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MULTIMODALITY MEDICAL IMAGE FUSION USING BLOCK BASED INTUITIONISTIC FUZZY SETS

Rajkumar Soundrapandiyan*, Rishin Haldar, Swarnalatha Purushotham and Arvind Pillai

School of Computing Science and Engineering, VIT University, Vellore, INDIA

ABSTRACT

Image fusion combines more than one image from various environments into a single image. This can be useful for subsequent processing of the image, especially in medical imaging where it can help in disease diagnosis. This paper uses the block based Intuitionistic Fuzzy Sets(IFS) to fuse the multimodality medical images. IFSs can effectively handle the inherent uncertainties of digital images. Initially, in this model, entropy is used to deduce the optimal parameter value for defining the membership and non-membership function. This, in turn generates the Intuitionistic Fuzzy Images (IFI) from the original image. Finally, the IFIs are partitioned into image blocks and then recombined by the generated membership function. This paper compares the proposed method with popular ones like Principal Component Analysis (PCA), simple averaging (AVG), Laplacian Pyramid Approach(LPA), Discrete Wavelet Transform (DWT) and MPA (Morphological Pyramid Approach) on various performance measures such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Universal Image Quality Index (UIQI), Mean and Standard Deviation (STD). The experimental results show better image visualization generated through the proposed method compared to the other methods, in overall.

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KEY WORDS

Medical image fusion; Intuitionistic fuzzy image; Entropy; Quantitative measures; Multimodality images.

***Corresponding author:** Email: rajkumars@vit.ac.in

INTRODUCTION

DNA microarray Image fusion is widely used as an effective technique for analysis of images [1]. These images are obtained from various domains like satellite images, biometrics, robotics, remote sensing etc., and there are customised image sensors for each of these domains. Consequently, the data obtained from these specialised sensors may be incompatible with each other. For example, in medical imaging, the image generated by an MRI machine gives clear details of soft tissues while a CT (X-Ray) machine gives clear details of bone structures. In this scenario, if we are required to find the clear details of both, or more, of the features, where the data is incompatible, image fusion can be an effective tool to address the issue. This gives us the motivation to apply image fusion on medical images.

Image fusion can be carried out by mainly two techniques, spatial fusion and transform fusion. Based on the unification phases, fusion can be done in three levels, namely pixel, feature and decision levels. Pixel level fusion combines the pixel values directly and creates a composite image. The simplest method just takes the average of the pixel values of source images. Laplacian pyramids [2], PCA [3] are some of the other techniques which use pixel value fusion. In order to improve upon the degraded performance of the average policy of fusion algorithm, many multi-resolution transform techniques emerged, like pyramid decomposition, wavelet transforms [4] etc. Fusion of the images by singular value decomposition (SVD) [5] works quite well on pixel basis and outperforms PCA. The MSVD [6] technique, which looks into multiple properties like sphericity, isotropy and self-similarity of signals, performs faster than SVD. Image fusion technique also generated a highly featured picture using multi-scale decomposition. The various attempts in using multi-scale transform showed that shifting of invariance is highly desirable for image fusion. In this context, NSCT [7], a complete transform, has been very effectively utilized in image fusion.

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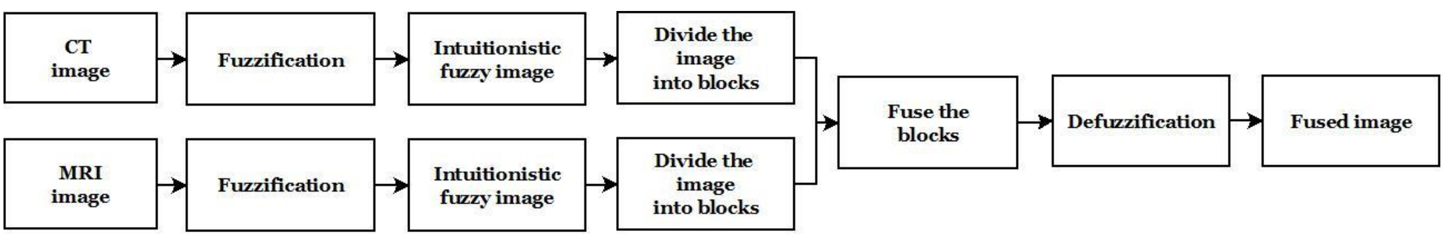
Image processing, however, has many uncertainties at every phase. Fuzzy sets [8] have been known to remove these uncertainties, especially in luminance and contrast of the image. In medical images, poor luminance increases the uncertainty of the image, and IFS [9], an improvement on the traditional fuzzy set, has been quite successful in removing these uncertainties. Thus, by using the multimodal properties of the image as well as using fuzzy sets, the image fusion can be extremely effective. One paper [10] uses Intuitioinstic Fuzzy Sets on multimodal images to fuse the images, and the results were very encouraging.

