Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 167 (2020) 413–422

Procedia Computer Science

www.elsevier.com/locate/procedia

International Conference on Computational Intelligence and Data Science (ICCIDS 2019)

Comparative Analysis of Various Image Fusion Techniques for Brain Magnetic Resonance Images

Anish Vijan[a] , Parth Dubey[a], Shruti Jain[a]*

[a]Jaypee University of Information Technology, Solan, Himachal Pradesh, India

Abstract

Medical diagnosis of any human health problems can be accurately investigated by fusing the images. In image fusion, data is combined from different pictures that enable us large information in one picture only. Image Fusion plays an important role in medical imaging applications by helping the radiologists for finding the abnormality in CT and MR brain images. Multimodality (MM) is one of the fusion techniques. In MM, fusion of different modalities like Computed Tomography (CT), Positron Emission Tomography (PET) and Magnetic Resonance Imaging (MRI) scans is performed. Every modality is having various characteristics with various types of functional information and complementary anatomical. The commonly scanning techniques used for finding brain strokes and tumor are MRI and CT. In this paper different slices; T1 weighted (T1), T1 contrast enhancing (T1ce), T2weighted (T2), and Fluid Attenuated Inversion Recovery (Flair) of brain MR images of the same patient are fused for diagnosing brain pathology and abnormality. Multiple experiments were conducted by using Discrete Wavelet transform (DWT), Laplacian Pyramid Transform technique and Principle Component Analysis (PCA) fusion techniques. The comparative analysis has been performed on different fused images which have more information content. The performance measure considered here includes peak signal to noise ratio, mean square error, and signal to noise ratio. Different experiments were performed and the fusion of Flair and T2 slices of brain MR images yields better results in terms of SNR and PSNR using different fusion techniques.

*Keywords:*Magnetic Resonance Images, Image fusion, Discrete Wavelet transform, Principal Component Analysis, Pyramidal Fusion

* Corresponding author. Shruti Jain, Tel.:+91-9318039036 .
E-mail address: jain.shruti15@gmail.com

10.1016/j.procs.2020.03.250

1. Introduction

Magnetic Resonance (MR) imaging has turned out to be set up for research device in numerous zones of medical areas [1, 2]. MR images are widely used in tumor diagnosis due to its excellent soft tissue discrimination and high resolution [3, 4]. Notwithstanding T1 weighted (T1), T1 contrast enhancing (T1ce), T2weighted (T2), and Fluid attenuated Inversion Recovery (Flair) imaging, many particular MR strategies have been intended to extricate metabolic or biophysical data. Dynamic difference material– upgraded imaging and as of late proton spectroscopy assumes a significant job in oncologic imaging [5, 6, 7]. When these methods are consolidated, it can help the doctor in finding or observing a routine treatment. One of the significant points of interest of the diverse sorts of MR imaging is the capacity of the administrator to control picture stand out from an assortment of selectable parameters that influence the sort and nature of the data provided [5].

Individuals have an extraordinary vision senses. In image fusion, data is combined from different pictures that enable us large information in one picture only [8, 9, 10]. The human mind is an incredible case for an information fusion framework. The mind will consolidate the visuals and discover the subtleties covered up in a solitary view. Numerous perspectives will improve the choices by utilizing diverse cameras [11, 12]. The fused data helps in shaping new pictures, and it contains all the imperative highlights of the specific picture [13, 14]. There is tremendous headway in the picture innovation, multisensory sources which picked up their significance in the assortment of fields. Image fusion can occur in medicinal imaging, remote detecting, machine vision and the barrier employments [15]. Image fusion enables us to lessen the measure of the picture without overlooking the vital highlights. Different sorts of the picture fusion are Multi transient combination, Multi-center combination, Multimodal combination [16], Multispectral Fusion [17, 18], Multiview combination.

Authors in [19], describes the multi-sensor image fusion technique. They calculated fusion via programmed assessment and expand its effectiveness. Authors in [20], gave a top-notch data in picture combination utilized in satellites by using Intensity Modulation, Smoothing Filter-based Multiplication, Brovey High Pass Filter (HPF), Intensity Hue Saturation (IHS) and Principle Component Analysis (PCA) for the picture combination. The results outperforms with HPF and Smoothing Filter-based Modulation. Zhang and Wang [21], motivated for separating objects goals satellite pictures. This gave us characterization, including division, picture combination for extracting critical data. Lobby [22], exhibited the multisensor information combination which helps in deciding the usefulness in safeguard and different applications. Pajares and Cruz [23], detailed how to combine information from different pictures of the same site dependent on wavelet disintegration. The pictures can be fused with the same or distinctive goals level. Authors contemplated that the wavelet-based methods are practiced with the near results like built up systems. Yang *et al.* [24], referenced picture combination philosophy upheld the work by settling on new procedures for decision coefficients.

