

MACHINE LEARNING FRAMEWORK FOR MEDICAL IMAGE FUSION APPROACH

N. Karthika¹, Manupati Shruthi², Maripelli Rishitha², Mogili Poojitha², Kuthadi Keerthi²

^{1,2}*Department of Electronics and Communication Engineering*

^{1,2}*Malla Reddy Engineering College for Women (A), Maisammaguda, Medchal, Telangana.*

ABSTRACT

Fusion process gives highly informative image as it combines the information from two or more images into a single image. It has been utilizing widely in medical research field for computer aided brain surgery, Alzheimer's treatment, tumour detection and other clinical diagnosis. Effective fusion algorithms are required to obtain accuracy of successful diagnosis of diseases. Magnetic resonance (MR) and computed tomography (CT) images are most widely utilized images for analysing the human body. The main objective of any fusion approach is to transfer maximum information from the source images to the fused image with minimum information loss. It must minimize the artifacts in the fused image. In this work, a novel medical image fusion algorithm is proposed. Nonlinear anisotropic filtering (NLAF) in principal component analysis (PCA) domain, which preserve the texture information of fused images most effectively. NLAF is utilized to decompose the source images into approximation and detail layers. Final detail and approximation layers are computed with the support of PCA. Finally, fused image is generated from the linear combination of final detail and approximation layers. Qualitative and quantitative performance of the proposed algorithm is assessed with the help of image quality metrics like peak signal-to-noise ratio (PSNR), correlation coefficient (CC), entropy (E), root mean square error (RMSE) and structural similarity (SSIM) index. Extensive simulation results of the proposed hybrid algorithm are compared with the traditional and recent image fusion algorithms. Performance evaluation discloses that the proposed fusion approach outperforms the existing fusion methods.

Keywords: Image fusion, Nonlinear anisotropic filtering (NLAF), Medical field.

1. INTRODUCTION

Image fusion treats the different combinations of images sensed from different sensors which include multi-spectrum and high-spectrum, multi-angle viewing and multi-resolutions. This enhances the scope for accomplishing the quality of images. Multi-sensor images are used in several fields such as machine vision, remote sensing and medical imaging. Medical image fusion techniques provide better biomedical information for clinical evaluation. In medical diagnosis multimodal fused images has more significant role than individual image. The multi model medical image fusion is the process of combining compliment fusion techniques for clinical analysis. To support more accurate clinical information for physicians to deal with medical diagnosis and assessment, multimodality medical images are required such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), or Positron Emission Tomography (PET) [1,2] etc. For example, the CT image can provide dense structures like bones and implants with less distortion but cannot detect physiological changes. But the MRI can provide information of normal and pathological soft tissues and it cannot support the bone information. In this circumstance, a single image cannot be appropriate to deliver perfect clinical requirements for the physicians. Hence the fusion of the multimodal medical images are essential, and it has become a promising and very challenging research area in recent years [3].

Image fusion broadly defined as the representation of the visual information with more than one input image, as a single fused image without the introduction of distortion or loss of information [4]. The fusion of different images can reduce the ambiguity related to a single image. In recent days, obtaining human's anatomies and functions with high resolution and more instructive description becomes potential due to advancement in the field of medical imaging technology. The encouragement for the research in the analysis of medical images has been done by such development. In addition, the development of medical images vitality in the clinical applications rendered a straight effect on this field of research [5].

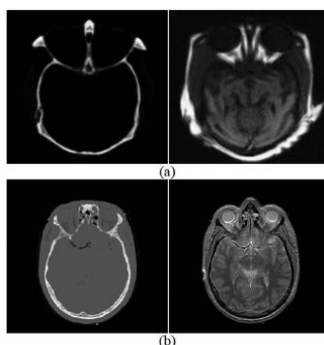


Fig. 1: CT and MR images (a) dataset 1 (b) dataset 2

Image Fusion

In computer vision, Multi sensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. But, the standard image fusion techniques can distort the spectral information of the multispectral data, while merging.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will be usually, two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on DWT, uniform rational filter bank, and Laplacian pyramid.

