Journal of Computer Science

Original Research Paper

Efficient Image Integration Technique: Mismatch of Subjective and Objective Analysis

[1]Setika Mehra, [2]Ayush Dogra, [3]Bhawna Goyal,
[3]Apoorav Maulik Sharma, [2]Rahul Shukla and [4]Shivendra Singh

[1]Amritsar College of Engineering and Technology, Amritsar, India
[2]Indian Institute of Technology (CBME), Ropar, India
[3]UIET, Panjab University, Chandigarh, India
[4]Lovely Professional University, Phagwara, India

Article history
Received: 30-07-2019
Revised: 28-09-2019
Accepted: 18-10-2019

Corresponding Author:
Ayush Dogra
Indian Institute of Technology (CBME), Ropar, India
Email: ayush123456789@gmail.com

Abstract: The paper intends to extract features with high visual quality during image fusion. An improved image fusion algorithm is presented, aiming to preserve necessary features and relevant information, simultaneously focusing on highly enhanced visual results. The resultant fused image obtained is superior to other images obtained from other state-of-the-art techniques with respect to visual quality. A novel and improved image fusion algorithm is presented, which outperforms the other eight state-of-the-art techniques of image fusion. The proposed methodology includes a combinational approach of anisotropic diffusion and Laplacian pyramid leading to image enhancement. The paper also reveals a contradiction of the visual results with respect to objective results.

Keywords: Image Fusion, Anisotropic Diffusion, Spatial Filters, Laplacian Pyramid Average Fusion Rule

Introduction

Image fusion is a well-accepted domain of image processing that aims at fabricating a more informative image from fusion of multi-modal source images. The fused image acquired is the concoction of source images thus extracting information and features from individual source images and superimposing them in fused image than the individual source images (Rajini and Roopa, 2017). Considering practical applications, CT images contain the details of bony structures whereas MRI images contain the details of soft tissues, ligaments or organs; by fusing these two images the resultant fused image can impart a comprehensive knowledge of both the scans in one single image getting away with the complexity of viewing two separate scans at the same time (Li *et al*., 2017). Similarly, NMR and SPECT image fusion resultant is used for recognizing AIDS dementia. Thus, image fusion plays a pivotal role in medical imaging. Besides medical imaging, image fusion participates in contributing a crucial role in concealed weapon detection where fusion of visible images imparting detailed texture information and infrared images imparting thermal radiation information is used for surveillance and security (Dogra *et al*., 2018). There are different levels of image fusion, namely pixel-level fusion, feature level fusion and decision level fusion (Ghassemian, 2016). Most of the algorithms deal with pixel-level image fusion. A significant amount of study and research has been done in the subject of image fusion and researchers have been working towards enhancement of the quality of fused images. The fundamental point to be noted is that there should always be a maximum transfer of information from individual source images to the fused image, without much loss of information and minimal addition of additional artifacts. The common feature is that the pixels surrounding each pixel are correlated. Working towards image fusion includes designing a method that helps in decorrelating the pixel.

In 1983, Laplacian pyramid was proposed for image enhancement with a high degree of accuracy. This method involves passing the original image through Gaussian pyramid, a low pass filter, then obtaining Laplacian images from subtracting the two consecutive Gaussian levels, followed by adjusting with quantization and finally reconstructing an image to produce a more enhanced image (Burt and Adelson, 1983). In 1989, the ratio of low pass pyramid was introduced to preserve details with a relatively high local luminance contrast (Toet, 1989). Data obtained through spatial and spectral resolutions are being integrated for remote sensing. In