Multi sensor information fusion has end up an area which needs greater standard formal solutions to a number of utility instances. Numerous conditions in photo processing require both high spatial and excessive spectral information in single photo. That is important in faraway sensing. But, the contraptions aren't capable of providing such statistics both by design and because of observational constraints. Future is full of advanced technologies. There have been researches going in the field of medical, like robots are made that can help doctors in surgeries and diagnosis by seeing 3D images of various organs and identify diseases that doctors cannot see normally. Israel is working on project "Rcadia" which is a startup that can help doctors whether the surgery is required or not and can detect fatty hard plaques in arteries. One viable solution for this is fusion. Combining information together can provide a better understanding of the images. In this paper author discusses the various fusion techniques consisting discrete wavelet transform (DWT), Laplacian Pyramidal and PCA to fuse different slices of Brain MR Images. By fusing the different slices, extraction of the region of interest (ROI) is easier because fusion gives better results. Performance parameters were evaluated for the fused images which show remarkable performance than the unfused images. The techniques used in this paper show the incredible performance in comparison with other state of art technique.

Rest of this paper is organized as follows. Section 2 explains the methodology of image fusion. Experimentation results of different fused images of various slices of brain MR images are depicted and discussed in section 3 and the conclusion of this paper along with its future scope is drawn in section 4.

2. Proposed Methodology of Image Fusion : This paper presents the different fundamental steps applied for fusing Medical images [3, 4]. The detailed steps involved in fusing brain MR images are shown in Figure 1. It consists of four important steps namely Preprocessing, Image registration, Image fusion, and Fusion performance evaluation. These steps helped in improving the quality and advancement in image fusion. All the simulations were carried out on MATLAB 2018a with 8GB RAM. There are different slices (T1, T1ce, T2, and Flair) of brain MR images. The tumor present in the brain can be segmented and classified [6, 7] where Flair slice is mostly used for segmentation.

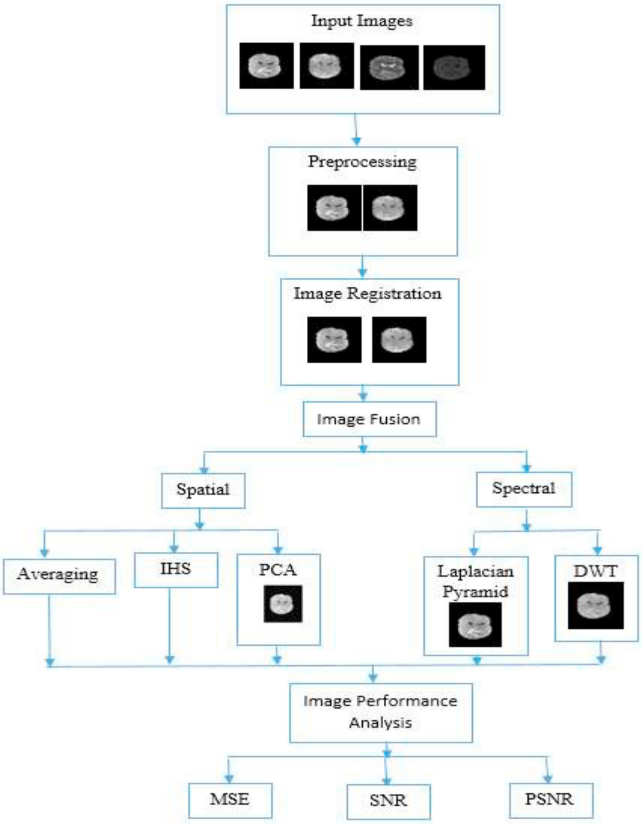


Fig 1: Methodology Adopted for Fusing Different Slices of Brain

2.1 *Pre-processing*: In the pre-processing stage, noise or artifacts recognized in the image are completely removed. Pre-processing should be done so as to get good quality fusion that cannot be accessible in most fusion methods[6, 7]. Later, image resampling is recognized to develop different constituent dimensions to give fine data.

2.2 *Image registration*: During this method, one amongst the major pictures are achieved as a reference image. Then geometric alteration is applied on the remaining images to synchronize them with the reference image. Once the registration method is done, the images are often more analyzed for feature extraction. The registration is usually done in the manual and automatic method. Many ways are adopted within image registration [25, 26].

2.3 *Image Fusion*: Fusion method is performed at three levels namely component, feature, and call. Component level fusion is used on an input image. Feature level fusion is not preferred on the extracted images. At the call level, fusion is used on a probabilistic call data of native call manufacturers. These call manufacturers are processed from the extracted options. Component level fusion schemes are referred for fusion compared to different level approach as a result of their potency and easy use. During this paper, our preference is on component level fusion schemes. The component level image fusion is mostly divided into two parts namely spatial domain fusion and spectral domain fusion [27- 30]. Spatial domain techniques change the image pixels. IHS, PCA and Averaging are the different types of spatial methods while pyramids (Gaussian, Laplacian, gradient, morphological and ratio of a low pass) and wavelets (DWT, Stationary wavelet transforms, Multiwavelet transforms) are the spectral techniques. In this paper authors are using DWT, PCA and Laplacian pyramid technique for fusing the images. The advantages and disadvantages of the three techniques are tabulated in Table 1.

