Quantitative Analysis of various Image Fusion techniques based on various metrics using different Multimodality Medical Images

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Abstract- **Image Fusion is the process of combining two or more input images to obtain a resultant image which is rich in relevant information as compared to the original input image. The fusion technique finds its application in many areas: Robot Vision, Satellite Imaging, Medical Imaging, Remote Sensing and Defense imaging. In that Medical Imaging being the prominent ones. For efficient diseases detection and treatment, images from different modalities are combined using fusion techniques. This paper describes different techniques for fusion of multimodality images and the resultant images are analyzed using different quantitative measure. Initially, three different pairs of image are taken as input: Magnetic Resonance Imaging (MRI T2) and Computed Tomography (CT), Magnetic Resonance Imaging (MRI FLAIR) and Computed Tomography (CT), Magnetic Resonance Imaging (MRI T2) and Single-photon emission computed tomography (SPECT). Each pairs of images are fused together using fusion techniques namely Redundancy Discrete Wavelet Transform (RDWT), Mamdani type minimum-sum-mean-of-maximum (MIM-SUM-MOM), Contourlet Transform (CONTRA) and Multiple Pulse Coupled Neural Network (MPCNN). The resultant is analyzed using quantitative metrics such as Entropy (EN), Standard Deviation (SD), and Mutual Information (MI). From the experimental results it is observed that MIM-SUM-MOM is efficient in providing better quality of images which is inferred from the values of EN. CONTRA gives better contrast as compare to other techniques which can be observed from the values of SD and also provides better retention of information from both the input images as displayed by the MI metric values.**

Keywords—Image Fusion; Medical Image Analysis; Multimodality images; Redundancy Discrete Wavelet Transform; Mamdani Type MIM-SUM-MOM; Contourlet Transform; Multiple Pulse Coupled Neural Network;

I. INTRODUCTION

Medical image from single modality provide information only from one perspective. For example, CT (Computed Tomography) helps image bodily structure depending upon the ability of the various body parts to block X-rays, MRI-T2 and MRI-FLAIR provides pictures of the organs and structures inside the body, SPECT helps in showing how blood flows through tissue, organs and so on. In real world, single modality medical image disease detection is quite complex. For efficient disease detection doctors need information from more than one modality. Medical Image Fusion is the technique of merging images belonging to different modality into a single resultant image to improve the capability and the reliability of the image as compared to the original image, thus providing better disease detection.

The evolution of image fusion started off by fusing simple image directly on the source images. The technique had the drawback that the fusion image produced had reduced contrast information. Thus came the era of pyramid decomposition based fusion. The principle was to take pyramid transforms on source images create a pyramid transformed fused image and then take its inverse [10]. Images fused using pyramid transform provided better contrast changes sensitive to the human eye and better localizations. Discrete Wavelet Transforms can be seen as a case of pyramid transforms but with better theoretical support [8]. The drawback of Pyramid Transform and DWT is that they suffered from shift variance [2]. To overcome these limitations in this paper are discussed RDWT, MIM-SUM-MOM, CONTRA and MPCNN.

Redundancy Discrete Wavelet Transform (RDWT) preserves both edge and component information. It also helps reduce shift variance in the fused image [1]. Mamdani type MIM-SUM-MOM provides better texture feature in the fused image and also enhance the features of both images. CONTRA is region based technique providing clear edge information. MPCNN is more computationally efficient.

The performance of the fusion techniques is evaluated based on different quantitative metrics such as Entropy (EN), Standard Deviation (SD) and Mutual Information (MI).

The remaining sections of this paper are organized as follows. In Section II, the system design is briefly reviewed; section-III describes experimental results and evaluates the performance of the fusion techniques based on the quantitative metrics. Conclusion and future work are summarized at the end.

II. SYSTEM DESIGN

In this system, initially three different pairs of images are taken as input namely: MRI-T2 and CT, MRI-FLAIR and CT, MRI-T2 and SPECT. Then each pair of registered input images belonging to different modalities is fused using fusion techniques. Finally, fused image information is analyzed with the help of quantitative metrics. An overall system structure is shown in Fig. 1.