1995 images were being fused using wavelet transform leading to fusion of different frequency ranges. Enhancement of edges can be acquired by fusing the high-frequency information with low frequency information (Chipman *et al*., 2002). In 2007, curvelet transform was being proposed for representing edges better than that in the wavelet domain. It helps in featuring the directional edges enabling an image to reflect high pass details, also enabling an image to be enhanced at high resolution as well (Nencini *et al*., 2007). In the same year, it was observed that region based image fusion is superior to pixel based image fusion. In region based image fusion, there is reduction in noise, blurring effects, provided considering the segmentation as priority while fusing the source images (Lewis *et al*., 2007). In the succeeding years, it was observed that Multi-resolution Singular Value Decomposition (MSVD) performs at par with wavelets. The main aim of MSVD is to take the place of finite impulse response with Singular Value Decomposition (SVD) (Naidu, 2011). In 2016, gradient transfer fusion and total variation minimization was proposed in which intensity distribution was carried out on infrared images and gradient variation was carried out on visible images leading to fusion of images with more details (Ma *et al*., 2016). Further proceeding to the newer techniques, in 2016, an edge preserving technique, anisotropic diffusion was proposed by decomposing the source images into base layers and details layers which when fused beats the existing techniques shown by evaluation its performance by means of objective metrics (Bavirisetti and Dhuli, 2016). In the proposed methodology, anisotropic diffusion (Bavirisetti and Dhuli, 2016) has been applied to section the source image into approximation and detail layers, Butterworth filter is used for sharpening the image (Makandar and Halalli, 2015), the fast guided filter is used for enhancing the image without the addition of gradient reversal artifacts (He and Sun, 2015; He *et al*., 2010) and Laplacian pyramid average fusion rule has been employed for enhancing the image with a high degree of accuracy. In this, an effort to increase visual quality has been attempted. It has been observed that the proposed technique surpasses the existing ones with reference to producing a high visual quality resultant fused image.

Proposed Methodology

The proposed image fusion algorithm aims at producing a fused image rich in visual quality while integrating source images. The proposed method varies from other algorithms with respect to generating highly informative fused image using different spatial domain techniques, therefore, enriching the quality of image. The block diagram for the proposed methodology is displayed in Fig. 1.

Step (1): Anisotropic Diffusion Filtering

Two source images R and S are taken on which anisotropic diffusion, an edge (non-homogeneous regions) preserving technique, that will smooth the homogeneous regions using partial differential equation is applied, given in Equation (1) where R = source image, t = time, c (a,b,t) = rate of diffusion, Δ = Laplacian operator, ∇ = Gradient operator:

$$R_t = c(a,b,t)\Delta R + \nabla c.\nabla R \quad (1)$$

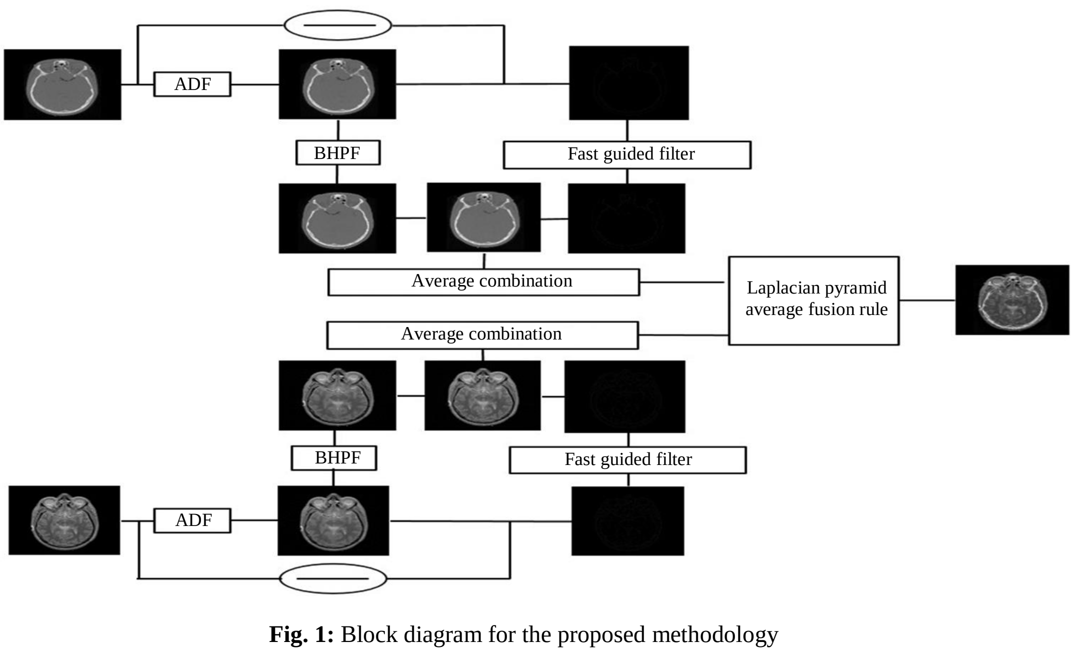


Fig. 1: Block diagram for the proposed methodology

DOI: 10.3844/jcssp.2019.1490.1497

The value of the parameters selected for anisotropic diffusion includes no. of iterations, which is responsible for smoothing. The higher the iteration value, the greater is the smoothing of the image obtained, delta = 0.5 is the constant used in anisotropic diffusion (Bavirisetti and Dhuli, 2016), $k = 30$ which is used to diffuse the homogeneous regions. The anisotropic diffusion holds responsible for maximum transfer of information to the fused image while retaining the edge information. Hence, anisotropic diffusion forms the basis of the fusion process.

Step (2): Detail Layer Computation

The main aim lies in the generation of high quality fused image; therefore, detail layer is computed and further enhanced. Here, anisotropic diffusion is used to decompose the source image into approximation and detail layers. By subtracting base layers from source images, detail layers are obtained, given in Equation (2) where $B_m(a,b)$ denotes m^{th} base layer is:

$$D_m(a,b) = R_m(a,b) - B_m(a,b) \tag{2}$$

Step (3): High Pass Filtering

A spatial filter, Butterworth high pass filter (Makandar and Halalli, 2015) that is accountable for sharpening the image is applied to the base layer with cut off frequency $D_0 = 100$ and order $n = 3$. This filter is subjected to highlight the fine details and focusing on the sharpness of the image by adjusting the order. The images after subjected to this high pass filter are more sharpened than the preceding images.

Step (4): Detail Layer Enhancement by Fast Guided Filter

On the other hand, the fast guided filter (He and Sun, 2015; He *et al*., 2010) is applied to the detail layer to acquire a more enhanced image with the property of preserving the edges while smoothing the image. Since this filter is resistant to the addition of gradient reversal artifacts, therefore, it is preferred than the bilateral filter. In this filter, a square window of radius $r = 8$ and eps which control the edge selectivity is chosen as 0.082^2.

Step (5): Combination of Base and Detail Layer

The resultant base and detail layer obtained of the source image R after applying spatial filters in the preceding steps are integrated together by means of average fusion rule in which the average of pixel intensities from the source images is considered in the fused image. Similarly, the average combination of the enhanced base and detailed layer of source image S is integrated and obtained.

Step (6): Laplacian Pyramid Based Fusion

Further, we fuse the resultant images obtained from the average fusion rule of the source images taken, R and S respectively by Laplacian Pyramid average fusion rule (Burt and Adelson, 1983). The fused image obtained focuses on delivering most of the information from the respective source images, consequently fetching a high visual quality image.

Objective Metrics

Multiple parameters have been developed for determining the total transfer of information in the resultant fused image, loss of information and additional artifacts added to the fused image (Shreyamsha Kumar, 2015; Dogra *et al*., 2017). Here, R and S are two source images taken, F is the fused image:

1. Mutual Information: Mutual information reflects the correlative information between the respective source images with the fused image:

$$MI = MI_{RF} + MI_{SF} \tag{3}$$

$$MI_{RF} = \sum_t \sum_U p_{R,F}(t,u) \log_2 \left(\frac{p_{R,F}(t,u)}{p_R(t)\, p_F(u)} \right) \tag{4}$$

$$MI_{SF} = \sum_t \sum_U p_{S,F}(t,u) \log_2 \left(\frac{p_{S,F}(t,u)}{p_S(t)\, p_F(u)} \right) \tag{5}$$

where, t = no. of rows, u = no. of columns, $p_{R,F}$ = joint probability mass function of R and F, $p_{S,F}$ = joint probability mass function of S and F, p_R and p_F are the marginal probability mass functions of R and F respectively, p_S and p_F are the marginal probability mass functions of S and F respectively. The new evaluation parameters include the following:

2. $Q^{RS/F}$ = Total information transfer from source images to fused images.
3. $L^{RS/F}$ = Loss of information
4. $N^{RS/F}$ = Artifacts/noise