Table 1 : Advantages and disadvantages of DWT , PCA and Laplacian Pyramid

S.No.	Fusion Techniques	Domain	Advantages	Disadvantages
1	DWT	Frequency	Better SNR	Poor Image Resolution
2	Laplacian Pyramid	Frequency	Good Image quality	Large processing Time
3	PCA	Time	High quality and fast processing	Color deformation and degradation

2.3.1 **DWT:** DWT model tells us resolution in the frequency domain; however it's not right for non stationary signals whose frequency response change in time [31]. DWT consists of three steps: decomposition of the pictures, combining the model coefficients and reconstruction of combined model coefficients. The DWT, supported time-scale illustration, uses degree sufficient to multi-resolution sub-band decay of assorted signals [28-30]. It had become the main tool for the signal processing and finds various resources in different areas like pattern recognition, audio compression, texture discrimination, etc. Two dimensional (2D) DWT and 2D Inverse DWT have a sufficient role in various images to writing an application. Our fundamental target is to combine distinctive cuts of MR pictures. Algorithm 1 explains the image fusion using DWT fusing technique.

$$F(x,y) = \frac{1}{\sqrt{a}} f(x,y)\psi\left(\frac{x-m}{a}, \frac{y-m}{b}\right) dxdy \tag{1}$$

Algorithm 1: Image fusion using DWT fusing Technique

Input: High-frequency bands fusion of *X* and *Y* images
Output: Fused image Z

START
Step 1: Reduce LH, HL, HH bands of image X and Y.
Step 2: Compute the spatial frequency of every matrix of image.
Step 3: Measure frequencies of respective X_{LL} and Y_{LL} and make the i^{th} block . Z of the combined image is expressed by Eq. (2).

$$Z_{LL}(m,n) = \begin{Bmatrix} X_{LL}(m,n) SF_{LL}^{x} > SF_{LL}^{Y} + TH \\ Y_{LL}(m,n) SF_{LL}^{x} < SF_{LL}^{Y} - TH \\ \left(\frac{X_{LL}(m,n)+Y_{LL}(m,n)}{2}\right) Otherwise \end{Bmatrix} \tag{2}$$

TH is user-defined threshold value.

END

There are two types of band fusion: Low-Frequency Band Fusion (BF) and High-Frequency BF.

a) *Low-Frequency BF:* Since the low bands of frequency is the first picture at a particular level, which are smooth and sub inspected adaptation. In light of the previous examination of the qualities, here for the low band, a most extreme choice (MS) combination guideline to create a solitary arrangement of coefficients is utilized. The plan chooses the biggest supreme wavelet coefficient at every area from the information pictures as the coefficient at that area in the intertwined picture. The fused image at low level considering X and Y as two input images at position m, n is expressed by Eq. (3).

$$Z_{LL} = |\max(X_{LL}(m, n), \max(Y_{LL}(m, n)| \tag{3}$$

b) *High-frequency BF*: For the high band groups, since the reason for the picture combination necessitates that the combined picture must not remove any helpful data contained in the source pictures and adequately safeguard the information of pictures, for example, edges and surfaces. Spatial bands estimate the general activity level in a picture X, with dimension $X(m, n)$ at position (m, n) the spatial bands is characterized by Eq. (4)

$$SF = \sqrt{(RF)^2} + \sqrt{(CF)^2} \tag{4}$$

where RF is the row frequency expressed by Eq. (5) and CF is the Column frequency expressed by Eq. (6)

$$RF = \sqrt{\frac{1}{MN}\sum_{m=1}^{M}\sum_{n=2}^{N}[X(m,n) - X(m,n-1)]^2} \tag{5}$$

$$CF = \sqrt{\frac{1}{MN}\sum_{n=1}^{N}\sum_{m=2}^{M}[X(m,n) - X(m-1,n)]^2} \tag{6}$$

2.3.2 **Laplacian Pyramidal**: Every level of this pyramidal transformation tells us the difference between levels of the Gaussian and Pyramid [32].The Pyramids are easy to analyze, indeed pyramid filtering is faster than the filtering done through Fourier transforms. The data is also available in a format that is sufficient to use since the nodes in each level tell us the information that is localized in both space and spatial frequency. Substantial compression can be attained by pyramid encoding fused with quantization and entropy coding. Texture analysis can also be done increasingly and simultaneously at all scales. Fig 2 shows the flow graph for fusing the images while Algorithm 2 shows the different steps followed using Laplacian Pyramid techniques.