This paper presents a new way to fuse more than one medical image, and builds on the efforts done [10]. This paper also uses the block based Intuitionistic Fuzzy Sets (IFS) to fuse the multimodal medical images. However, a new and customised entropy function is used to deduce the optimal parameter value for defining both the membership and the non-membership function. This generates the Intuitionistic Fuzzy Images (IFI) from the original images. Finally, the IFIs are partitioned into image blocks and then recombined by our generated membership function. The reconstructed fused image has high degree of luminance and contrast. The resultant pictures are provided for subjective evaluation. This paper also objectively compares the proposed method with popular methods like simple averaging (AVG) [11], Principal Component Analysis (PCA) [3], Laplacian Pyramid Approach(LPA) [2], Discrete Wavelet Transform (DWT) [12] and MPA (Morphological Pyramid Approach) [13] by various performance measures such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), Universal Image Quality Index (UIQI), Mean and Standard Deviation (STD). The experimental results are very encouraging and show that the proposed method, overall, has performed much better than these popular methods.

The following sections give the specific details of our work. Section II describes our proposed methodology along with the required computational models. Section III describes the performance measures through which we are evaluating our proposed technique. Section IV describes the experimental results and its subjective and objective comparison with the other popular methods. Finally, we conclude in Section V.

PROPOSED METHODOLOGY

The block diagram of our proposed method is shown in Fig. 1. The individual steps carried out in our proposed



method, are as follows:

Fig: 1. Block diagram of the proposed method

1. Read/Accept the input images. There are six datasets of images, each of size 256x256 pixels.
2. Fuzzification of input images using Equation (1).
3. Generation of intuitionistic fuzzy image using Equation (8).
4. Divide the image into blocks of size 3x3.
5. Fuse the each block based on the value of entropy using Equation (9).
6. Defuzzification of the fused image using Equation (10).

Fuzzification

Fuzzification [14] is the first step of fuzzy image processing**.** It consists of converting the image from spatial domain into the fuzzy domain. It can be defined as

$$\mu_{ij} = T(x_{ij}) = \left[1 + \frac{x_{\max} - x_{ij}}{F_d}\right]^{-F_e} \quad (1)$$

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Here x_{max} is the maximum intensity level for the given input image; F_e and F_d represent the exponential and denominational fuzzifiers, respectively. When $x_{max} = x_{ij}$ then, $\mu_{ij} = 1$ indicating the maximum brightness. Fuzzifier F_d is calculated using Equation (2) and F_e *is assigned to constant value 2.*

$$F_d = \frac{x_{\max} - x_{\min}}{\left(\frac{1}{2}\right)^{-1/x_{\min}} - 1} \quad (2)$$

2.2. Intuitionistic Fuzzy Image (IFI)

In general, pixel values of images have ambiguity and uncertainty. However, some uncertainty still remains while specifying the brightness of image pixels. The main objective of the proposed method is to remove the ambiguity in those image pixels. To address this issue, the image is converted from fuzzy domain to intuitionistic fuzzy domain. The intuitionistic fuzzy domain has an additional property of degree of hesitation compared to fuzzy domain. The hesitation degree is used to align the membership function values within a range. This can effectively remove the uncertain gray level values of ambiguous image pixels [10]. An Intuitionistic Fuzzy Set (IFS) is expressed in terms of □ (membership degree), □ (non-membership degree) and □ (hesitation degree) on a finite set X [19,22], by

$$IFS = \{(x, \mu_{IFS}(x), \gamma_{IFS}(x), \pi_{IFS}(x)) \mid x \in X\} \quad (3)$$