2. LITERATURE SURVEY

From the past decades, there has been a greater number of scientific research papers have been published on the topic of fusing the medical images. Essentially, image fusion techniques have been classified into three sorts. They are pixel level, feature level and decision level. Successful fusion methods based on morphological operators are discussed in [6-7]. Even though these methods are simple, fused image may not look good. In optimization-based approaches [8] and [9] fusion process is expressed as Bayesian optimization problem. But in general, this problem is difficult to solve. Markov random field [10] and generalized random walk [11] methods solve this problem by computing edge

aligned weights. Fused image may be over smoothed because of multiple iterations. In addition, artificial neural networks have gained a lot of interest in image fusion by the inspiration of biological signal fusion. Successful methods in this class are discussed in [12-13].

In addition to the above fusion schemes, multiresolution schemes have played a great role in image fusion. These schemes are motivated by the fact that human visual system (HVS) is sensitive to the edge information. That is, HVS can perceive even small changes in edge information. Both image pyramid and wavelet decomposition belong to multiresolution methods. These approaches require transform domain analysis. Image pyramid decomposes each given image into set of low-pass filtered images. Each filtered image represents the information of the given image in different scales. Gradient pyramid (Grad) [14], Laplacian pyramid [15], ratio of low-pass pyramid (Ratio) [16], Gaussian pyramid [17], contrast pyramid, filter-subtract-decimate pyramid, and morphological pyramid [18] methods are used for fusion. Wavelet transform based fusion algorithms have tremendous performance over the algorithms presented in the literature. Recent years, many extended versions of wavelet transform have done to improve the fusion performance further [19-25]. But these methods may introduce artifacts into the fused image. To overcome these problems optimization based fusion schemes are proposed. These methods take multiple iterations to find the optimal solution (fused image). These optimization methods may over smooth the fused image because of multiple iterations Principal component analysis is one of the finest methodologies for obtaining fused images from given MR and CT images [26]. In addition, edge preserving image fusion schemes are becoming popular these days. These methods use edge preserving smoothing filtering/process for fusion. Popular methods in this class are guided image filter [28], weighted least square filter [29-30], bilateral filter [31], cross bilateral filter [32], 3-D anisotropic diffusion [33] based methods. Most of these methods decompose each source image into base and detail layers. Either manipulated base layer or manipulated detail layer or both manipulated layers together are combined to get the fused image. Bilateral filter and cross bilateral filter fusion methods produces gradient reversal artifacts in the fused image whereas guided image fusion method produces halo effects in the fused image.

An efficient image fusion scheme should possess three properties.

- 1) It must transfer most of the useful information from source images into the fused image.
- 2) It should not loose useful information of source imagery in the fusion process.
- 3) It should not introduce any artifacts or extra information into the fused image.

A novel non-linear anisotropic filtering-based image fusion (NLAFF) in PCA domain is proposed to address the problems of the existing methods and by keeping the above properties in mind. Each source image is filtered using NLAFF process to extract approximate and detail layers. Useful information from approximate and detail layers are integrated into the fused image.

3. PROPOSED METHODOLOGY

This section describes the brief explanation of our proposed fusion frame work. Fused output image is obtained by implementation of NALF process to obtain the approximate and detail layers with PCA fusion rule. Proposed NLAFF-PCA fusion methodology shown in fig.2.

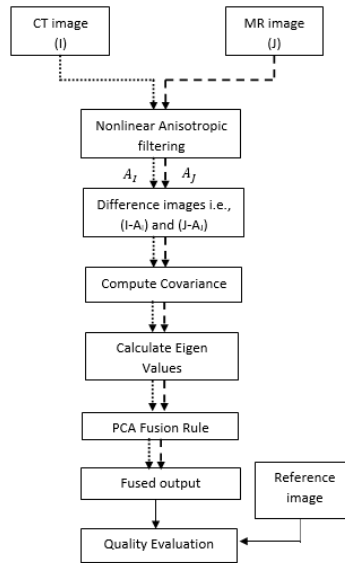


Fig. 2: Proposed NLAf-PCA fusion process flow.