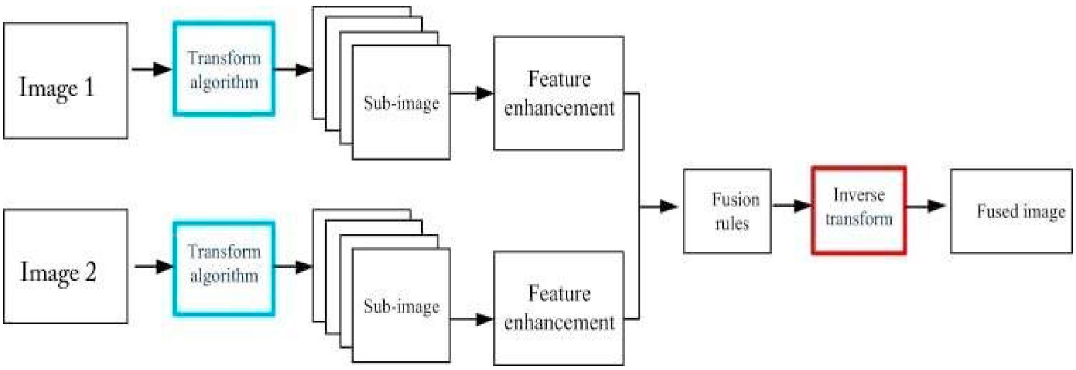


Fig 2: Flowgraph showing the fusion of two images using Laplacian Pyramidal technique

Algorithm 2: Image fusion using Laplacian Pyramidal fusing Technique

---

Input: High-frequency bands fusion of $L_{c1,k}$ and $L_{c2,k}$ images
Output: Fused image $L_{f,k}$

START

Step 1: The two input MR Images are converted into gray-scale images. The gray scale images are passed into the fusion algorithm as the base images of the input for the Laplacian Pyramids.

Step 2: The consecutive REDUCE operation is used to get the corresponding Laplacian pyramids generated for k levels with the zeroth level.

Step 3: Laplacian Pyramids are generated for the corresponding Gaussian pyramids. The Laplacian image is $L_k(i, j)$. As the Laplacian Pyramid has (k) levels the Gaussian pyramid will have ($k + 1$) levels.

Step 4.Firstly the Laplacian pyramid is generated at the output side. The Laplacian pixel values of the output of every Laplacian image is the value of pixel with its magnitude being the maximum of the two corresponding pixels in the two inputs at the same stage, i.e. for every k^{th} stage of the Laplacian pyramid eachpixel is expressed by Eq. (7)

$$L_{f,k}(i,j) = sign_k(i,j) * \max(|L_{c1,k}(i,j)|, |L_{c2,k}(i,j)| \tag{7}$$

$$sign_k(i,j) = \begin{cases} sgn\left(L_{c1,k}(i,j)\right), \left|L_{c1,k}(i,j)\right| > L_{c2,k}(i,j) \\ sgn\left(L_{c2,k}(i,j)\right), \left|L_{c1,k}(i,j)\right| < L_{c2,k}(i,j) \end{cases}$$

where $$sgn\left(L_{m,l}(i,j)\right) = \begin{cases} -1, L_{m,l}(i,j) > 0 \\ +1, L_{m,l}(i,j) < 0 \end{cases}$$

where L_k is the Laplacian Pyramid function at k^{th} level, $L_{c1,k}$and $L_{c2,k}$ Laplacian Image of the first Image and second Image respectively

END

2.3.3 **PCA:** PCA modifies between the MS groups into a new arrangement of not so relevant components. To use this methodology the main parts of the MS picture groups are taken. After this, the principal component that has the main data of the image is substituted by PAN image [33]. At last, the main component changes over the RGB groups of the multi-spectral image from the standard parts. The PCA uses the vector model to reduce the measure of large data sets which implies by not using the scientific projection; the image is reduced into a couple of factors (foremost parts). Fig 3 shows the flow graph for fusing images using PCA and the steps followed for PCA are represented in Algorithm 3.

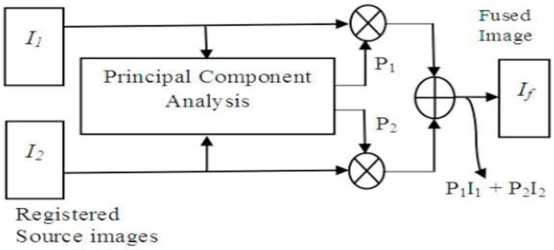


Fig 3: Flowgraph showing the fusion of two images using the PCA technique

Algorithm 3: Image Fusion using PCA Fusion Technique

Input: High-frequency bands fusion of input images $I_1(x, y)$ and $I_2(x, y)$
Output: Fused image $I_f(x, y)$

START

Step 1: Weighted average is used for the image fusion . Eigenvector is identified from the most astounding Eigenvalue of the covariance matrix of each source are predominantly used to get weights for the picture. It ascertains the best depiction of the data.