From the above new evaluation parameters, we can conclude with the following expressions:

$$Q^{\frac{RS}{F}} + L^{RS/F} + N^{RS/F} = 1 \tag{6}$$

$$N_m^{\frac{RS}{F}} = \frac{\sum_{\forall i} \sum_{\forall j} RM_{i,j} \left[\left(1 - Q_{i,j}^{RF}\right) w_{i,j}^{R} = \left(1 - Q_{i,j}^{SF}\right) w_{i,j}^{S} \right]}{\sum_{\forall i} \sum_{\forall j} \left(Q_{i,j}^{RF} + Q_{i,j}^{SF} \right)}$$

Where:

$$RM_{i,j} = \begin{pmatrix} 1,\ g_{i,j}^{F} > g_{i,j}^{R}\ and\ g_{i,j}^{F} > g_{i,j}^{S} \\ 0,\ otherwise \end{pmatrix} \tag{7}$$

Equation (7) indicates locations of fusion artifacts where fused gradients are stronger than the input.

$g_{i,j}^{R}, g_{i,j}^{S}, g_{i,j}^{F}$ are the edge strengths of *R, S* and *F* respectively. $Q_{i,j}^{RF}$ and $Q_{i,j}^{SF}$ are gradient information preservation estimation of the source images *R* and *S* respectively. $w_{i,j}^{R}$ and $w_{i,j}^{S}$ are perceptual weights of source images *R* and *S* respectively. The method for calculating $g_{i,j}^{R}$, $g_{i,j}^{S}$, $g_{i,j}^{F}$, $Q_{i,j}^{RF}$, $Q_{i,j}^{SF}$, $w_{i,j}^{R}$ and $w_{i,j}^{S}$ is stated in (Petrovic, 2001; Petrovic and Xydeas, 2005). With the newly obtained modified fusion artifact measure $N_m^{\frac{RS}{F}}$ Equation (6) can be revised as:

$$Q^{\frac{RS}{F}} + L^{RS/F} + N_m^{\frac{RS}{F}} = 1 \tag{8}$$

Experimental Results

In the proposed paper various state-of-the-art techniques like anisotropic diffusion, wavelet transform, curvelet transform, complex wavelets, Laplacian pyramid, gradient transfer, multi-resolution singular value decomposition, ratio of low pass pyramid and the proposed technique have been performed on medical images with spatial resolution of 256×256 pixels gathered from (https://sites.google.com/view/durgaprasadbavirisetti/datasets) Intel core i7, 7 gen. The entire implementation is done on MATLAB. The parameters of all algorithms have been set to ensure maximum fusion performance in order to obtain maximum details from the fused image.

Results and Discussion

The performance assessment of the fused images using the technique that has been put forward along with eight important state-of-the-art techniques used for comparative analysis. The source images (Fig. 2) are the inputs of data sets for medical images. The proposed technique along with eight state-of-the-art techniques is applied to all the data sets but to reduce redundancy the results of two data sets is presented in Fig. 3 and 4 for subjective analysis. For objective analysis, graphs of objective metrics are depicted in Fig. 5. The medical images are subjected to the proposed technique for edge preservation, highlighting and enhancement of features therefore increasing the visual quality of the resultant fused image. The results obtained are examined both subjectively and objectively for better fusion results. It has been observed that the values of the parameters chosen produce the best visual results.

A. Subjective Analysis

It is fair to say, desirable and better fusion results are obtained if the source images carry an extensive and considerable amount of information. The source images are integrated to fabricate a more revealing and enhanced construction of the fused image. The result of two datasets from eight fusion techniques along with the proposed technique is presented in Fig. 3 and 4 for visual analysis. From the proposed technique results, we can draw a conclusion that our technique performs better with respect to conserving and enhancing the features during the fusion process thus intensifying the overall visual performance of the image. An enhanced level of visualization and constructiveness is increased manifold in subjective results. The details and sharpened edges are clearly visible to reveal complete information. The values of the parameters chosen are optimum to produce results which contain not only important information but also relevant amount of information. The key to image fusion is to construct an image which is informative, minimal in artifacts/noise and striking to the human visual system. The fused results worked out in terms of visual traits and quality. It is observed that the acquired fused images from respective source images contain impeccable information with the proposed algorithm giving a clear cut edge to the other techniques.