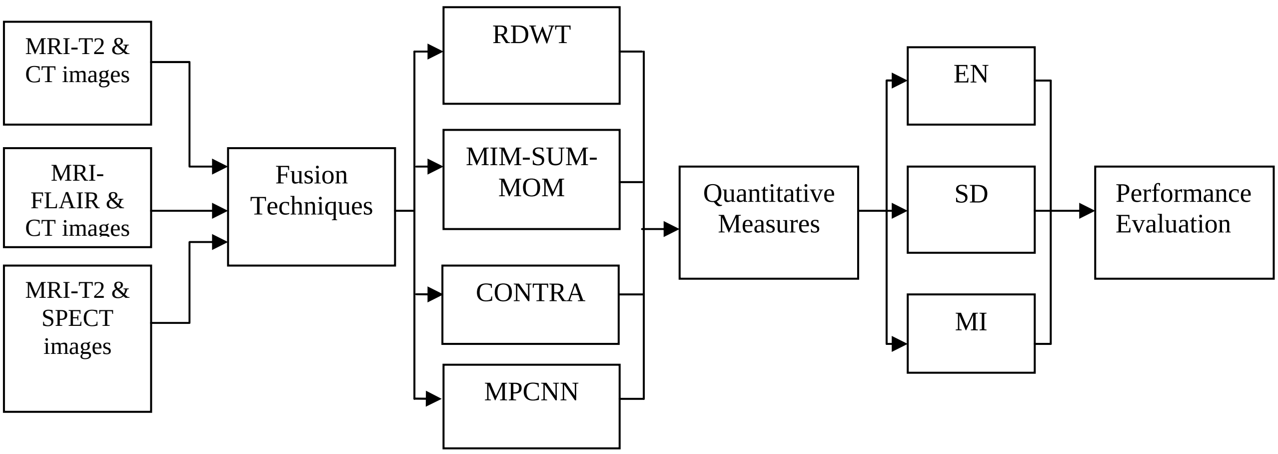

Figure 1. An Overall System Structure

A. Redundancy Discrete Wavelet Transform

RDWT is a pixel based fusion techniques. This is implemented in three steps process. In the first step two images of different modality (eg. MRI-T2 and CT, MRI-FLAIR and CT, MRI-T2 and SPECT) are taken as input. They are decomposed into four subbands each (LL, LH, HL, HH band respectively) using Haar Transform. In the second step, the coefficients of the LL subband are averaged to get the approximate band of the fused image and the remaining three subbands coefficients are also fused using entropy. The three high subbands namely (LH, HL, HH) is further divided into blocks of 3*3 and the entropy of each block is calculated. If entropy of block from first image is greater, then the block from first image is chosen as output else the block from the second block is chosen. Thus the LH, HL, HH subbands of the fused images are calculated [11].Finally, the inverse discrete wavelet transform is applied to the fused coefficients to reconstruct the resultant fused image [9]. The block diagram of the RDWT is shown in Fig. 2. The details of the step as follows:

1) Decomposition: In this step two different modality registered medial images (CT namely (A) and MRI-T2 namely (B)) are consider as input. These images are decomposed into one level using haar wavelet transform. It forms four subbands are LL (A_{LL} , B_{LL}), LH (A_{LH} , B_{LH}), HL (A_{HL} , B_{HL}), HH (A_{HH} , B_{HH}) respectively.

2) Fusion rules:

a) Lowpass subband fusion: Here the decomposed LL (A_{LL} , B_{LL}) parts fused using average methods. The fusion rule of average method is defined as:

$$AB_{LL}^{F} = mean(A_{LL}, B_{LL}) \tag{1}$$

b) Highpass subband fusion: The highpass subbands are fused with entropy method. The entropy method fuse the high subbands in the form of block wise. The entropy calculation defined as:

$$e_{jk}^{i} = \ln\sqrt{\left(\mu_{jk}^{i} - \sum_{x,y=1}^{3,3} AB_{jk}^{i}(x,y)/\sigma_{jk}^{i}\right)^{2} / m^{2}} \tag{2}$$

where j=(LH, HL, HH) denotes the subbands, k represents the block number, m=3 is size of each block and i = (1,2) is used to differentiate the two input images A and B. μ^i_{jk} and σ^i_{jk} are the man and standard deviation of the each DWT coefficients. Using the entropy values fused image AB_{LH}^F, AB_{HL}^F and AB_{HH}^F are calculated. The fused image block is AB_{jk}^F derived from Eq. 3. (i.e) A is selected if the entropy value of the detailed block of A image is greater than the detailed block of B image, otherwise derived from B.