Non-Linear Anisotropic Filtering

The NLAf process will smooth a given image at homogeneous regions while preserving the nonhomogeneous regions (edges) using partial differential equations (PDE). It overcomes the drawbacks of non-linear isotropic filtering, which uses inter-region smoothing. So, edge information is lost. In contrast, NLAf uses intraregional smoothing to generate coarser resolution images. At each coarser resolution edges are sharp and meaningful. The NLAf equation uses flux function to control the diffusion of an image I as,

$$I_t = \mathbb{F}(x, y, t)\Delta I + \nabla \mathbb{F} \cdot \nabla I \tag{1}$$

Where $\mathbb{F}(x, y, t)$ is flux function, Δ is a Laplacian operator, ∇ is a gradient operator and t is time or scaling constant.

We can also term (1) as heat equation. Forward-time-central space (FTCS) scheme is used to solve this equation. The solution for this PDE is

$$I_{i,j}^{t+1} = I_{i,j}^t + \beta [\mathbb{F}_N \cdot \bar{\nabla}_N I_{i,j}^t + \mathbb{F}_S \cdot \bar{\nabla}_S I_{i,j}^t + \mathbb{F}_E \cdot \bar{\nabla}_E I_{i,j}^t + \mathbb{F}_W \cdot \bar{\nabla}_W I_{i,j}^t] \tag{2}$$

In above eq., $I_{i,j}^{t+1}$ is the coarser resolution image at $t + 1$ scale which depends on the previous coarser scale image $I_{i,j}^t$. β is a stability constant satisfying $0 \leq \beta \leq 1/4$. Nearest neighbour differences in north, south, east and west directions denoted as $\bar{\nabla}_N, \bar{\nabla}_S, \bar{\nabla}_E, \bar{\nabla}_W$ respectively. They are defined as

$$\begin{aligned} \bar{\nabla}_N I_{i,j} &= I_{i-1,j} - I_{i,j} \\ \bar{\nabla}_S I_{i,j} &= I_{i+1,j} - I_{i,j} \\ \bar{\nabla}_E I_{i,j} &= I_{i,j+1} - I_{i,j} \\ \bar{\nabla}_W I_{i,j} &= I_{i,j-1} - I_{i,j} \end{aligned}$$

Similarly, the flux functions are denoted as $\mathbb{F}_N, \mathbb{F}_S, \mathbb{F}_E$ and \mathbb{F}_W respectively.

$$\left. \begin{aligned} \mathbb{F}_{N_{i,j}}^t &= g \left(\left\| (\nabla I)_{i-1/2,j}^t \right\| \right) = g(|\bar{\nabla}_N I_{i,j}^t|) \\ \mathbb{F}_{S_{i,j}}^t &= g \left(\left\| (\nabla I)_{i+1/2,j}^t \right\| \right) = g(|\bar{\nabla}_S I_{i,j}^t|) \end{aligned} \right\} \tag{4}$$

$$\mathbb{F}_{E_{i,j}}^t = g \left(\left\| (\nabla I)^t_{i,j+1/2} \right\| \right) = g(|\bar{\nabla}_E I_{i,j}^t|)$$

$$\mathbb{F}_{W_{i,j}}^t = g \left(\left\| (\nabla I)^t_{i,j-1/2} \right\| \right) = g(|\bar{\nabla}_W I_{i,j}^t|)$$

In eq. (4), $g(\cdot)$ is a monotonically decreasing function with $g(0) = 1$. Different functions can be used for $g(\cdot)$. But Perona and Malik [36] suggested two functions as mentioned below

$$g(\nabla I) = e^{-\left(\frac{\|\nabla I\|}{k}\right)^2} \tag{5}$$

$$g(\nabla I) = \frac{1}{1+\left(\frac{\|\nabla I\|}{k}\right)^2} \tag{6}$$

These functions offer a trade-off between the smoothing and texture preservation. First function is useful if the image consists of high-contrast edges over the low-contrast edges. Second function is useful if the image consists of wide regions over the smaller regions. Both functions consist of a free parameter k . This constant k is used to decide the validity of a region boundary based on its edge strength.