Based on the Equation (1), the degree of the membership function of IFI is computed as

$$\mu_{IFS}(x_{ij};\lambda) = 1 - (1 - \mu_x(x_{ij}))^{\lambda}, \quad \lambda \geq 0 \quad (4)$$

The degree of the non-membership function is computed as

$$\gamma_{IFS}(x_{ij};\lambda) = (1 - \mu_x(x_{ij}))^{\lambda(\lambda+1)}, \lambda \geq 0 \quad (5)$$

The degree of hesitation is defined as

$$\pi_{IFS}(x_{ij};\lambda) = 1 - \mu_{IFS}(x_{ij};\lambda) - \gamma_{IFS}(x_{ij};\lambda) \quad (6)$$

The parameter varies for each image. To select the single unique optimum □ value from each image, entropy (ENT) used. The entropy is defined

$$ENT(IFS;\lambda) = \frac{1}{P \times Q} \sum_{i=0}^{P-1} \sum_{j=0}^{Q-1} \frac{2\mu_{IFS}(x_{ij};\lambda)\gamma_{IFS}(x_{ij};\lambda) + \pi_{IFS}^2(x_{ij};\lambda)}{\mu_{IFS}^2(x_{ij};\lambda) + \gamma_{IFS}^2(x_{ij};\lambda) + \pi_{IFS}^2(x_{ij};\lambda)} \quad (7)$$

In Equation (7), the value of □ corresponds to the highest value of entropy. Finally, the IFI is defined as

$$x_{IFS} = \{(x_{ij}, \mu_{IFS}(x_{ij};\lambda), \gamma_{IFS}(x_{ij};\lambda), \pi_{IFS}(x_{ij};\lambda))\} \; x_{ij} \in \{0, 1, \ldots\ldots, L-1\} \quad (8)$$

Entropy based image fusion

To fuse the images, the obtained resultant image of x^{F1} and x^{F2} from Equation (8) is decompose into m X n blocks and denote the T^{th} image block of two decomposed images by x^{F1T} and x^{F2T} respectively. The entropy based fusion process is defined as

$$x_{ij}^{fuse} = \begin{cases} \min\left(x_{ij}^{F1T}, x_{ij}^{F2T}\right) \; if \;\; ENT(x_{ij}^{F1T}) > ENT(x_{ij}^{F2T}) \\ \max\left(x_{ij}^{F1T}, x_{ij}^{F2T}\right) \; if \;\; ENT(x_{ij}^{F1T}) < ENT(x_{ij}^{F2T}) \\ \frac{x_{ij}^{F1T}}{x_{ij}^{F2T}} \qquad otherwise \end{cases} \quad (9)$$

where max and min represent the maximum and minimum operations in IFS.

Defuzzification

Equation (10) expresses the defuzzification process to convert the image from fuzzy domain [23] to the spatial domain

$$F(i,j) = T^{-1}\left(x_{ij}^{fuse}\right) = x_{\max} - F_d * \left(\left(x_{ij}^{fuse}\right)^{-1/F_e} \right) + F_d \quad (10)$$

where F(i,j) is the final fused image.

EVALUATION MEASURES

The measurement and analysis on the fused images are done both objective as well as subjective quality measures. This effectively helps in better assessment of the information in the images. For the subjective measure, pictorial representations of the images are provided. For the objective analysis, the following measures are used. In all the measures defined here, R_{ij} and F_{ij} represent the intensity value of the reference (original) image and the fused image at coordinates i, j respectively and P, Q denote the width and height of the image.