$$AB_{jk}^F = \begin{Bmatrix} AB_1^F, if e_{jk}^1 > e_{jk}^2 \\ AB_2^F, otherwise \end{Bmatrix} \quad (3)$$

3) Reconstruction of fusion image: Finally, inverse DWT applied into fused coefficient to derive the original fused image as shown in Eq. 4.

$$AB^F = IDWT\,(AB_{LL}^F, AB_{LH}^F, AB_{HL}^F, AB_{HH}^F) \quad (4)$$

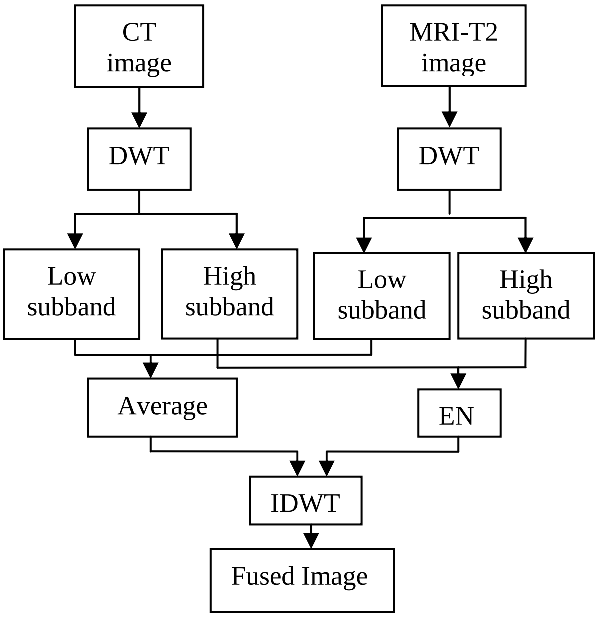

Figure 2. Block diagram of Redundancy Discrete Wavelet Transform

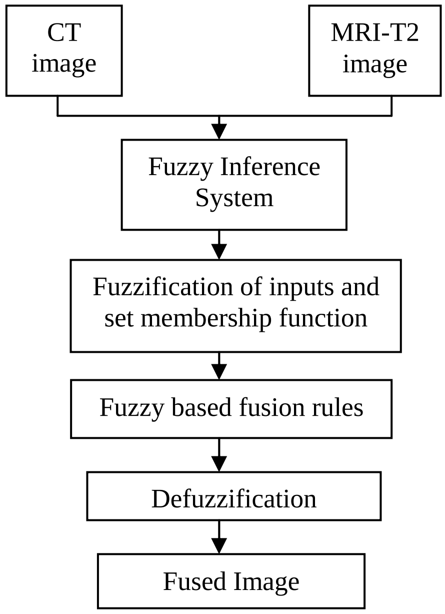

Figure 3. Block diagram of mamdani type MIN-SUM-MOM

B. Mamdani type MIN-SUM-MUM

Mamdani type minimum sum mean of maximum is another pixel based fusion technique. It consists of three steps. In first step, two registered images are taken as input. These input images are classified based on their gray levels (0-255) into fuzzy sets. To make the fuzzy sets we define the membership function using five linguistic variables such as VS - very small, S - small, M - medium, L - large, VL – very large. Here membership function is triangular used). In second step, twenty five different fuzzy rules (of the form “IF-THEN”) comprising the fuzzy inference system are defined [1].Using these fuzzy rules and the membership function the images are fused [12]. Finally, the fused image is constructed by defuzzification of the output gray level values pixel by pixel [3]. The block diagram of the mamdani type MIN-SUM-MOM is shown in Fig. 3. The information of three steps as follow as:

1) Fuzzification of inputs and developing membership function: The registered two different modality medical images are taken as input. These input images are fuzzed with their gray levels (0-255). To fuzzify input used five linguistic variables and triangular membership functions. The linguistic variables and its intensity values are VS - very small {0}, S – small {63}, M – medium {128}, L – large {191}, VL – very large {255}. The triangular membership function and its fuzzy sets shown in Fig. 4.

