“Bodh”, BPIT’s International Journal of Technology & Management
ISSN: 2454-8421, Volume 7, Issue 2, July- Dec 2021, Page 31-44

Light Stimulated Rat (LSR) Algorithm Based Multimodal Image Fusion for MRI Images

Jayant Bhardwaj[1], Pawan Sharma[2]

[1,2]*Department of Electronics and Communication, Bhagwan Parshuram Institute of Technology, Delhi, India,*
[1]jayantbhardwaj@bpitindia.com, [2]pawan061971@gmail.com

Abstract - Fusion of MRI images enhances the level of information in a great way. The features of individual images not only get clubbed but the diagnostic approach for diseases will also get increased. In this research a detailed study on the image fusion strategies in medical images has been carried out. In this research paper a novel bio inspired optimization Light stimulated rat algorithm has been employed for Multimodal MRI Images Image Fusion. The proposed work has been compared with the state-of-the-art Fusion method and it has been identified that the proposed work out performs with great merit over the other fusion methods and the proposed research work can be considered novel for the transform based medical image fusion schemes. Discrete wavelet transform based MRI decomposition and reconstruction scheme has been employed in this proposed work.

Keywords--- fusion, information, medical images

I. INTRODUCTION

In the direction of diagnostic analysis with different medical modalities sufficient efforts are being done to extract meaningful features and hence information in the form of digital images so that any decision can be established about an ailment in the body[1],[2].From many years a lot of image processing techniques like image deblurring, image enhancement, denoising etc. have been evolved to extract out maximum information from the source medical images[3],[4].Multimodal Image fusion is also an important and growing technique in this domain. Two modality images are so fused with each other pixel wise that the third image consists of the features of both images [5], [6], [28],[29].The motive of this pixel level image fusion method is to eliminate the redundancy of image feature and common information and to reserve the complementary information from both images to the third image i.e. fused image[7],[8]. This process of image fusion not only conserves the memory of a computer system but also helps in reduction of decision time of a doctor or of an automatic disease diagnosis system[9],[10],[26]. Every modality of an image technology such as MRI, generates an image with a salient feature or information [11],[12],[27].

Some modalities provide information about the peripheral region of organs while some provide detailed information about central features of an organ. In case of human brain MRI imaging Flair and T2 are such two modalities for these purposes respectively.T1C and T1 are also two important modalities which provide the fluid information and information regarding minute discontinuities in the tissues of the brain respectively. In transform domain fusion methods such as wavelet based, contourlet(CT) ,non-subsampled contoulet (NSCT) and curvelet transform (CVT) etc. the signal processing like image decomposition at frequency level is performed on image coefficients .According to information measure ,the fusion technique is broadly grouped in three ,that is pixel, feature and decision. In the pixel class the direct operations are performed on pixels of images to fuse[13],[14].In the feature class the operations are performed at frequency level to enhance the detailed prime features of images like edges, points and corners etc. At the decision class the images are fused by applying classifier rules and fuzzy logic etc. to the image coefficients [15],[16]. Fig.1 and Fig.2 provide a conceptual view about the medical modalities of MRI.

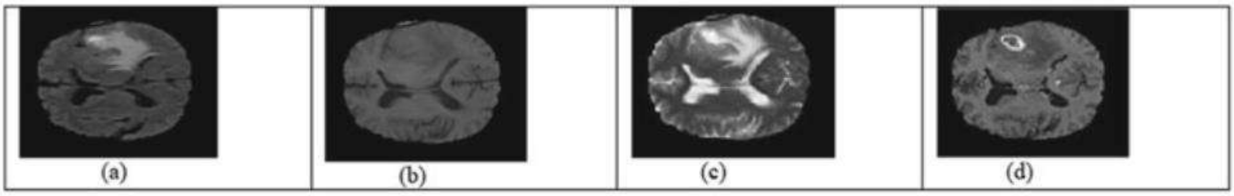

Fig.1 Dataset-1 modalities

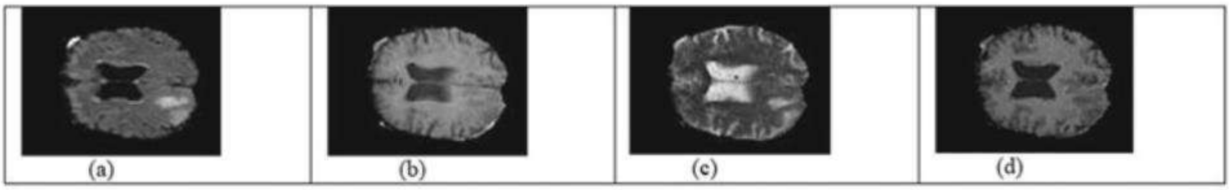

Fig.2.Dataset-2 modalities

The fusion result for above Fig 2 is shown in the result section in fig.7.