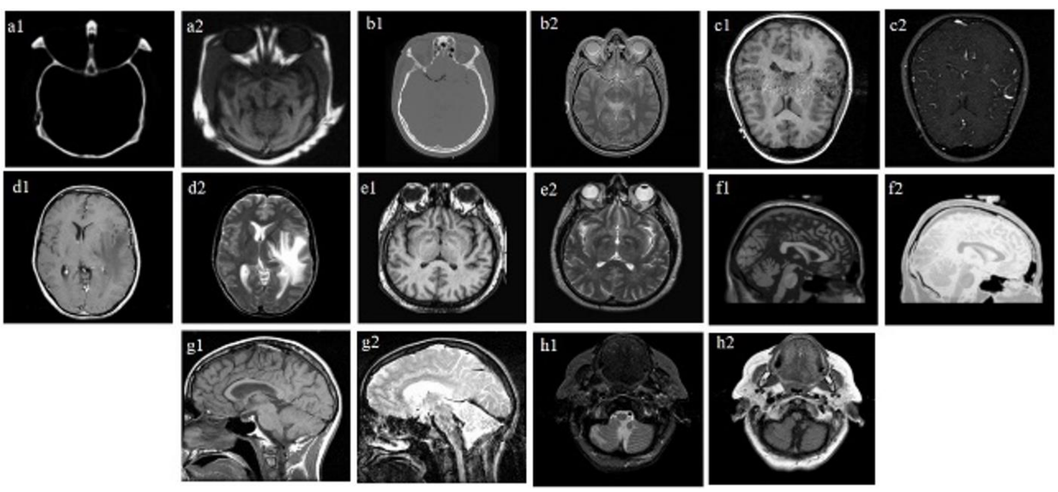


Fig. 2: Source images (https://sites.google.com/view/durgaprasadbavirisetti/datasets)

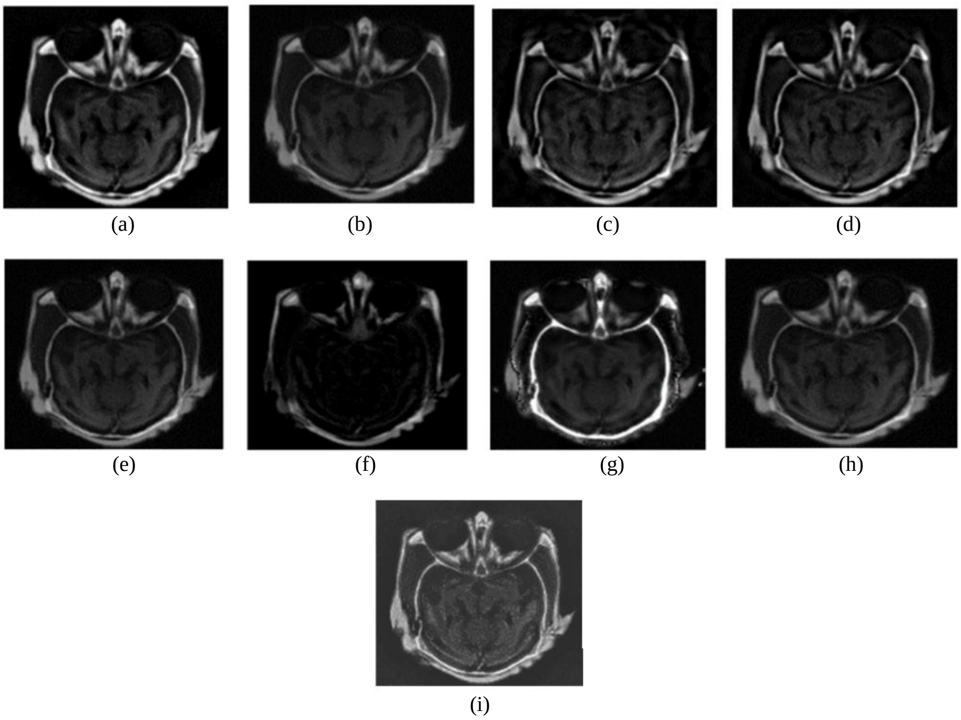


Fig. 3: A (fused result of a1 and a2); (a) Laplacian Pyramid (Burt and Adelson, 1983); (b) Wavelet Transform (Chipman *et al*., 2002); (c) Curvelet Transform (Nencini *et al*., 2007); (d) Complex Wavelet (Lewis *et al*., 2007); (e) Multi resolution singular value decomposition (Naidu, 2011); (f) Gradient Transfer (Ma *et al*.,2016); (g) Ratio of low pass pyramid (Toet, 1989); (h) Anisotropic diffusion (Bavirisetti and Dhuli, 2016); (i) Proposed technique