Root Mean Square Error (RMSE)

It is a [21] method to measure the differences between values predicted by an ideal (reference) image and the fused images. It is calculated as

$$RMSE = \sqrt{\frac{1}{P \times Q} \sum_{i=1}^{P} \sum_{j-1}^{Q} (R_{ij} - F_{ij})^2} \quad (11)$$

RMSE for the reference and fused images will increase with decrease in similarity, and approaches zero whenever they are similar.

Mean Absolute Error (MAE)

It is a method which measures the mean of the absolute error between the reference and fused images.

$$MAE = \frac{1}{P \times Q} \sum_{i=1}^{P} \sum_{j=1}^{Q} \left| R_{ij} - F_{ij} \right| \quad (12)$$

MAE also increases with decrease in similarity between reference and fused images and vice versa.

Peak Signal to Noise Ratio (PSNR)

PSNR [15] is a method used to measure the quality of the fused image with respect to the reference image. It is defined as:

$$PSNR = 10\log_{10}\left(MAX^2 / MSE\right) \quad (13)$$

$$MSE = \frac{1}{pq} \sum_{i=0}^{p-1} \sum_{j=0}^{q-1} [R(i,j) - F(i,j)]^2 \quad (14)$$

where *MAX* is the maximum value in an image and *MSE* is the mean square error value of the image.

Structural Similarity Index (SSIM)

It provides a way to measure the similarity between the two images. SSIM is an improved version of the peak signal to noise ratio [16]. It is defined as

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$$SSIM = \frac{((2\mu_F \mu_R + C_1) * (2\sigma_{FR} + C_2))}{((\mu_F^2 + \mu_R^2 + C_1) * (\sigma_F^2 + \sigma_R^2 + C_2))} \quad (15)$$

where μ_F and μ_R denote the average intensities of image F and R, σ_F and σ_R denote the variance of image F and R, σ_{FR} gives the covariance of F and R , C_1 and C_2 are constants. The SSIM index value varies from -1 to 1. When two images are identical, this value will turn out to be 1.

Universal Image Quality Index (UIQI)

It is a method to measure the quality of the images [14]. This quantifies the amount of data that has been transferred from the ideal image to the resultant fused image. UIQI defines image distortion by a combination of three factors, namely contrast distortion, loss of correlation and luminance distortion.

$$UIQI = \frac{(4 * \sigma_{RF})(\mu_R + \mu_F)}{(\mu_R^2 + \mu_F^2)(\sigma_R^2 + \sigma_F^2)} \quad (16)$$

where σ_{RF} is the covariance of RF, μ_F and μ_R denote the average intensities of image F and R, σ_F^2 and σ_R^2 denote the variance of image F and R. The UIQI index value varies from -1 to 1. Once again, a 1 indicates the identical nature of the two images.

Mean (MEAN)

The mean intensity estimates the luminance of an image. This is deduced by

$$MEAN = \frac{1}{P \times Q} \sum_{i=1}^{P} \sum_{j=1}^{Q} \left| F_{ij} \right| \quad (17)$$

Standard Deviation (SD)

It shows the extent of variation or dispersion from the average or mean [17,20]. Standard deviation takes into account the original image and the acquired transmission noise. Absence of any noise in the transmitted image increases its effectiveness and portraits the image's contrast. SD can be calculated as

$$SD = \sqrt{\frac{1}{P \times Q} \sum_{i=1}^{P} \sum_{j=1}^{Q} \left(F_{ij} - MEAN \right)^2} \quad (18)$$

RESULTS AND PERFORMANCE EVALUATION

The experimental results of the fusion techniques are analyzed with six brain images taken from CT and MRI (T2). Each CT image, combined with T2, are considered as one set for fusion. This, in turn, totally derives six combinations of input dataset. All images have the same size of 256 * 256 pixels, with 256-level gray scale.

Subjective evaluation of results

Figure-2 gives the subjective comparison of the results from average method, PCA method, Laplacian method, DWT method, MPA method and proposed method. Fig.3. evident that the proposed method generated results with good visualization (i.e. high luminance and contrast) than other existing methods.