Step 2: The heading of the most extreme difference is utilized to register the first principle component. The second principle component is coordinated to be arranged in the subspace vertical of the first. Inside this subspace, this component focuses the sign of change. The third principle component is in the fluctuation heading in the subspace vertical to the initial two, etc.

Step 3: Two column vectors and their empirical values are subtracted of images $I_1(x, y)$ and $I_2(x, y)$. The resulting vector is n x 2, where the length of the image vector is n.

Step 4. Compute the eigenvector and eigen values for the subsequent vectors. The eigenvectors identified with the bigger eigen values are considered. The standardized parts P_1 and P_2 (aggregate of P_1 and P_2 equivalent to 1) are determined from the eigenvector.

The combined image using PCA is expressed by Eq. (8):

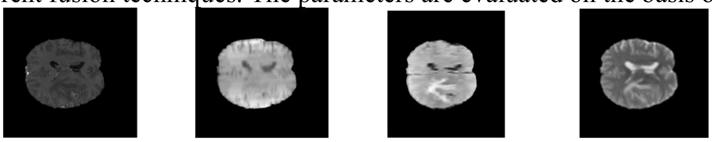
$$I_f(x, y) = P_1 I_1(x, y) + P_2 I_2(x, y) \tag{8}$$

END

2.4 *Performance Analysis*: During the fusion method, some important data of pictures are lost and visually data or artifacts are introduced during fusing of the image. Hence, fusion algorithms can be analyzed for higher performance. These performance analyses are examined by visual examination (qualitatively) or fusion metrics (quantitatively). The general necessities of an image combining process are that it should preserve all right and useful pattern information from the main images. At the same time it should not instigate artifacts that would interfere with subsequent analyses [6, 7]. Some image fusion performance parameters are Peak Signal to noise ratio (PSNR), Entropy (EN), Mean squared error (MSE), Signal to Noise Ratio (SNR) and Normalized Cross Correlation (NCC). In this paper, PSNR, MSE, and SNR performance evaluation techniques are used.

3. Results and Discussion

Algorithms and Applications give us a representative set of the recent advancements in research and development in the image fusion, explaining both spatial and spectral domain. In this paper, different slices of brain MRI are fused with the help of different fusion techniques. The parameters are evaluated on the basis of performance indices.



(a) (*b*) (c) (d)

Fig 4 : MR images with different slices(a) T1ce (b)T1 (c)Flair (d)T2

Information/image preprocessing could be a data preparing system that includes improving raw data into a clear arrangement. Genuine data is generally conflicting, deficient and ailing in beyond any doubt practices which are likely going to have few mistakes. Fig 4 shows the different slices of MR images. The different images revive the same format from the information taken from different devices. The aim of image registration is to give the input image into an arrangement with the base data by using an abstraction conversion to the input image. In this paper, authors have converted the image in 255 × 255 matrix. Signal Fusion techniques fuse received data from various sensors into a single composite image in an appropriate and proper manner. Different information is obtained by combining two different slices of the brain. Based on Algorithm 1, the results obtained using DWT technique for the fused slices are shown in Fig 5. Due to the constraint of the space, only four fused images are shown. The performance parameter was evaluated for individual slices and all the fused images are tabulated in Table 2.

Table 2: Performance analysis using DWT fusing technique

Images	**T1ce**	**T1**	**Flair**	**T2**	**T1ce + T1**	**T1ce + Flair**	**T1ce + T2**	**T1 + Flair**	**T1 + T2**	**Flair + T2**
MSE	123.91	124.17	121.77	123.22	**125.86**	126.98	126.76	128.07	129.31	127.27
SNR	11.2	11.46	21.26	15.11	10.84	10.84	10.84	11.11	11.11	**20.91**
PSNR	27.23	27.22	27.31	27.26	**27.17**	27.13	27.14	27.09	27.05	27.12

Table 2 depicts that fusing T2 slice and Flair results in highest SNR which can be further used for other applications.

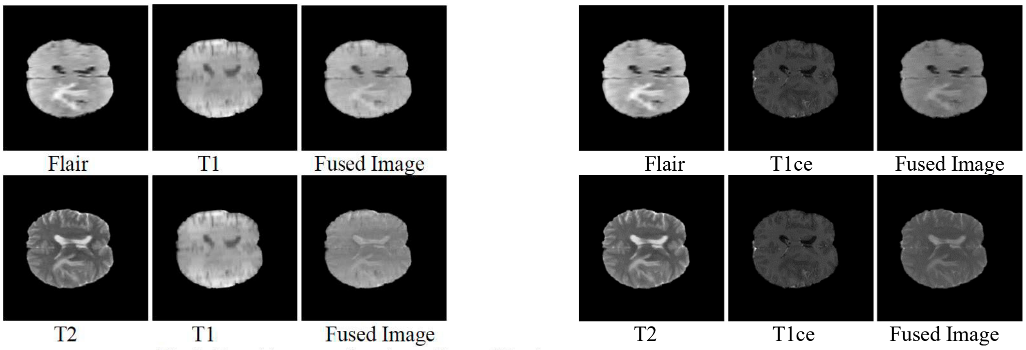


Fig 5: Fused images of various slices of Brain MR using DWT fusion technique

Based on Algorithm 2, the results obtained using Laplacian Pyramid technique for the fused slices is shown in Fig 6. The performance parameter was evaluated for individual slices and all the fused images are tabulated in Table 3.