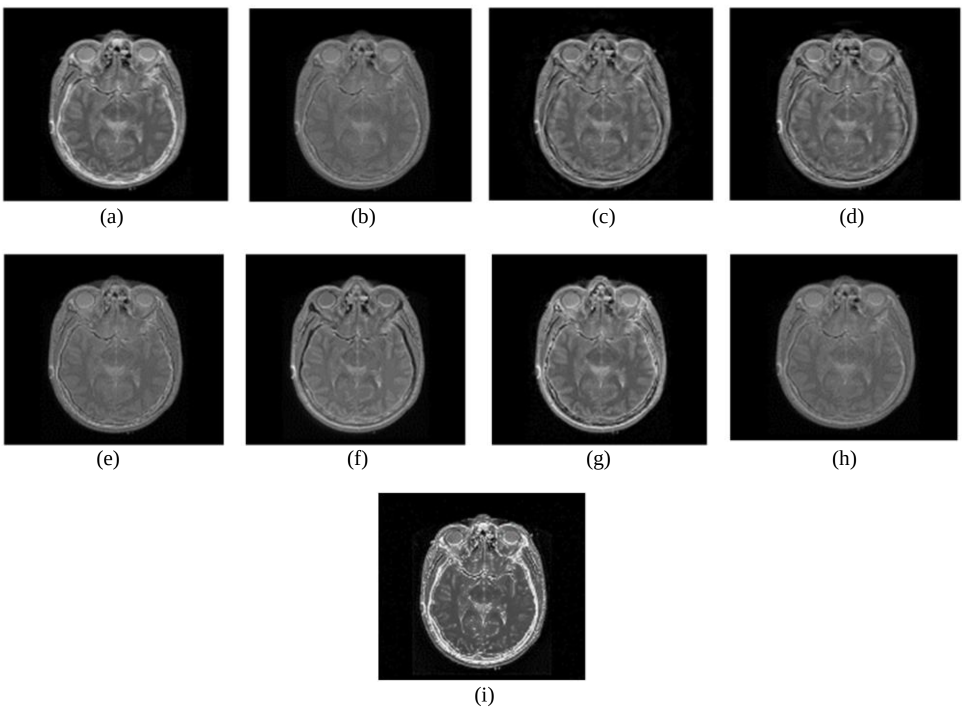
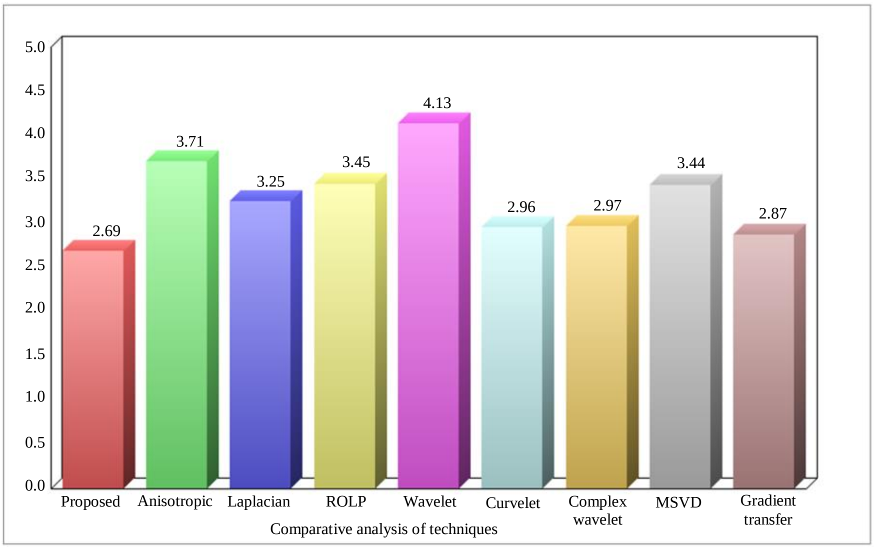
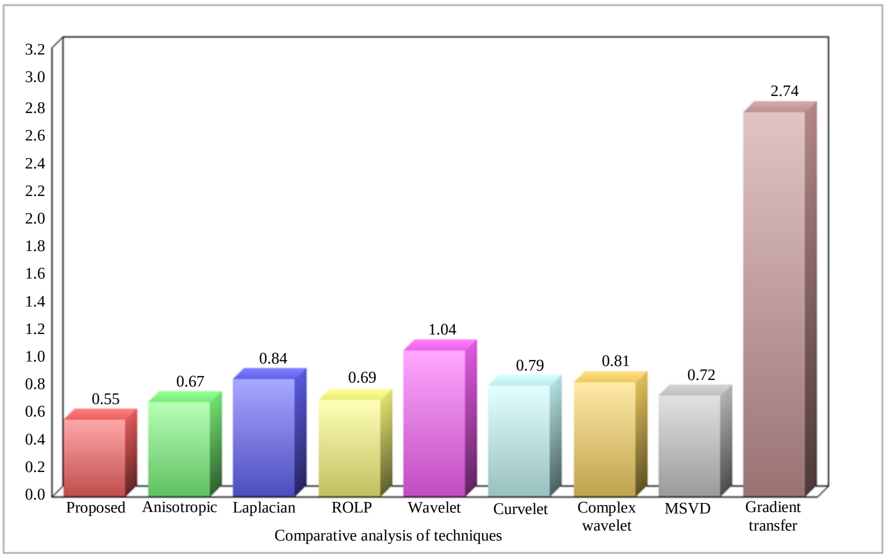