II. METHODOLOGY

This section discusses the methodology employed using Image Decomposition and Fusion rule

A. Image Decomposition

The methodology used here is basically a signal decomposition into different coefficients of frequency for individual images and further mix them into each other with in limits of signal processing and its operators[17],[18]. Fig.3 presenting the Schematic diagram of the proposed Image Fusion method.

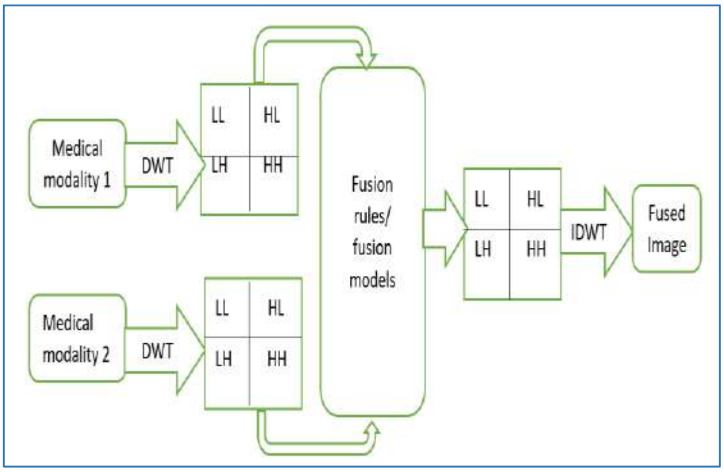

Fig.3 Schematic diagram of the proposed Image Fusion

B. Fusion Rule

In the fusion rule a metaheuristic scheme for optimization is applied. The strange behaviour of rats with exposure to light is mimicked in the fusion model [19-21]. The MI of each pixel is calculated and the way a rat finds the maximum displacement on light stimulation is modeled to raise the value of MI per pixel. Further the pixels are clubbed to each other and the final image reconstructed after the process of reconstruction by some appropriate transform tool [22-25].

RESULT AND DISCUSSION

The results for the proposed fusion scheme are illustrated in Fig. 4 to Fig. 7. The results have been evaluated qualitative as well as quantitatively. The evaluation measures values of mutual information and other parameters like RMSE and PSNR proves the merit of this fusion method. Two data sets from a famous MRI data set are tested .The proposed method is compared with three very renown techniques of fusion. These are Wavelet and Halo-whale method, SWT-NSCT combined method and simple NSCT method. Our proposed method is outperforming the compared one method. The effectiveness of the proposed method is deliberately explained in this section. Table I and Table II are providing a view of satisfactory results.

Table 1 Comparative analysis using dataset-1

Metrics	Wavelet + HW Fusion	SWT + NSCT	NSCT	Proposed
Mutual information	1.4673	1 4669	1.4299	1.5765
PSNR (in ffi)	37.8289	37.8848	36.8904	44.0957
RMSE	6.5101	6.5281	6.5409	5.4940

Table 2 Comparative analysis using dataset-2

Metrics	Wavelet + HW Fusion	SWT + NSCT	NSCT	Proposed
Mutual information	1.4612	1.4550	1.4508	1.4960
PSNR (in dB)	32.991	33.470	32.498	35.541
RMSE	10.0053	10.0510	9.9689	9.6404