Performance Evaluation

For the objective measures, the measures discussed in the section III are used. The results generated from the proposed method for each of the measures used to quantify the results, are compared with the average method, PCA method, laplacian method, DWT method and MPA method. The comparative analyses of each of the measures are tabulated in **[Table-1, 2, 3 and 4].** The results for the RMSE measure are tabulated in **[Table-1]**. It is evident from Table 1 that the RMSE is lower for proposed method compared to other five methods, which means that proposed method introduces very less error.

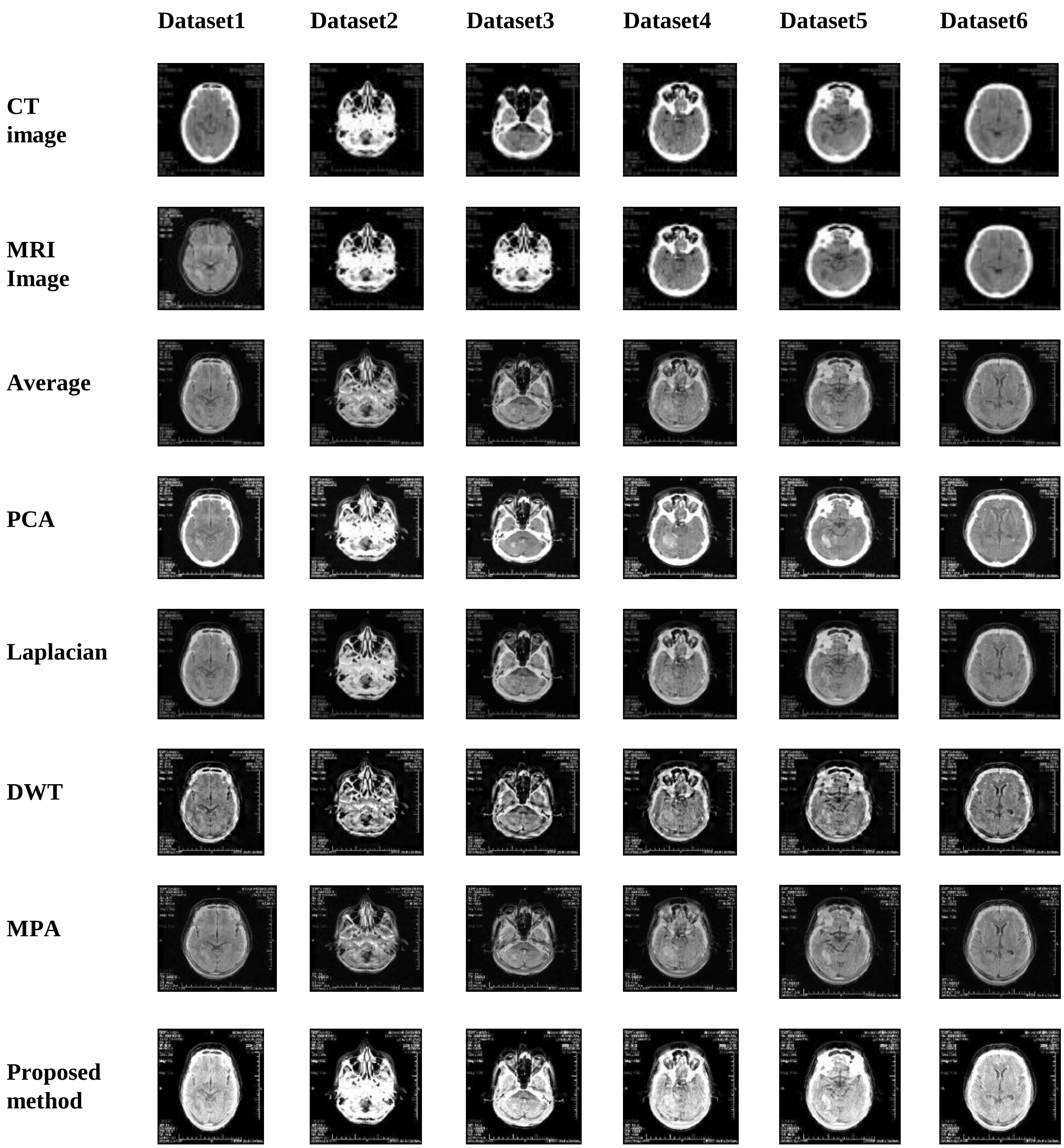

Fig: 2. Comparison (subjective) of the fusion results over 6 images

Table: 1. Comparative analysis of RMSE

Fusion method	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6
Average	0.1897	0.2015	0.2112	0.1987	0.1936	0.2007
PCA	0.1833	0.2216	0.2097	0.2001	0.1867	0.1972

