Size(w)=5. A Fuzzy Inference System(FIS) with 25 set of rules and 5 membership functions of Gaussian nature are used. The output membership functions are also taken to be Gaussian in nature.
The results are compared using conventional metrics (tabulated in Table1): Average Pixel Intensity (API), Standard Deviation (SD), Fusion Symmetry (FS), Correlation Coefficient (CC). Objective Performance metrics are (tabulated in Table2) $Q^{AB/F}$(total information transferred from input to output), $L^{AB/F}$(total loss of information), $N^{AB/F}$(artifacts in fused image). A favorable outcome is defined as high values of API, SD, FS, CC, $Q^{AB/F}$, $L^{AB/F}$ and low value of $N^{AB/F}$.

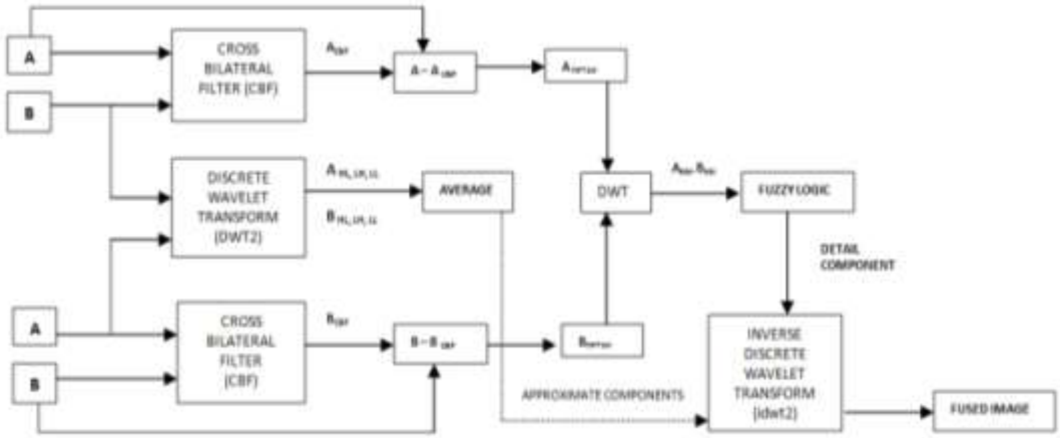
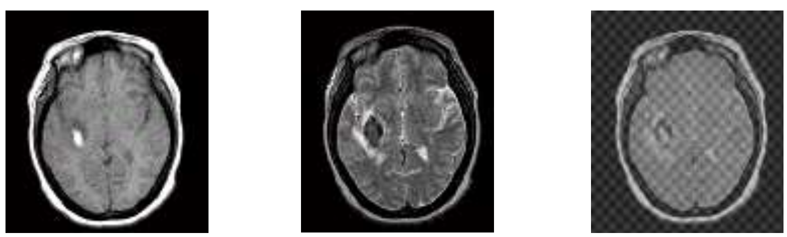
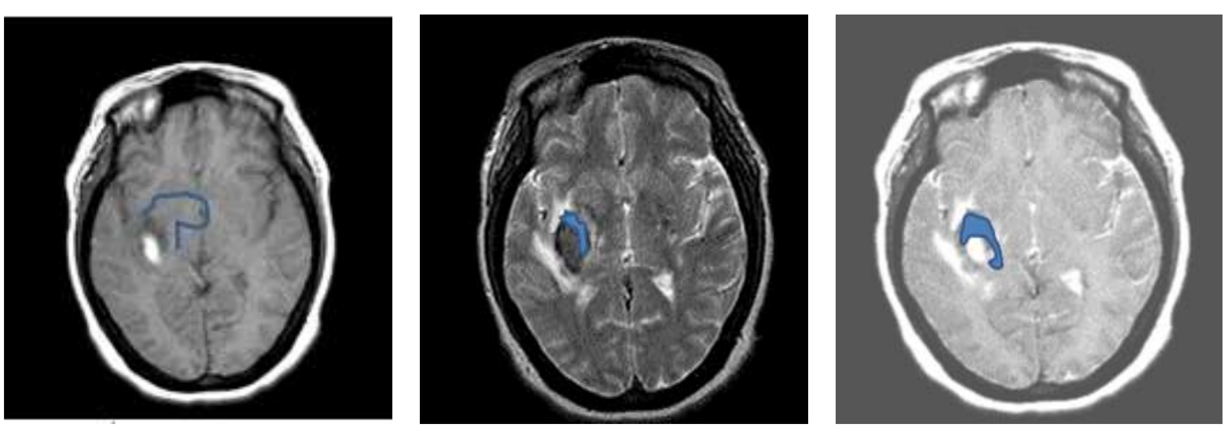