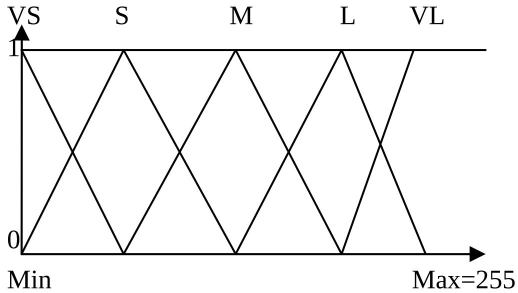

Figure 4. Triangular membership functions and its fuzzy sets

W2

		VS	S	M	L	VL
	VS	VS	S	M	L	VL
	S	S	S	M	L	VL
W1	M	M	M	M	L	VL
	L	L	L	L	L	VL
	VL	VL	VL	VL	VL	VL

Figure 5. Fuzzy rule based matrix

2) Fusion rules: In fusion rule, the rules are defined in the form of “IF-THEN”. These rules are designed in the form of combination of different modality (e.g. CT and MRI-T2) images defined as

$$\beta(t) = \max\{W1, W2\} = \{(M, L \rightarrow L\} \tag{5}$$

where W1 and W2 represent pixel gray level values of CT and MRI-T2 images respectively. The meaning of equation (5) that if W1is medium gray level and W2 is large gray level then output is large gray level. Likewise there are 25 possible combinations are available. These possible combinations are represented by a 5 X 5 matrix as shown in Fig. 5.

3) *Defuzzification:* To get the gray level of the image defuzzification operations used. It is defined as

$$\alpha_F(t) = \{t \in T \mid \beta(t) = \sup_{t \in T} \beta(t)\} \tag{6}$$

where $\alpha_F(t)$ is a set whose element is higher value β(t) as t belongs to T.

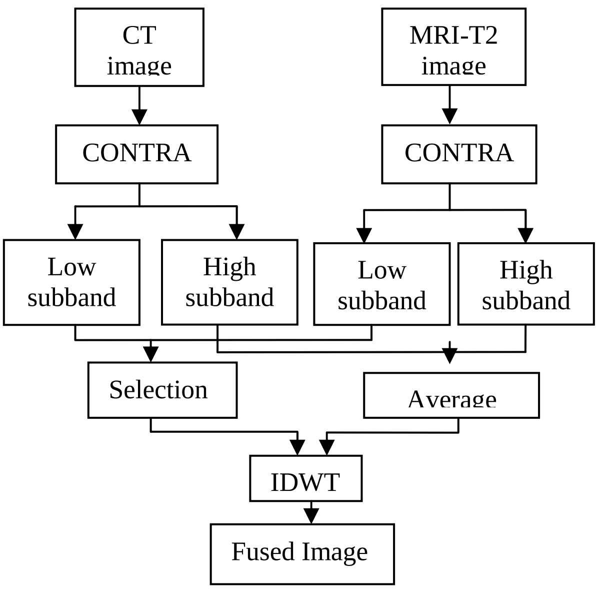

Figure. 6. Block diagram of Contourlet Transform

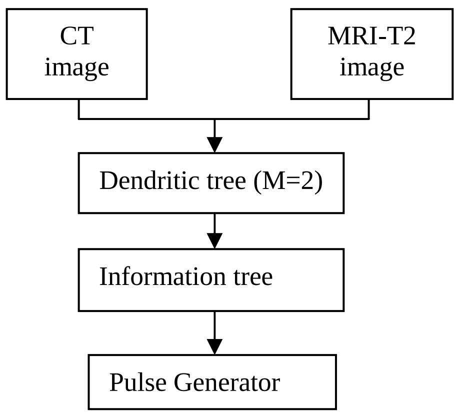

Figure. 7. Block diagram of MPCNN

C. Contourlet Transform

Contourlet Transform is a region based transform that takes place in three phases (decomposition, fusion rules and reconstruction) [7]. In the decomposition phase the input images are passed through a double filter bank scheme to efficiently decompose the images. The scheme consists of two filters namely a Laplacian Pyramid to record edge information and a directional bank filter to capture discontinuity information. In the fusion rules phase, the lowpass subband coefficients are fused using either of the two fusion rules selection or averaging. This rule is selected based on the saliency factor. As for the highpass subbands coefficients only selection combination rule is used. In the reconstruction phases the image reconstruction is done using inverse Contourlet Transform to obtain the desired fused image [11]. The block diagram of CONTRA is exposed in Fig. 6. The detail explanation of phases as follow as:

1) Decomposition: In this stage, the registered two input images (A, B) are decomposed (LL, LH, HL, HH) with efficient double filter bank scheme such as Laplacian Pyramid (LP) and Directional Filter Bank (DFB). Laplacian pyramid used to derive the edge point. Directional filter bank is used to connect the discontinuities point in linear structure.