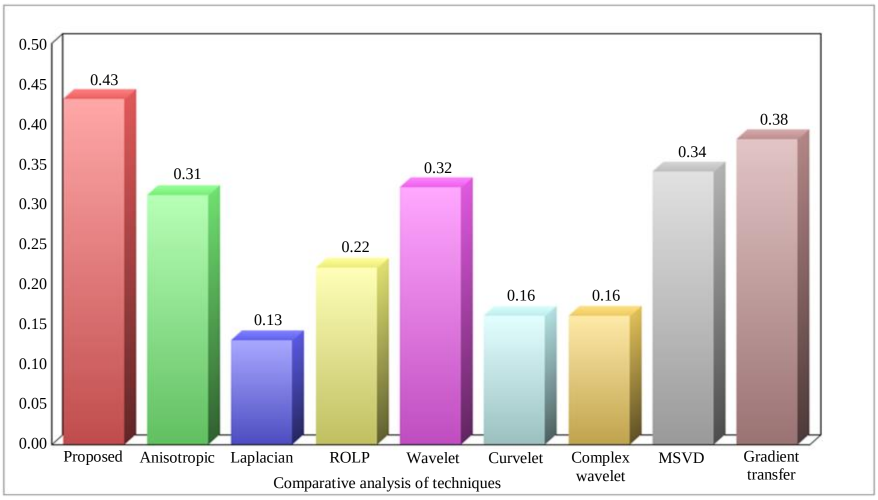
Fig.4: B (fused result of b1 and b2); (a) Laplacian Pyramid (Burt and Adelson, 1983); (b) Wavelet Transform (Chipman *et al*., 2002); (c) Curvelet Transform (Nencini *et al*., 2007); (d) Complex Wavelet (Lewis *et al*., 2007); (e) Multi resolution singular value decomposition (Naidu, 2011); (f) Gradient Transfer (Ma *et al*., 2016); (g) Ratio of low pass pyramid (Toet, 1989); (h) Anisotropic diffusion (Bavirisetti and Dhuli, 2016); (i) Proposed technique


5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
2.69
3.71
3.25
3.45
4.13
2.96
2.97
3.44
2.87
Proposed
Anisotropic
Laplacian
ROLP
Wavelet
Curvelet
Complex wavelet
MSVD
Gradient transfer
Comparative analysis of techniques