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Laplacian	0.1874	0.2145	0.1998	0.1972	0.1956	0.2382
DWT	0.1832	0.2127	0.1964	0.1945	0.1904	0.1823
MPA	0.2136	0.2454	0.2270	0.2273	0.2228	0.2148
Proposed	0.1827	0.2125	0.2073	0.1918	0.1860	0.1859

Table: 2. Comparative analysis of MAE

Fusion method	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6
Average	0.0773	0.1097	0.0927	0.0908	0.0866	0.0743
PCA	0.0663	0.0648	0.0943	0.0686	0.0674	0.0671
Laplacian	0.0837	0.1087	0.0943	0.0931	0.0920	0.1206
DWT	0.0880	0.1166	0.1004	0.0992	0.0961	0.0886
MPA	0.0996	0.1269	0.1093	0.1103	0.1078	0.0990
Proposed	0.0624	0.0703	0.0726	0.0661	0.0627	0.0655

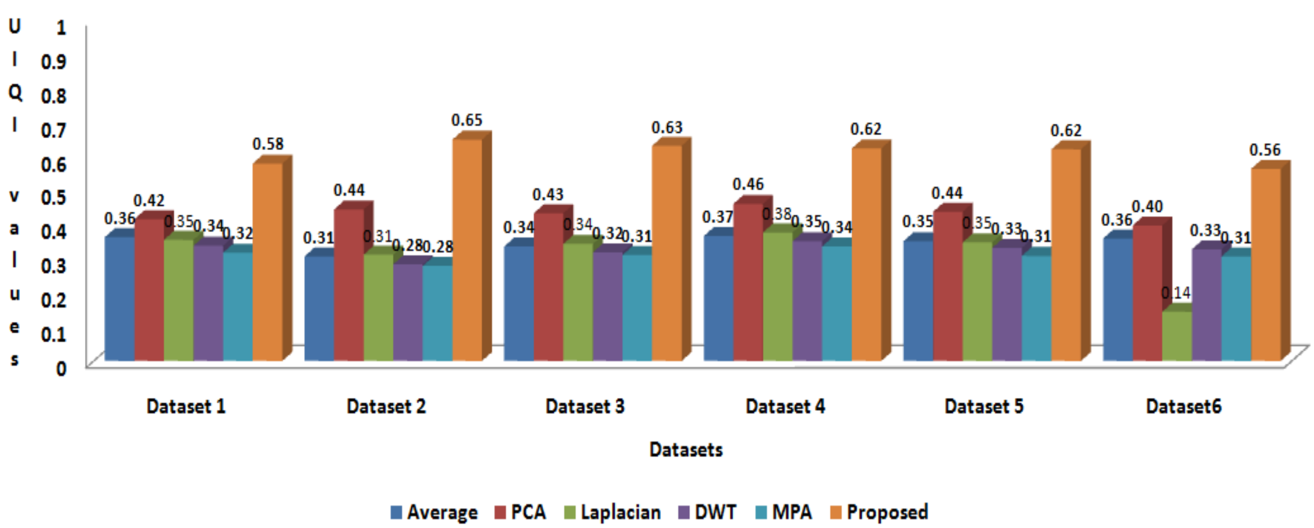
Table: 3. Comparative analysis of PSNR

Fusion method	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6
Average	62.3742	60.38421	59.8876	61.3645	62.0019	61.3658
PCA	62.3781	60.3652	60.2332	62.3118	62.1187	62.4722
Laplacian	62.6763	61.5024	62.1178	62.2349	62.3056	60.5905
DWT	62.8700	61.5745	62.2671	62.3508	62.5352	62.9158
MPA	61.5384	60.3347	61.0116	61.0001	61.1724	61.4890
Proposed	62.8955	61.5819	61.7968	62.4722	62.7387	62.7452