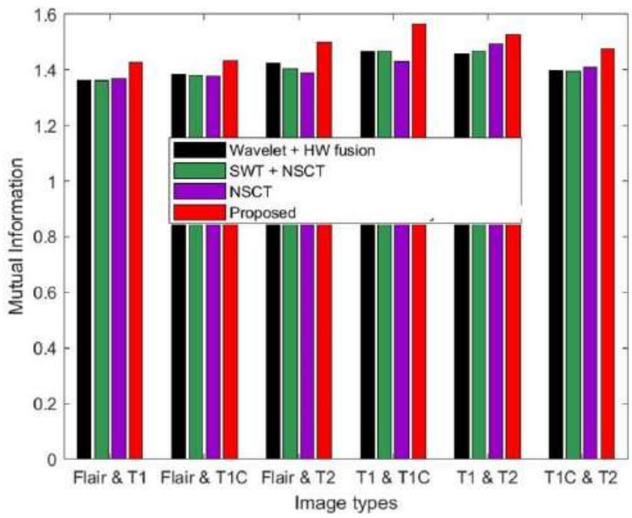

Fig.4.MI values for each modality set fusion

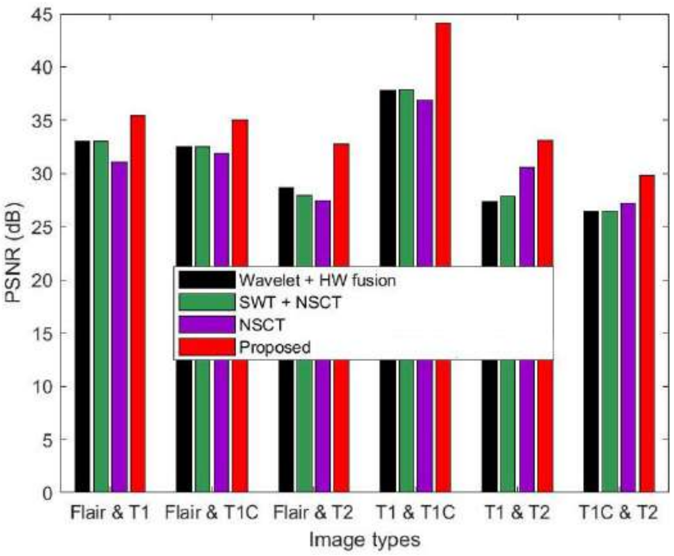

Fig.5 PSNR value for each modality set fusion

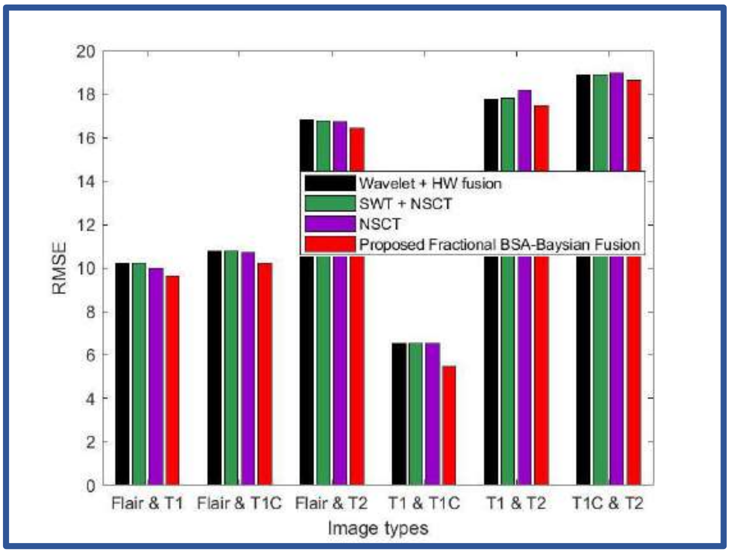

Fig.6 RMSE for each modality set fusion

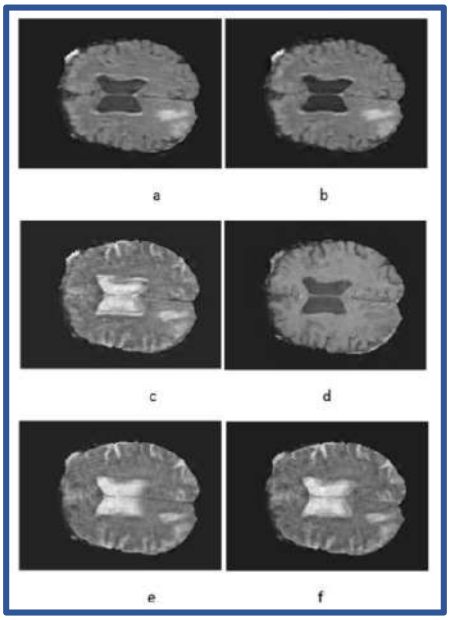

Fig.7 MRI Fusion

REFERENCES

[1]S. Singh and D. Gupta, “Detail Enhanced Feature-Level Medical Image Fusion in Decorrelating Decomposition Domain,” IEEE Trans. Instrum. Meas., vol. 70, no. November, 2021, doi: 10.1109/TIM.2020.3038603.