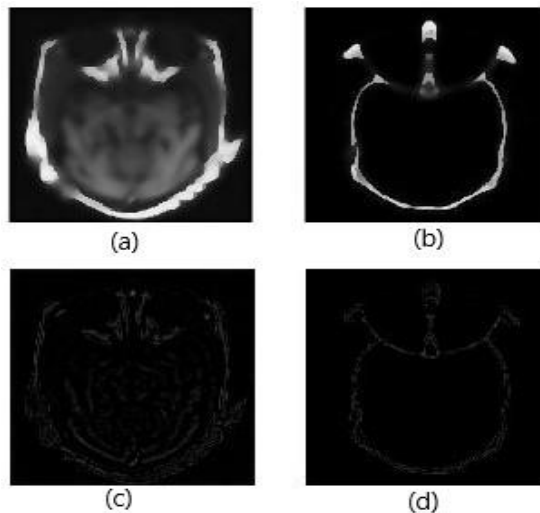


Fig. 3: (a) approximate layer of MR image (b) approximate layer of CT image (c) detail layer of MR image (d) detail layer of CT image.

A. Extraction of approximated and detail layers from source images using NLAf

Let the source MR and CT images are denoted as $I_n(x, y)$, $J_n(x, y)$ respectively with a size of $p \times q$ and these two images are co-registered images. As shown in figure 4.1, these two source images are passed through the NLAf block to obtain the approximate layers.

$$A_{I_n}(x, y) = nlaf(I_n(x, y)) \tag{7}$$

$$A_{J_n}(x, y) = nlaf(J_n(x, y)) \tag{8}$$

(3) Where $A_{I_n}(x, y)$ and $A_{J_n}(x, y)$ are n^{th} approximate layers and $nlaf$ is a sub function that process the source image (refer section II for more information). Now, the detail layers are obtained by subtracting the output of NLAf by utilizing eq. (7) and (8).

$$D_{I_n}(x, y) = I_n(x, y) - A_{I_n}(x, y) \tag{9}$$

$$D_{J_n}(x, y) = J_n(x, y) - A_{J_n}(x, y) \tag{10}$$

Fig demonstrates that the output layers obtained from NLAF process i.e., approximation and detail layers of MR and CT images.

Algorithm: NLAF-PCA based fusion process

Step 1: Select and read MR and CT source images from the MATLAB current directory (data set2 shown in figure 1).

Step 2: Convert the source images into gray scale in case of RGB images.

Step 3: Apply NLAF process to obtain approximate layers of MR and CT images as described in section II.

Step 4: Subtract the source images from the obtained approximate layers to get the detail layers of MR and CT images.

Step 5: Compute the covariance of detail layers obtained from step 4.

Step 6: Calculate the Eigen vectors for step 5 output.

Step 7: Now, apply PCA fusion rule to obtain final fused output of MR and CT images.

B. Principal Component Analysis

One of the difficulties inherent in multivariate statistics is the problem of visualizing data that has many variables. Fortunately, in data sets with many variables, groups of variables often move together. One reason for this is that more than one variable might be measuring the same driving principle governing the behaviour of the system. In many systems there are only a few such driving forces. But an abundance of instrumentation enables you to measure dozens of system variables. When this happens, you can take advantage of this redundancy of information. You can simplify the problem by replacing a group of variables with a single new variable.

(1) Definition

Principal component analysis is a quantitatively rigorous method for achieving this simplification. The method generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components form an orthogonal basis for the space of the data.

(2) Principal components

The first principal component is a single axis in space. When you project each observation on that axis, the resulting values form a new variable. And the variance of this variable is the maximum among all possible choices of the first axis. The second principal component is another axis in space, perpendicular to the first. Projecting the observations on this axis generates another new variable. The variance of this variable is the maximum among all possible choices of this second axis. The full set of principal components is as large as the original set of variables. But it is commonplace for the sum of the variances of the first few principal components to exceed 80% of the total variance of the original data.