Table: 4. Comparative analysis of SSIM

Fusion method	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6
Average	0.9983	0.9969	0.9976	0.9977	0.9979	0.9985
PCA	0.9982	0.9966	0.9980	0.9975	0.9976	0.9987
Laplacian	0.9976	0.9962	0.9969	0.9970	0.9972	0.9956
DWT	0.9978	0.9964	0.9971	0.9971	0.9974	0.9979
MPA	0.9962	0.9945	0.9954	0.9954	0.9957	0.9963
Proposed	0.9984	0.9969	0.9981	0.9977	0.9979	0.9987

The results of the MAE measure are shown in **[Table-2].** It is observed that the proposed method introduced the least error for five of the six datasets. The results of the PSNR measure are shown in **[Table-3]**. It is apparent from Table 3 that the PSNR value of each and every dataset is superior for the proposed method, indicating a higher image quality. The results of the SSIM measure are shown in **[Table-4]**. Table 4 clearly shows that the SSIM value of every dataset is closest to 1, compared to the other five methods, indicating the maximum similarity to the original image.



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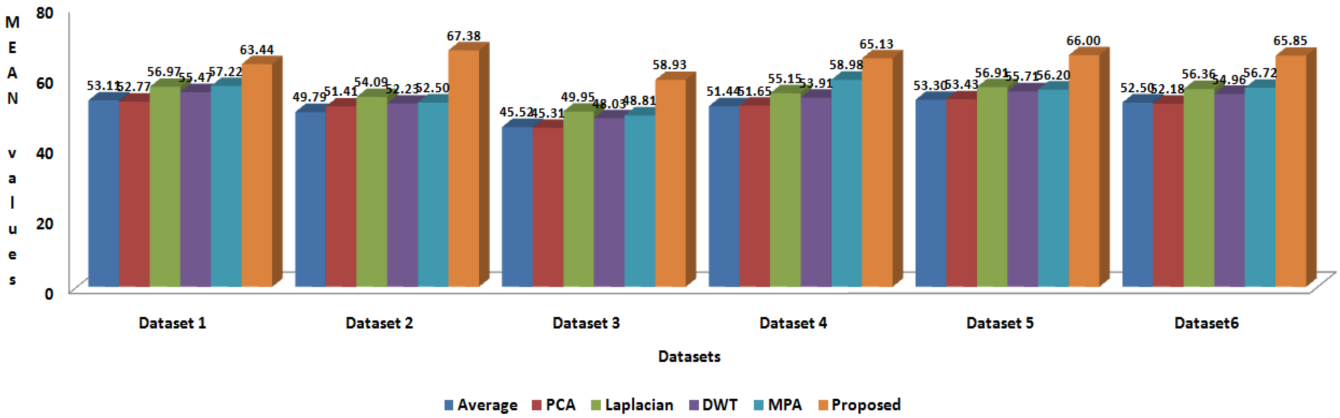