Fig.5 Image Fusion (Proposed Method)



(a) MR-T1 (b) MR-T2 (c) FUSED IMAGE

Fig. 6 Multi-Modality MRI source images in (a) and (b), fused image by proposed method in (c)



(a) MR-T1 (b) MR-T2 (c) FUSED IMAGE

Fig. 7 Subjective Analysis-Contouring on Multi-Modality MRI source images in (a) and (b), fused image in (c)

The results indicate that the proposed method has achieved better values for the metrics: SD (63.6862), FS (1.9995) and CC (0.7182) except for API which is less than the method in[1].The objective metrics values indicate higher transfer of information from source to final image with $Q^{AB/F}$ =0.8940, lesser artifacts in final fused image with $N^{AB/F=}$0.0131 and loss of information $L^{AB/F}$=0.0929.The Sum column of Table2 imparts a condition on the objective metrics that the sum of $Q^{AB/F}$, $N^{AB/F}$ and $L^{AB/F}$ should be 1.It is observed from the figure 6 that the fused image by proposed method has information from both the modalities with minimum information loss and artifacts.

The output (Fused Image) of the proposed method on source images MR-T1, MR-T2 is shown in figure 6. Visual evaluation is performed using the original image and final output (Fused Image) in order to confirm the mathematical results.The subjective verification is done by a human expert i.e. Radiologist. The expert in Radiology can check visually the information transferred to the final image, mapping the missing information from the input with output, as well as presence of artifacts in the final output. The results obtained from Fuzzy Logic were compared by the Radiologist and Radiation Safety Officer (RSO) on the ONCENTRA **[**6][1]and empirically, the results were equivalent and could be used clinically.

As depicted in Figure 7, MR-T1 and MR-T2 images comparison shows that there is a marked difference in the amount of cystic space and edema and a world of differences when they are fused. The total edematous area increases and the tumor area decreases and there is a lot of planning issues because of this missing information.

TABLE 1 Conventional metrics evaluation

INPUT IMAGE	API	SD	FS	CC
PROPOSED	48.2381	**63.6862**	**1.9995**	**0.7182**
[1]	**54.7351**	57.6902	1.6142	0.6565
[10]	46.3165	52.3071	1.6899	0.6374
[13]	36.4330	51.3242	1.7651	0.5563
[11]	40.1711	46.8869	1.7126	0.6185
[12]	44.1301	51.3010	1.6880	0.6011

Fusion increases the planning accuracy and without a PET scan imaging, which could help further we are able to save a lot of normal tissues, inflamed tissues and can actually localize the tumor to a greater accuracy.

TABLE2 Objective evaluation metrics

MEASURE	$Q^{AB/F}$	$L^{AB/F}$	$N^{AB/F}$	SUM
PROPOSED	**0.8940**	0.0929	**0.0131**	1
[1]	0.8932	0.0961	0.0950	1
[10]	0.8065	0.1856	0.0735	1
[13]	0.6900	0.2776	0.2172	1
[11]	0.7760	0.2137	0.0924	1
[12]	0.7300	0.2531	0.1310	1

7 Conclusions

The proposed solution offers cheaper software option compared with others already available like ONCENTRA, SYNGO etc. It presents a free interactive modality as currently patients are not being involved into diagnostics and therapeutic procedures. The proposed method has effectively consumed the CBF’s capabilities to get detailed image, which is further supposed to be good input for fuzzy inference system. The fuzzy logic has dealt with the range of all the possible values and has tackled the un-uniform values as well. Though surfacing the rules in fuzzy logic was difficult but was outlined by calculating the metrics for each output and going all along the loop again till the better results are perceived. So, for replacing this tiring task experiments can be conducted

[1]ONCENTRA creates workflow and optimizes the planning accuracy for wide varieties of clinical high-dose rate (HDR) treatments, such as skin, gynecologic (GYN), breast, prostate, and many other applications.

with other AI (Artificial Intelligence) techniques and can be considered as a future work.

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