C. Fusion Rule

After obtaining the approximate and detail layers from the source MR and CT images PCA is applied to find out principal components (as described in section III) for getting better analysis over conventional fusion algorithms presented in the literature. Now, to get a fused output image a rule must be utilized to obtain optimum output from the proposed NLAF-PCA fusion process. We first combine the approximate layers of MR and CT images. Then sum the detail layers by multiplying with the

principal components denoted as p obtained by PCA algorithm. Finally, integrate these two process outputs to obtain fused image.

$$D(x, y) = p(1) * D_{In}(x, y) + p(2) * D_{Jn}(x, y)$$

$$A(x, y) = A_{In}(x, y) + A_{Jn}(x, y)$$

$$F(x, y) = A(x, y) + D(x, y)$$

4. RESULTS AND DISCUSSION

All the experiments have been done in MATLAB 2016b version under the high-speed CPU conditions for faster running time. Aim of any fusion algorithm is to integrate required information from both source images in the output image. Fused image cannot be judged exclusively by seeing the output image or by measuring fusion metrics. It should be judged qualitatively using visual display and quantitatively using fusion metrics. In this section, we are presenting both visual quality and quantitative analysis of proposed and existing algorithms such as, Wavelet based methods discrete wavelet transform (DWT) [25], stationary wavelet transform (SWT) [24]. Analysis of fusion metrics along with image quality assessment (IQA) metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), correlation coefficient (CC), root mean square error (RMSE) and entropy (E) are considered to verify the effectiveness of the proposed algorithm. The objective of any fusion algorithm is to generate a qualitative fused image. For better quality, fused image should have optimal values for all these metrics. The fusion metric with best value is highlighted in bold letter.

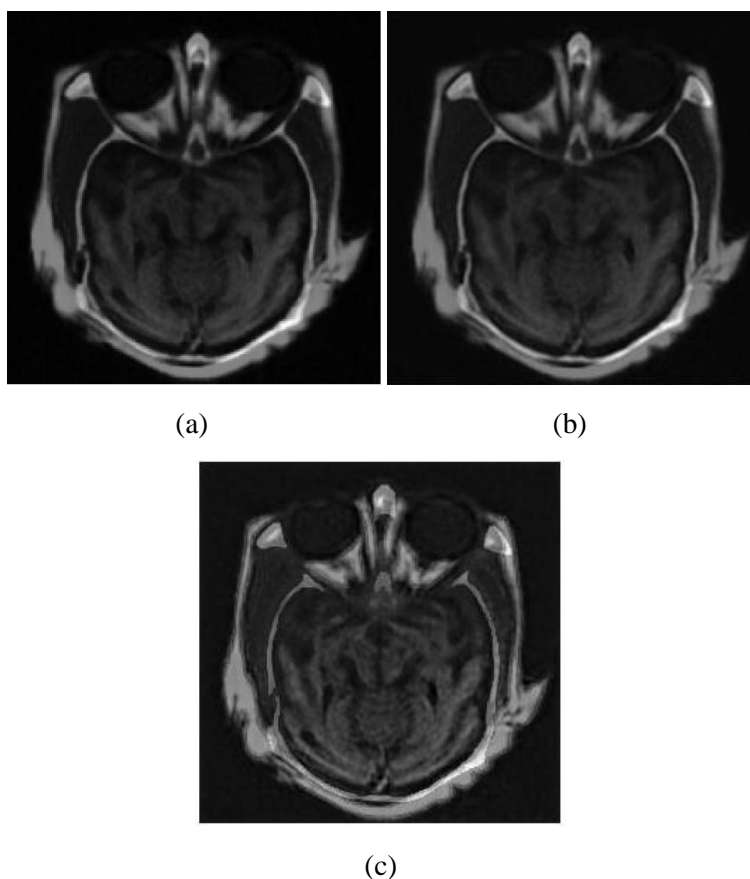


Fig. 4: Visualization of fused output images with data set 1 (a) DWT (b) SWT and (c) Proposed method.