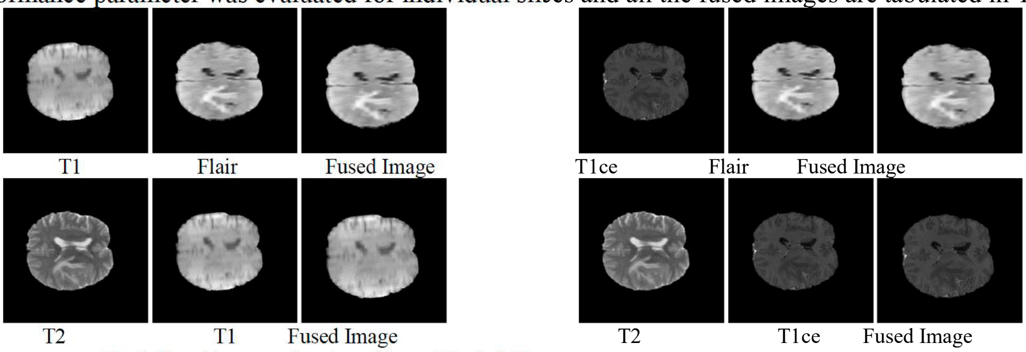


Fig 6: Fused images of various slices of Brain MR using Laplacian Pyramid fusion technique

Table 3: Performance analysis using Laplacian Pyramid

Images	**T1ce**	**T1**	**Flair**	**T2**	**T1ce + T1**	**T1ce + Flair**	**T1ce + T2**	**T1 + Flair**	**T1 + T2**	**Flair + T2**
MSE	123.91	124.17	121.77	123.22	123.67	124.35	**122.35**	124.1	123.63	125.51
SNR	11.2	11.46	21.26	15.11	10.01	13.12	11.24	12.99	12.39	**14.88**
PSNR	27.23	27.22	27.31	27.26	27.24	27.22	27.27	27.23	27.24	**27.29**

Table 3 depicts that fusing T2 slice and Flair results highest SNR and PSNR which can be further used for other applications like pattern recognition or image processing. Based on Algorithm 3, the results obtained using PCA technique for the fused slices are shown in Fig 7. The performance parameter was evaluated for individual slices and all the fused images are tabulated in Table 4.

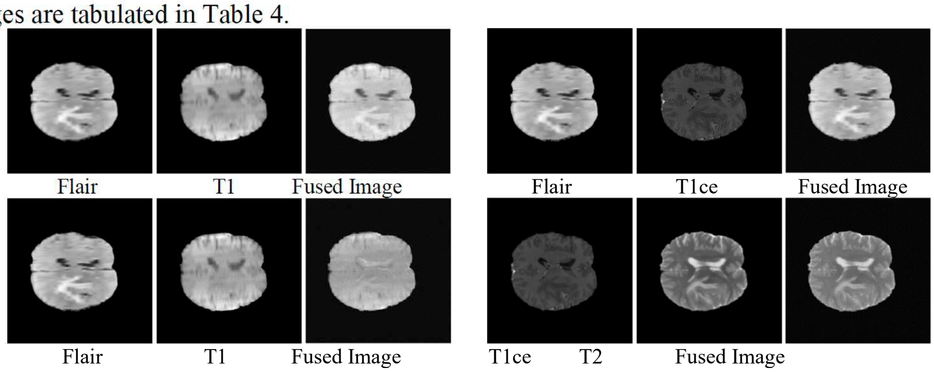


Fig 7: Fused images of various slices PCA fusion technique

Table 4: Performance analysis using PCA

Images	T1ce	T1	Flair	T2	T1ce + T1	T1ce + Flair	T1ce + T2	T1 + Flair	T1 + T2	Flair + T2
MSE	123.91	124.17	121.77	123.22	39.06	38.98	39.44	41.43	39.45	**32.36**
SNR	11.2	11.46	21.26	15.11	7.34	7.3	7.35	7.52	7.38	**7.67**
PSNR	27.23	27.22	27.31	27.26	32.23	32.29	32.23	31.99	32.2	**38.99**