[2] A. V. Nikolaev et al., “Quantitative Evaluation of an Automated Cone-Based Breast Ultrasound Scanner for MRI-3D US Image Fusion,” IEEE Trans. Med. Imaging, vol. 40, no. 4, pp. 1229–1239, 2021, doi: 10.1109/TMI.2021.3050525.
[3] K. He, J. Gong, L. Xie, X. Zhang, and D. Xu, “Regions preserving edge enhancement for multisensor-based medical image fusion,” IEEE Trans. Instrum. Meas., vol. 70, 2021, doi: 10.1109/TIM.2021.3066467.
[4]N. Geng, Z. Chen, Q. A. Nguyen, and D. Gong, “Particle swarm optimization algorithm for the optimization of rescue task allocation with uncertain time constraints,” Complex Intell. Syst., vol. 7, no. 2, pp. 873–890, 2021, doi: 10.1007/s40747-020-00252-2.
[5]K. Mishra and S. K. Majhi, “A binary Bird Swarm Optimization based load balancing algorithm for cloud computing environment,” Open Comput. Sci., vol. 11, no. 1, pp. 146–160, 2021, doi: 10.1515/comp-2020-0215.
[6]O. S. Faragallah et al., “A comprehensive survey analysis for present solutions of medical image fusion and future directions,” IEEE Access, vol. 9, no. Januar. 11358–11371, 2021, doi: 10.1109/ACCESS.2020.3048315.
[7] M. Arif and G. Wang, “Fast curvelet transform through genetic algorithm for multimodal medical image fusion,” Soft Comput., vol. 24, no. 3, pp. 1815–1836, 2020, doi: 10.1007/s00500-019-04011-5.
[8] K. Padmavathi, C. S. Asha, and V. K. Maya, “A novel medical image fusion by combining TV-L1 decomposed textures based on adaptive weighting scheme,” Eng. Sci. Technol. an Int. J., vol. 23, no. 1, pp. 225–239, 2020, doi: 10.1016/j.jestch.2019.03.008.
[9] D. Xu, Y. Wang, S. Xu, K. Zhu, N. Zhang, and X. Zhang, “Infrared and visible image fusion with a generative adversarial network and a residual network,” Appl. Sci., vol. 10, no. 2, 2020, doi: 10.3390/app10020554.

[10] J. Bhardwaj and A. Nayak, "Haar wavelet transform–based optimal Bayesian method for medical image fusion," Med. Biol. Eng. Comput., vol. 58, no. 10, pp. 2397–2411, 2020, doi: 10.1007/s11517-020-02209-6.
[11] R. Hou, D. Zhou, R. Nie, D. Liu, and X. Ruan, "Brain CT and MRI medical image fusion using convolutional neural networks and a dual-channel spiking cortical model," Med. Biol. Eng. Comput., vol. 57, no. 4, pp. 887–900, 2019, doi: 10.1007/s11517-018-1935-8.
[12] I. Aljarah, H. Faris, S. Mirjalili, N. Al-Madi, A. Sheta, and M. Mafarja, "Evolving neural networks using bird swarm algorithm for data classification and regression applications," Cluster Comput., vol. 22, no. 4, pp. 1317–1345, 2019, doi: 10.1007/s10586-019-02913-5.
[13] Y. Wang, Z. Wan, and Z. Peng, "A Novel Improved Bird Swarm Algorithm for Solving Bound Constrained Optimization Problems," Wuhan Univ. J. Nat. Sci., vol. 24, no. 4, pp. 349–359, 2019, doi: 10.1007/s11859-019-1406-6.
[14] Y. Yang, J. Wu, S. Huang, Y. Fang, P. Lin, and Y. Que, "Multimodal Medical Image Fusion Based on Fuzzy Discrimination with Structural Patch Decomposition," IEEE J. Biomed. Heal. Informatics, vol. 23, no. 4, pp. 1647–1660, 2019, doi: 10.1109/JBHI.2018.2869096.
[15] S. D. Ramlal, J. Sachdeva, C. K. Ahuja, and N. Khandelwal, "An improved multimodal medical image fusion scheme based on hybrid combination of nonsubsampled contourlet transform and stationary wavelet transform," Int. J. Imaging Syst. Technol., vol. 29, no. 2, pp. 146–160, 2019, doi: 10.1002/ima.22310.
[16] A. Dogra, B. Goyal, and S. Agrawal, "Medical image fusion: A brief introduction," Biomed. Pharmacol. J., vol. 11, no. 3, pp. 1209–1214, 2018, doi: 10.13005/bpj/1482.
[17] P. H. Venkatrao and S. S. Damodar, "HWFusion: Holoentropy and SP-Whale optimisation-based fusion model for magnetic resonance imaging multimodal image fusion," IET Image Process., vol. 12, no. 4, pp. 572–581, 2018, doi: 10.1049/iet-ipr.2017.0573.