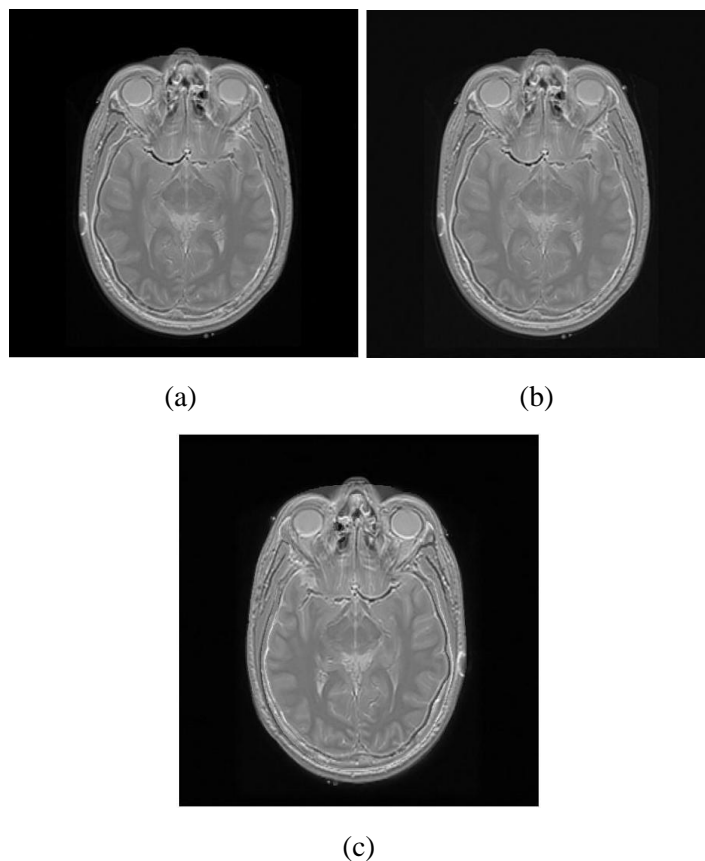


Fig. 5: Visualization of fused output images with data set 2 (a) DWT (b) SWT and (c) Proposed method.

Table. 1: Quantitative analysis of fusion methods for dataset 1.

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT [24]	62.253	0.1967	0.7928	0.986	6.11
DWT [25]	62.257	0.1966	0.7935	0.986	6.099
Proposed method	65.06	0.142	0.913	0.997	6.24

Table. 2: Quantitative analysis of fusion methods for dataset 2.

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT [24]	68.95	0.0909	0.933	0.988	0.9684
DWT [25]	68.98	0.0906	0.934	0.988	0.9683
Proposed method	74.18	0.049	0.973	0.999	5.16

Quantitative analysis with IQA shown in table 1 for the test results presented in figure 5.1, which gives the analysis of dataset 1. Table 1 consists of various fusion metric parameters such as PSNR, RMSE, CC, SSIM and entropy. The best values are highlighted in bold letters. Our proposed method obtained far better values over all the existing fusion methods discussed in the literature. We also tested the qualitative analysis of dataset 2 with the similar fusion metric parameters considered for dataset 1.

5. CONCLUSIONS

A new texture preserving fusion approach is proposed for MR and CT images by utilizing NLAFF-PCA methodology. NLAFF has utilized to extract the approximate and detail layers from the MR and CT source images. Then the principal components computed according to the PCA algorithm. Finally, fusion is applied to obtain a fused image with texture preservation. Performance of proposed NLAFF-PCA fusion process is assessed with several medical image fusion methodologies presented in the literature. Comparative analysis is done according to the image quality metrics and shown that the proposed NLAFF-PCA fusion process performed superior to the conventional medical fusion algorithms.