Fig: 5. Comparative analysis of MEAN

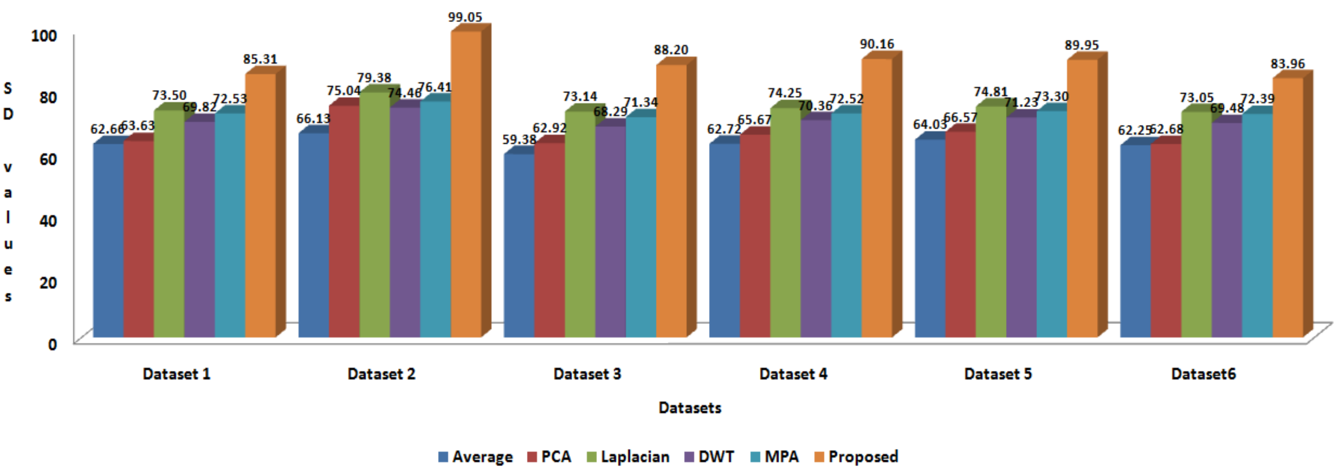

Fig: 6. Comparative analysis of SD

The UIQI values in **Figure 4** show that the results of the proposed method for every dataset is closest to 1, compared to others, thus indicating the maximum similarity.

The results in **Figure 5** show that the mean value for the proposed method is more than the other approaches, signifying more texture information on the resultant image. The impressive results are also visible in **Figure-6**, which shows the values for the standard deviation measure.

CONCLUSION

In this paper, image fusion using block based intuitionistic fuzzy sets has been proposed. Since, the entropy provides texture information of an image, the technique of block comparison with the entropy adopted in the paper

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as well as the adaptive calculation of the necessary parameter for the process sums up its novelty. The experimental results show that proposed method provides better visualization than average method, PCA method, laplacian method, DWT method and MPA method. In addition, proposed method confers better result compared to the other existing methods for both the objective and quantitative measures. Furthermore, the fused image obtained from proposed method has been found to be more informative and thereby can be used for efficient disease diagnostics.

CONFLICT OF INTEREST

Authors declare no conflict of interest.

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ABOUT AUTHORS

Mr. Rajkumar Soundrapandiyan is currently working as Assistant Professor (Senior) in School of Computing Science and Engineering, VIT University, Tamil Nadu, India. He received his BE in Computer Science and Engineering and ME in Computer Science and Engineering from Anna University, Chennai, India in 2008 and 2010 respectively. He is pursuing his PhD at VIT University, Vellore, India. He has published more than ten research papers in reputed international conferences and journals. He is a life member of CSI. His research interest includes digital image processing, computer vision, object detection and target recognition.

Mr. Rishin Haldar is currently working as Assistant Professor (Senior) in School of Computing Science and Engineering, VIT University, Tamil Nadu, India. He received his BE in Computer Science and Engineering from Karnatak University, Dharwad and MS in Computer Science from George Mason University, Fairfax, USA. He is a life member of CSI. His research interests include artificial intelligence, soft computing, bioinformatics and semantic web.

Swarnalatha Purushotham is an Associate Professor, in the School of Computer Science and Engineering, VIT University, at Vellore, India. She pursued her Ph.D degree in Image Processing and Intelligent Systems. She has published more than 50 papers in International Journals/International Conference Proceedings/National Conferences. She is having 14+ years of teaching experiences. She is a member of IACSIT, CSI, ACM, IACSIT, IEEE (WIE), ACEEE. She is an Editorial board member/reviewer of International/ National Journals and Conferences. Her current research interest includes Image Processing, Remote Sensing, Artificial Intelligence and Software Engineering.

Mr. Arvind Pillai is pursuing his B.Tech in Computer Science and Engineering in VIT University, Tamil Nadu, India. His research interest includes digital image processing, computer vision and object detection