[18] B. J and N. A, “Cascaded Lifting Wavelet and Contourlet Framework Based Dual Stage Fusion Scheme for Multimodal Medical Images,” J. Electr. Electron. Syst., vol. 07, no. 04, 2018, doi: 10.4172/2332-0796.1000292.
[19] P. Hill, M. E. Al-Mualla, and D. Bull, “Perceptual Image Fusion Using Wavelets,” IEEE Trans. Image Process., vol. 26, no. 3, pp. 1076–1088, 2017, doi: 10.1109/TIP.2016.2633863.
[20] A. Dogra, B. Goyal, and S. Agrawal, “From multi-scale decomposition to non-multi-scale decomposition methods: A comprehensive survey of image fusion techniques and its applications,” IEEE Access, vol. 5, pp. 16040–16067, 2017, doi: 10.1109/ACCESS.2017.2735865.
[21] F. E. Z. A. El-Gamal, M. Elmogy, and A. Atwan, “Current trends in medical image registration and fusion,” Egypt. Informatics J., vol. 17, no. 1, pp. 99–124, 2016, doi: 10.1016/j.eij.2015.09.002.
[22] D. P. Bavirisetti and R. Dhuli, “Fusion of Infrared and Visible Sensor Images Based on Anisotropic Diffusion and Karhunen-Loeve Transform,” IEEE Sens. J., vol. 16, no. 1, pp. 203–209, 2016, doi: 10.1109/JSEN.2015.2478655.
[23]R. Srivastava, O. Prakash, and A. Khare, “Local energy-based multimodal medical image fusion in curvelet domain,” IET Comput. Vis., vol. 10, no. 6, pp. 513–527, 2016, doi: 10.1049/iet-cvi.2015.0251.
[24] V. Bhateja, H. Patel, A. Krishn, A. Sahu, and A. Lay-Ekuakille, “Multimodal Medical Image Sensor Fusion Framework Using Cascade of Wavelet and Contourlet Transform Domains,” IEEE Sens. J., vol. 15, no. 12, pp. 6783–6790, 2015, doi: 10.1109/JSEN.2015.2465935.
[25] S. V and B. R. Kumar, “Directive Contrast Based Multimodal Medical Image Fusion in NSCT with DWT Domain,” Int. J. Eng. Trends Technol., vol. 9, no. 6, pp. 288–294, 2014, doi: 10.14445/22315381/ijett-v9p257.

[26] G. Bhatnagar, Q. M. J. Wu and Z. Liu, "Directive Contrast Based Multimodal Medical Image Fusion in NSCT Domain," in IEEE Transactions on Multimedia, vol. 15, no. 5, pp. 1014-1024, Aug. 2013, doi: 10.1109/TMM.2013.2244870.
[27]A. Mohammad-Djafari, “A Bayesian Approach for Data and Image Fusion,” no. June, pp. 386–408, 2003, doi: 10.1063/1.1570554.
[28] I. Daubechies and W. Sweldens, “Factoring Wavelet Transforms into Lifting Steps,” J. Fourier Anal. Appl., vol. 4, no. 3, 1998, doi: 10.1007/bf02476026.
[29] BRATS, 2015 https://smir.ch/BRATS/Start,accessed May 2019.