REFERENCES

- [1] Peter J. Burt, Edward H. Adelson, "The Laplacian Pyramid as a Compact Image Code", IEEE Transactions on Signal Processing, vol. 31, no. 4, pp. 532-540, April 1983.
- [2] K Sharmila, S Rajkumar, V Vijayarajan, "Hybrid method for Multimodality Medical image fusion using Discrete Wavelet Transform and Entropy concepts with Quantitative Analysis", Proceedings of IEEE International conference on Communication and Signal Processing, April 2013.
- [3] Jorge Nunez, Xavier Otazu, Octavi Fors et al., "Multiresolution Based Image Fusion with Additive Wavelet Decomposition", IEEE Transactions on Geoscience and Remote Sensing, vol. 37, no. 3, pp.4-11, May 1999.
- [4] Petrović, V. S., & Xydeas, C. S., "Gradient-based multiresolution image fusion", IEEE Transactions on Image Processing, Vol. 13, no. 2, pp. 228-237, Feb 2004.
- [5] Suetens P. Fundamentals of medical imaging. Cambridge: Cambridge University Press; 2009.
- [6] De I, Chanda B, Chattopadhyay B. Enhancing effective depth of-field by image fusion using mathematical morphology. Image Vis Comput. Vol. 24, pp. 1278–1287, 2006.
- [7] Yang B, Li S. Multi-focus image fusion based on spatial frequency and morphological operators. Chinese Opt Lett. Vol. 5, pp. 452–453, 2007.
- [8] Fasbender D, Radoux J, Bogaert P. Bayesian data fusion for adaptable image pan-sharpening. IEEE Trans Geosci Remote Sens. Vol. 46, pp. 1847–1857, 2008.
- [9] Habiba Khemila and Chibani Belgacem Rhaimi, "Bayesian Fusion: Application in Medical Imaging", 17th International Conference on Science and Techniques of Control and Computer Engineering, pp. 87-92, Sousse, Tunisia, 2016.
- [10] Shen R, Cheng I, Shi J, Basu A. Generalized random walks for fusion of multi-exposure images. IEEE Trans Image Process. Vol. 20, pp. 3634–3646, 2011.
- [11] Xu M, Chen H, Varshney PK. An image fusion approach based on Markov random fields. IEEE Trans Geosci Remote Sens. Vol. 49, pp. 5116–5127, 2011.
- [12] Newman EA, Hartline PH. Integration of visual and infrared information in bimodal neurons of the rattlesnake optic tectum. Science (New York, NY). Pp. 213-789,1981.
- [13] Waxman AM, Aguilar M, Fay DA, Ireland DB, Racamato JP. Solid-state color night vision: Fusion of low-light visible and thermal infrared imagery. Lincoln Lab J. Vol. 11, pp. 41–60, 1998.
- [14] N Suresh Kumar and R Prabhakaran, "A Novel Approach for High Intension Image with Gradient Pyramid", SSRG International Journal of Mobile Computing Application, Vol. 4, No. 3, pp. 13-17, 2017.
- [15] Jianguo Sun, Qilong Han, Liang Kou, Liguozhang, Kejia Zhang, and Zilong Jin, "Multi-focus Image Fusion Based on Laplacian Pyramids", Journal of Optical Society of America A, Vol. 35, No. 3, pp. 480-490, 2018.
- [16] A Toet, "Image Fusion by a Ratio of Low-pass Pyramid", Pattern Recognition Letters, Vol. 9, No. 4, pp. 245-253, 1989.