There is a drastic change in the MSE of the combined image as compared to the Input Images. In PCA the limited components are taken and therefore only limited pixels are analyzed so lower values of MSE are calculated for the fused images in comparison with the normal image. From the results it is interpreted that the various quality analysis performed on different fusion techniques. The best results are obtained by fusing Flair and T2 slices of MR images of brain on the basis of SNR and PSNR. The fusion of T1 and T1ce for DWT and T1ce and T2 for Laplacian and T2 and Flair for PCA yields 125.86, 122.35 and 32.36 respectively in terms of MSE. MSE mainly depends on the image intensity scaling which is one of the disadvantages. To overcome this problem, PSNR is used. It scales the MSE according to the image range expressed by Eq. (9) which is measured in decibels (dB).

$$\mathrm{PSNR} = -10 \log_{10} e(\mathrm{MSE} / S^2) \tag{9}$$

where S is the maximum pixel value. The PSNR measure is also not ideal but it is commonly used parameter evaluation technique. Its disadvantage is its signal strength which is not dependent on the actual signal strength but is estimated as S^2 . So SNR is used as the main evaluation parameter. Table 5 shows the SNR and PSNR value of different fused images using different image fusion techniques. Table 6 shows the comparison of our methodology with other state of the art technique which results in 38.99dB SNR using PCA technique.

Table 5: Performance metrics results of best fusion using different fusion techniques for SNR and PSNR

	Images	SNR(dB)	PSNR(dB)
DWT	Flair + T2	**20.91**	**27.12**
Laplacian	Flair + T2	**14.88**	**27.29**
PCA	Flair + T2	**7.67**	**38.99**

Table 6: Comparison with Existing papers in terms of PSNR

	Images	DWT (dB)	PCA (dB)
Deepa [3]	T1 + T2 (image 3)	34.56	30.28
	T1 + T2 (image 4)	41.86	38.59
Implemented Work	Flair + T2	27.12	**38.99**

4. Conclusion

Image Fusion plays a great part in medical imaging applications by helping the radiologists for finding the abnormality in CT and MR brain images. A various image combining algorithms have been implemented and its performance is analyzed for different slices of brain MR Images. From the results it is analyzed that fusion of Flair and T2 slices of brain MR images results in better performance in terms of SNR and PSNR. On the basis of MSE, the best results were obtained by combining T1ce and T1 slice for DWT, T1ce and T2 slice for Laplacian Pyramid and T2 and flair slice for PCA technique. In future the analysis of fusion techniques by a hybrid technique will be employed without changing the nature of the medical images.

References

[1] Patel, Krupa (2015) "Fusion Algorithms for Images Based on Principal Component Analysis and Discrete Wavelet Transform", *International Journal for Innovative Research in Science & Technology.* **1(9)**: 180-182.

[2] Jacobs, Michael, Ibrahim, Tamer, Ouwerker, Ronald (2007) "MR Imaging: Brief Overview and Emerging Applications", Jul 1.*https://doi.org/10.1148/rg.274065115*