2) Fusion rules:

a) Lowpass subband fusion: The lowpass subband coefficients are approximation of the source images. To fuse lowpass subband (LL) many researchers used average methods. It has disadvantage of cannot get high quality of fused approximation subband. So, here local energy based combination of two distinct modes (selection mode, average mode) used to calculate the final fused coefficient.

First local energy E(x,y) is calculated by centering the current coefficient in the approximate subband LL [7]. Then the salience factor (M^{AB}_j) calculated to determine whether the selection mode or average mode used to fuse the approximation coefficient. Then the salient factor compared to a predefined threshold t. If salient factor greater than the threshold ($M^{AB}_j(x,y) > t$) on this condition, average mode applied. For condition $M^{AB}_j(x,y) <= t$ selection mode used.

b) Highpass subband fusion: The highpass subbands are fused using maximum selection method. The maximum selection is defined as

$$T^F_{i,j}(x,y) = \max(d^A_{i,j}(x,y) + d^B_{i,j}(x,y)) \tag{7}$$

where i (=LH, HL, HH) denotes the subbands, j is block number, $d_{i,j}$ is highpass subband block image and $T_{i,j}^F$ is highpass subband coefficient fused image.

3) Reconstruction of fusion image: To derive fused image from the fused lowpass subband coefficient and highpass subband coefficient applied inverse contourlet transform.

D. Multiple Pulse Coupled Neural Network

The MPCNN model consists of three phase's namely dendritic tree, information fusion and pulse generator [13]. In first phase, dendritic tree which captures the input in form of two stimulus: one external stimulus and the other from surrounding neurons. In our model m=2 i.e. two input images. In second phase, information fusion used to fuse the two images. In last phase, pulse generator which generates the output pulse [4]. The block diagram of MPCNN is shown in Fig. 7. The brief discussion about each phases as follow as:

1) Dendritic tree: The role of dendritic tree is receive the different M inputs but here used M=2 i.e there are two different modality of registered images consider as input. These inputs are capture from external stimulus, surrounding neurons and both stimuli taken into model at a similar time. The mathematical model of the input defined as:

$$H^M_{i,j}(n) = f^M(y[n-1]) + S^M_{i,j} \tag{8}$$

where S^M (M=1 , 2) are two input images, $f^M(.)$ is the feed function, H^M refers to the channel of M inputs and n represent the current iteration from 1 to N (N=20 total number of iteration used in implementation).

2) Information fusion: In this phase the received channel signals are combined together and internal activity of the neuron calculated as :

$$U_{i,j}[n] = \prod_{M=2}^{M}(1+\beta^M H^M_{i,j}[n]) + \sigma \tag{9}$$

where β^M is the weighting factor of the M^{th} channel. β range from 0 to 1. σ is a level factor. To derive fused image from $U_{i,j}[n]$ (internal neuron) linear function used.

3) Pulse generator: The pulse generator ($y_{i,j}[n]$) is used to find out firing the event from the current iteration by comparing internal neuron with dynamic threshold ($T_{i,j}[n]$) of the neuron is defined as:

$$y_{i,j}[n] = \begin{cases} 1, U_{i,j}[n] > T_{i,j}[n-1] \\ 0, else \end{cases} \tag{10}$$

$$T_{i,j}[n] = \exp(-\alpha_T)T_{i,j}[n-1] + V_T y_{i,j}[n] \qquad (11)$$

where V_T is a normalized constant and α_T is time constant respectively.

E. Metrics for Quantitative Analysis

Metrics helps in quantifying the results obtained. Qualitative and quantitative assessment of the fused images is carried out using the following metrics:

1) Entropy (EN): Entropy is often calculated to measure the information content of the image. A higher value of Entropy display better fusion results. The entropy of an image is calculated using the formulae:

$$EN = -\sum_{i=0}^{L-1} p_i \log_2 p_i \qquad (12)$$

where L is the maximum intensity value for a pixel in the image (in this case 255) and p_i is the normalized histogram frequency of the fused image [1].