- [17] Chhamman Sahu and Raj Kumar Sahur, "Pyramid based Image Fusion", International Journal of Engineering and Computer Science, Vol. 3, No. 8, pp. 7890-7894, 2014.
- [18] Neha Uniyal and S K Verma. "Image Fusion using Morphological Pyramid Consistency Method", International Journal of Computer Applications, Vol. 95, No. 25, pp. 34-38, 2014.
- [19] Y.Lifeng, Z. Donglin, W. Weidong and B. Shanglian "Multi-modality medical image fusion based on wavelet analysis and quality evaluation" Journal of Systems Engineering and Electronics, vol. 12, no. 1, pp. 42–48, Mar. 2016.
- [20] P. Chai, X. Luo and Z. Zhang, "Image Fusion Using Quaternion Wavelet Transform and Multiple Features" IEEE Access, vol. 5, pp. 6724 – 6734, Mar. 2017.
- [21] X. Xu, Y. Wang and S. Chen "Medical image fusion using discrete fractional wavelet transform" Biomedical Signal Processing and Control, vol. 27, pp. 103–111, May. 2016.
- [22] S. S. Chavan, A. Mahajan, S. N Talbar, S. Desai, M. Thakur and A. Dcruz "Nonsubsampled rotated complex wavelet transform (NSRCxWT) for medical image fusion related to clinical aspects in neurocysticercosis" Computers in Biology and Medicine vol. 81, no. 1, pp. 64–78, Feb. 2017.
- [23] E. Daniel, J. Anitha and J. Gnanaraj "Optimum Laplacian wavelet mask based medical image using hybrid cuckoo search – grey wolf optimization algorithm", Knowledge-Based Systems vol. 131, no. 1, pp. 58–69, Sep. 2017.
- [24] Prakash O., Khare A., "CT and MR Images Fusion Based on Stationary Wavelet Transform by Modulus Maxima", Computational Vision and Robotics, Advances in Intelligent Systems and Computing, Vol. 332, pp. 199-204, Springer, New Delhi, 2015.
- [25] Bhavana V and Krishnappa H K., "Multi-modality Medical Image Fusion Using Discrete Wavelet Transform", 4th International Conference on Eco-friendly Computing and Communication Systems (ICECCS), Vol. 70, pp. 625-631, 2015.
- [26] Meisen Pan, Jianjun Jiang, Fen Zhang and Qiusheng Rong, "Medical Image Registration and Fusion Using Principal Component Analysis", The International Arab Journal of Information Technology, Vol. 14, No. 4, pp. 512-520, 2017.
- [27] B Sudharani, A V Kiranmai and N Suguna, "Image Fusion Using Fast Discrete Curvelet Transform", International Journal of Computer Science, Mathematics and Engineering, Vol. 3, No. 12, pp. 7-9, 2016.
- [28] Shutao Li, Xudong Kang, and Jianwen Hu, "Image fusion with guided filtering", IEEE Transactions on Image Processing: A Publication of the IEEE Signal Processing Society, Vol. 22, No. 7, pp. 2864–2875, 2013.
- [29] Zeev Farbman, Raanan Fattal, Dani Lischinski, and Richard Szeliski, "Edge-preserving decompositions for multi-scale tone and detail manipulation", In ACM Transactions on Graphics (TOG), Vol. 27, No. 3, 2008.
- [30] Yong Jiang and Minghui Wang, "Image fusion using multiscale edge preserving decomposition based on weighted least squares filter", IET Image Processing, Vol. 8, No. 3, pp.183–190, 2014.
- [31] Kishor P Upla, Sharad Joshi and Mehul C Patel, "An edge preserving multi-resolution image fusion: Use of joint bilateral filter", IEEE International Symposium on Geoscience and Remote Sensing, Quebec City, Canada, 2014.
- [32] B K Shreyamsha Kumar, "Image fusion based on pixel significance using cross bilateral filter", Signal, Image and Video Processing, Vol. 9, No. 5, pp. 1193-1204, 2015.
- [33] Fatih Kahraman, C Deniz Mendi, and M Gokmen, "Image frame fusion using 3d anisotropic diffusion, In 23rd International Symposium on Computer and Information Sciences, pp. 1–6, Istanbul, Turkey, 2008.

- [34] Guru Prasad S, M Z Kurian and H N Suma, "Fusion of CT and PET Medical Images using Hybrid Algorithm DWT-DCT-PCA", 2nd International Conference on Information Science and Security, Seoul, South Korea, 2015.
- [35] Samet Aymaz and Cemal Kose, "Multi-Focus Image Fusion Using Stationary Wavelet Transform (SWT) and Principal Component Analysis (PCA)", 10th International Conference on Electrical and Electronics Engineering, pp. 1176-1180, Bursa, Turkey, 2018.
- [36] Pietro Perona and Jitendra Malik, "Scale-space and edge detection using anisotropic diffusion", IEEE Transactions on Pattern Analysis and Machine Intelligence, Vol. 12, No. 7, pp. 629-639, 1990.