[3] Deepa, B. Sumithra, M.G (2017) "Performance Analysis of Various Image Fusion Techniques for Detection of Brain Abnormality", *International Journal of Computer & Mathematical Sciences*, **6(9)**, 168-176.
[4] Yuqian Li, XinLiu, Feng,Wei (2017) "An Advanced MRI and MRSI data fusion scheme for enhancing unsupervised brain tumor differentiation", Elsevier, *computers in biology and medicine* **8(1)**, 121-129.
[5] Swathi P.S, M. S. Sheethal and Paul,Vince (2016)"Survey on Multimodal Medical Image Fusion Techniques", *International Journal of Computer Science & Engineering Technology* , **6(1)**, 33-39.
[6] Dogra,Jyotsna, Prashar,Navdeep, Jain,Shruti, Sood,Meenakshi **(**2018**)** "Improved Methods for Analyzing MRI Brain Images",Network Biology. **8(1)**, 1-11.
[7] Dogra,Jyotsna, Prashar,Navdeep, Jain,Shruti, Sood,Meenakshi **(**2017**)** " Segmentation of Magnetic Resonance Images of Brain using Thresholding Techniques", *4th IEEE International Conference on signal processing and control (ISPCC 2017)*, Jaypee University of Information technology, Waknaghat, Solan, H.P, India, 311-315.
[8] James A.P.,.Dasarathy B.V (2014) "Medical image fusion : A Survey of the State of the Art" , Information Fusion, **19**, 4 -19.
[9] S. Krishnamoorthy, K. P. Soman,(2010)" Implementation and Comparative Study of Image Fusion Algorithms" .*International Journal of Computer Applications* , **9(2)**.
[10] Pohl C., Genderen J.L.V. (1998) "Multisensor image fusion in remote sensing: concepts, methods and applications. J. Remote sensing" ,**19(5),** 823-854.
[11] Ghassemian and Hassan (2016) "A Review of Remote Sensing Image Fusion Methods." Information Fusion ELSEVIER, **32,** 75-89.
[12] Peli, Tamar, Peli, Eli, Ellis, Kenneth, Stahl, Robert, "Multispectral Image Fusion for Visual Display", Sensor Fusion: Architecture, Algorithms and Applications.
[13] Sahu, Deepak, M.P. Parsai **(**2012**)** "Different Image Fusion Techniques," *International Journal of Modern Engineering Research*, **2(5)** pp. 4298-4301.
[14] Mahajan, Shaveta, Singh, Arpinder **(**2014**)** "A Comparative Analysis of Different Image Fusion Techniques." *International journal of Computer Science*, **2(1)**.
[15] Suthakar,Johnson, Esther, Monica , Annapoorani, Samuel, Richard **(**2014**)** "Study of Image fusion- Techniques, Method and Applications", *International Journal of Computer Science and Mobile Computing*, **3(11)**, 469- 476.
[16] Rajalingam B., Priya R. **(**2017**)** " A Novel Approach For Multimodal Medical Image Fusion Using Hybrid Fusion Algorithms for Disease Analysis", *International Journal Of Pure And Applied Mathematics,***117(15)** , 599-619
[17] Rajini, K. C., Roopa S. **(**2017**)** " A Review on Recent Improved Image Fusion technologies", *The international Conference on Wireless Communications, Signal Processing and Networking,* 149-153, March 22-24, 2017.
[18] Soman, C. R., Jacob A. **(**2016**)** " DWT Based Image Fusion Of Panchromatic And Multispectral Images ",*International Journal Of Engineering Science And Computing,***6(9)** , 2179-2184.
[19] Dong, Jiang ,Zhuang, Dafang , Huang, J. Fu **(**2009**)** "Advances in Multi-Sensor Data Fusion: Algorithms and Applications", *Sensors (Basel)*. **9(10)**:7771-7784.
[20] Wang, X., Jiang, K., Wenbo, Li., BingyuSun S,. **(**2012**)**"Application of Wavelet Transform in image fusion based on remotely sensed data", 9th *International Conference on Fuzzy Systems and Knowledge Discovery*, 1745-1750.
[21] Zhang**,**Yun and Wang**,**Ruiseng**(**2004**)** "Multi-resolution and multi-spectral image fusion for urban object extraction".
[22] Hall D.L. **(**1992**)** "Mathematical Techniques in Multisensor Data Fusion" *Pennsylvania State University*, Artech House, Boston, London, January 1992.
[23] Pajares,Ganzalo, Cruz,Jesus Manuel04**)** "A wavelet-based image fusion tutorial", Pattern Recognition, **37**, 1855 – 1872 .
[24] Yang, Yong, Huang, Shuying ,Gao,Junfeng ,Qian,Zongsheng **(**2014**)** "Multi-focus Image Fusion Using an Effective Discrete Wavelet Transform Based Algorithm" , *Measurement Science Review*, **14(2)**.
[25] Zitová,Barbara and Flusser,Jan**(**2003**)** "Image registration methods: a survey", *Image and vision computing,* 21(11): 977-1000.
[26] Fonseca L.M.G. and Manjunath B.S. **(**1996**)**, "Registration Techniques for Multisensor-Remotely Sensed Imagery, *Photogrammetric Engineering & Remote Sensing,* **62 (9)**, 1049-1056.
[27] Jain,Shruti, Chauhan D.S.**(**2016**)** "Mathematical Analysis of Receptors for Survival Proteins". *International Journal of Pharma and Bio Sciences.***6(3)** : 164-176.
[28] Bhusri, Sahil, Jain, Shruti and Virmani,Jitendra **(**2016**)** Classification of Breast Lesions Using the Difference of Statistical Features, *Research Journal of Pharmaceutical, Biological and Chemical Sciences*, **7 (4),** 1365-1372.
[29] Rana Shelza., Jain,Shruti, and Virmani, Jitendra **(**2016**)** SVM-Based characterization of focal kidney lesions from B-Mode ultrasound images, *Research Journal of pharmaceutical, biological and chemical sciences (RJPBCS).***7(4)** : 837-846.
[30] Sharma, Shreya,. Jain,Shruti, S Bhusri **(**2017**)** Two Class Classification of Breast Lesions using Statistical and Transform Domain features, *Journal of Global Pharma Technology* **9(7)**: 18-24.
[31] Jain , Shruti **(**2018**)**, Classification of Protein Kinase BUsing Discrete Wavelet Transform, *International Journal of Information Technology*, **10(2)** : 211-216.
[32] Abhilash, G Rama Murthy T.V., Naidu V. P. S (2015**), "**Image Fusion for Enhanced Vision System using Laplacian Pyramid" ,*International Journal of Engineering Research & Technology,* **4(8),** 507-512.
[33] Jin, B. and Li S. (2011) "Applications of Remote Sensing Data Fusion Technology Based on Improved IHS Transform in the ASEAN Geospatial Public Service Platform", 2011 International Symposium on Image and Data Fusion.