2) Standard Deviation (SD): Standard Deviation is often used to measure the strength of the signal. A higher value of SD represents that the image has a high contrast and vice versa. The formulae to calculate SD is [1]:

$$\sigma = \sqrt{\frac{\sum_{j=1}^{M}\sum_{k=1}^{N}(x_{(j,k)} - m)^2}{MN}} \qquad (13)$$

where the size of image is M X N, $x_{(j,k)}$ represents the intensity value of the (j,k)th pixel and m is the mean of all intensity values of the image.

3) Mutual Information (MI): Mutual information of two registered I_1 and I_2 is given by

$$M(I_1, I_2) = EN(I_1) + EN(I_2) - EN(I_1, I_2) \qquad (14)$$

where EN represents the entropy of the corresponding images and $EN(I_1,I_2)$ represents the joint entropy of the two images. A higher value of $M(I_1,I_2)$ represents better fusion of the two images [5].

III. EXPERIMENTAL RESULTS

For experimental result of the fusion techniques are tested with thirteen different datasets. Each dataset consists of two different modality images of same patient. These datasets are grouped into three classes: Class 1 consists of dataset 1-6 where each dataset contains combination of CT and MRI-T2 images [1], Class 2 consists of dataset 7-12 which contains MRI-FLAIR and CT images, and finally MRI-T2 and SPECT images make up the dataset 13 classified as Class 3. All the images belong to the same patient. The dataset consists of images of size 256 x 256 and a gray level scale of 256 pixels.

Some of the input images and corresponding fused images are shown in Fig. 8 - 10. The resultant fused images are then analyzed using metrics mentioned in section II. The values of the metrics are tabulated in the Table I-III.

Class-1 | CT image | MRI image | RDWT | CONTRA | MIN-SUM-MOM | MPCNN

Dataset1

Dataset3

Dataset5

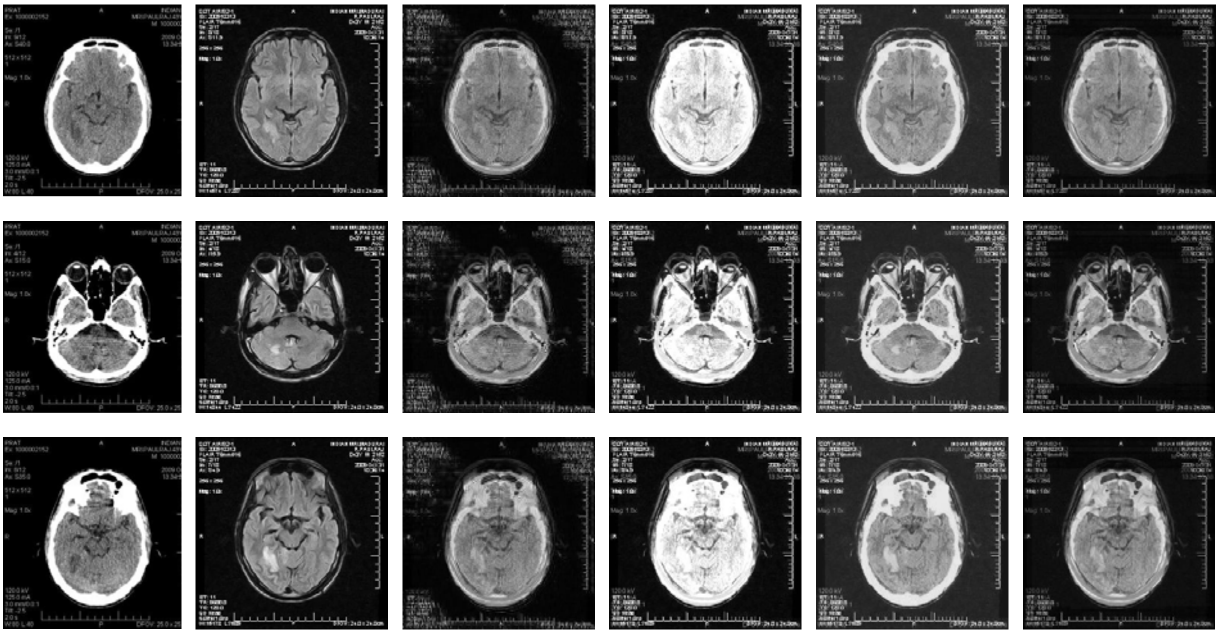

Figure. 8. Sample input and output images of Class-1

Class-2 | CT image | MRI image | RDWT | CONTRA | MIN-SUM-MOM | MPCNN

Dataset8

Dataset10

Dataset12

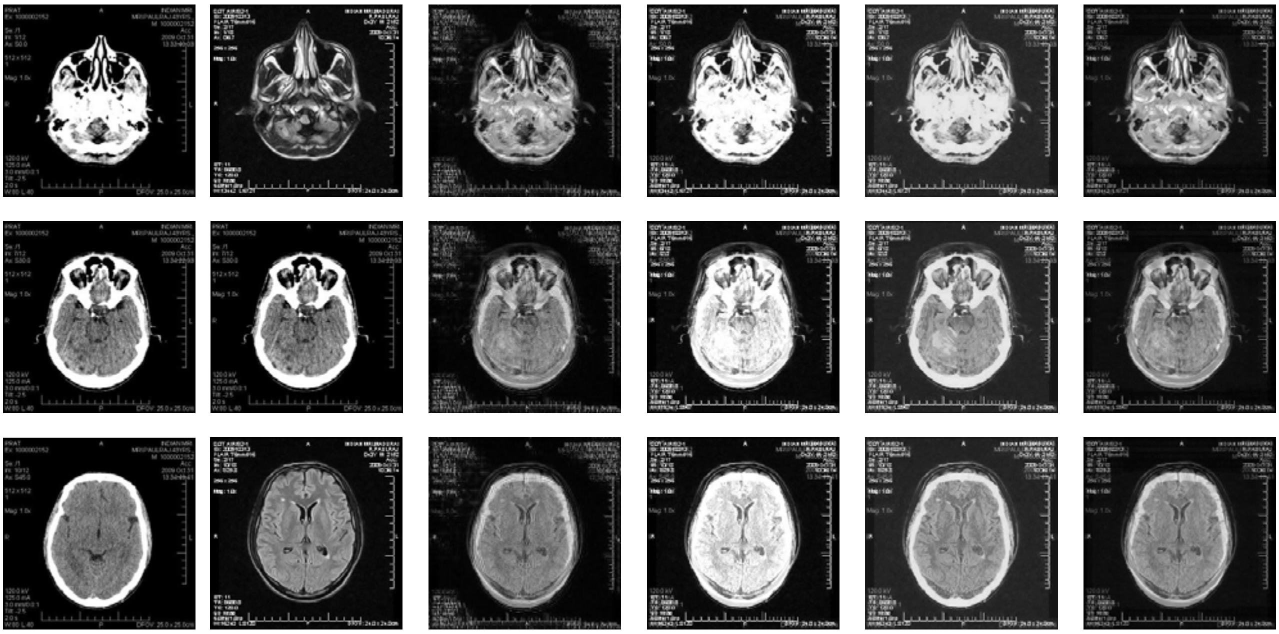

Figure. 9. Sample input and output images of Class-2

Class-3 | MRI image | SPECT image | RDWT | CONTRA | MIN-SUM-MOM | MPCNN

Dataset13

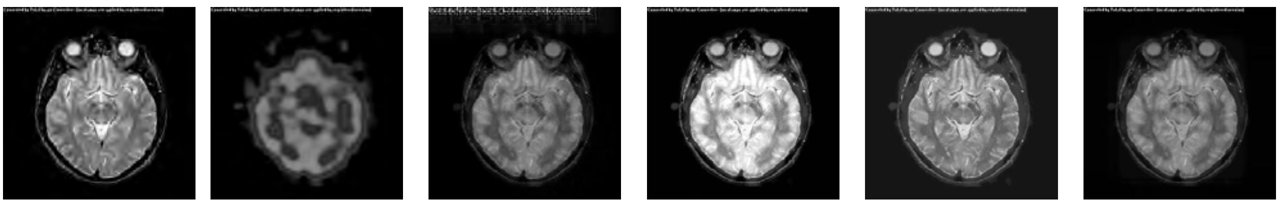

Figure. 10. Sample input and output images of Class-3

TABLE I. COMPARISON OF IMAGE FUSION ALGORITHM FOR CLASS 1

Metrics	Algorithms	Dataset1	Dataset2	Dataset3	Dataset4	Dataset5	Dataset6
EN	RDWT	6.6691	6.6574	6.5770	6.7225	6.7160	6.6288
	CONTRA	6.4650	6.2380	6.4040	6.4040	6.4080	6.4320
	MIN-SUM-MOM	6.8662	6.6725	6.7823	6.8820	6.8825	6.8329
	MPCNN	6.6730	6.7514	6.6613	6.7225	6.7451	6.6336
SD	RDWT	16.7796	17.7561	18.0479	14.9694	16.9170	17.4596
	CONTRA	17.0500	19.1900	18.0400	18.5800	18.0600	17.7000
	MIN-SUM-MOM	13.9765	15.4516	15.2871	14.6830	14.0568	14.4903
	MPCNN	14.8105	14.7092	14.8874	14.9694	14.6741	15.0164
MI	RDWT	6.0777	6.0050	6.0905	6.0518	6.0275	6.0861
	CONTRA	6.3280	6.3670	6.2700	6.2720	6.3060	6.3240
	MIN-SUM-MOM	6.0586	6.1234	6.0400	6.0012	6.0293	6.0649
	MPCNN	6.0989	6.0134	6.0840	6.0518	6.3060	6.1192

TABLE II. COMPARISON OF IMAGE FUSION ALGORITHM FOR CLASS 2

Metrics	Algorithms	Dataset7	Dataset8	Dataset9	Dataset10	Dataset11	Dataset12
EN	RDWT	6.6090	6.6574	6.5770	6.6675	6.7160	6.6288
	CONTRA	6.3495	6.2376	6.4038	6.4041	6.4083	6.4320
	MIN-SUM-MOM	6.7853	6.6725	6.7823	6.8820	6.8825	6.8329
	MPCNN	6.6223	6.7514	6.6613	6.7225	6.7451	6.6336
SD	RDWT	18.4088	17.7561	18.0479	17.5170	16.9127	17.4596
	CONTRA	19.2075	19.1856	18.0400	18.5830	18.0644	17.7000
	MIN-SUM-MOM	15.7172	15.4516	15.2871	14.6830	14.0568	14.4903
	MPCNN	15.9565	14.7092	14.8874	14.9694	14.6741	15.0164
MI	RDWT	6.0695	6.0050	6.0905	6.0566	6.0275	6.0861
	CONTRA	6.3135	6.3674	6.2704	6.2718	6.3060	6.3240
	MIN-SUM-MOM	6.0622	6.1234	6.0400	6.0012	6.0293	6.0649
	MPCNN	6.1096	6.0134	6.0840	6.0518	6.3060	6.1192

TABLE III. COMPARISON OF IMAGE FUSION ALGORITHM FOR CLASS 3

Metrics	Algorithms	Dataset13
EN	RDWT	5.3890
	CONTRA	5.0338
	MIN-SUM-MOM	4.8691
	MPCNN	5.6749
SD	RDWT	43.7131
	CONTRA	57.4866
	MIN-SUM-MOM	59.2226
	MPCNN	33.4402
MI	RDWT	5.0123
	CONTRA	5.7300
	MIN-SUM-MOM	5.0054
	MPCNN	5.4732

IV. CONCLUSION AND FUTURE WORK

In this paper we have analyzed four image fusion techniques namely RDWT, MIN-SUM-MOM, Contourlet Transform and MPCNN using different quantitative metrics. As a result of the experiment it is observed that Mamdani type MIM-SUM-MOM provides better quality of image as can be verified by the Entropy metric. The Contourlet Transform provides better contrast information as derived from the values of Standard Deviation and also Contourlet Transform provides the better retention of information from both the source images in the fused image as verified by the higher values of Mutual Information. The above information is verified from the Table I-III and same justified with the visualization of the fused image also.

The fusion techniques find many applications in real life. It reduces the storage space required, since single fused image is stored instead of multiple images. Efficient retrieval is possible, since less number of images (fused) has been stored in the knowledge base. It also helps prevent data replication, i.e. storing the same patient data for each modality is avoided.

In future we hope to develop better fusion techniques that can be used to fuse color images and thus help doctors diagnose disease efficiently.

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