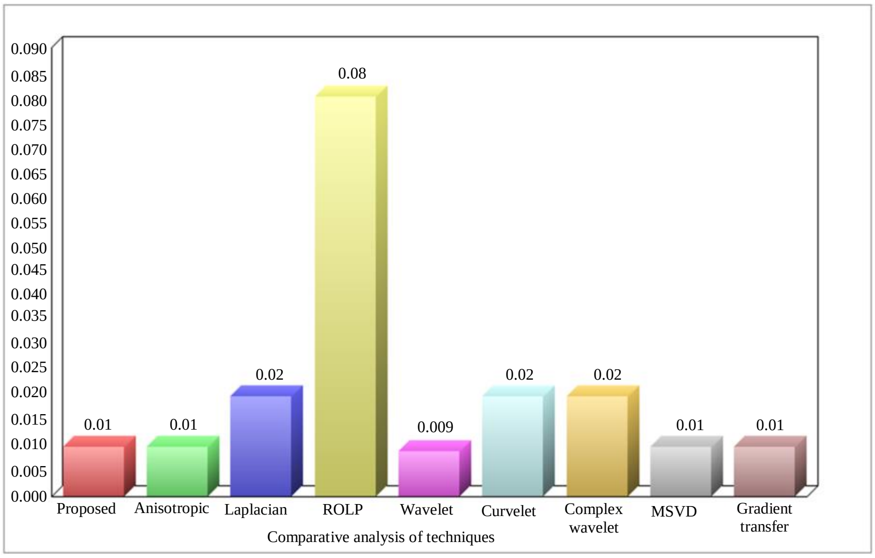
(a)


3.2
3.0
2.8
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
0.55
0.67
0.84
0.69
1.04
0.79
0.81
0.72
2.74
Proposed
Anisotropic
Laplacian
ROLP
Wavelet
Curvelet
Complex wavelet
MSVD
Gradient transfer
Comparative analysis of techniques

(b)


0.50
0.45
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
0.43
0.31
0.13
0.22
0.32
0.16
0.16
0.34
0.38
Proposed
Anisotropic
Laplacian
ROLP
Wavelet
Curvelet
Complex wavelet
MSVD
Gradient transfer
Comparative analysis of techniques

(c)



(d)

Fig. 5: Objective evaluation for fused results (a) Mutual information (b) $Q^{RS/F}$ (c) $L^{RS/F}$ (d) $N^{RS/F}$

B. Objective Analysis

After surpassing the visual quality through subjective evaluation for proposed algorithm, different algorithms are compared on the justification of objective analysis. Major image fusion objective metrics are implemented to evaluate fusion performance for quantitative analysis. While looking at Fig. 5 for comparative analysis of various techniques, it is noticed that our proposed technique stands lowest in terms of information transfer. Though our proposed technique lags behind marginally in terms of objective analysis but as it is stated in (Dogra *et al*., 2019), it is unfair to depend mainly on objective analysis since it is not the only criteria. It is noticed that there is an inconsistency between subjective and objective analysis. In the domain of medical imaging, the main focus relay on the visual analysis of the image. The doctors carefully examine the scans to determine the useful information from it. On account of subjective and objective analysis, it can be concluded that the proposed technique outshines the existing ones regarding subjective analysis but lags marginally in terms of objective analysis.

Conclusion

In the presented paper, a novel image fusion algorithm has been presented which yields high visual quality of fused image results from the source images, depicting the details and features incorporated from the source images without the addition of gradient artifact. The results of the proposed algorithm exceed the benchmark techniques in terms of subjective analysis but fall short in terms of good objective analysis. The outcome of our proposed technique drives us towards a crucial research issue of disagreement of subjective and objective analysis. It strikes an effort to determine whether subjective or objective analysis should be the chief goal from the medical aspect.

Acknowledgment

The authors express sincere gratitude and sincere thanks to Editor In Chief and reviewers of the journals to give their deep insights which increases the appeal of the article.

Author’s Contributions

All the authors contributed in experimentation, drafting and proof reading of the article.

Ethics

Keeping in view of the standard ethical practices, the authors read, agreed and approved to publish the presented manuscript addressing it as original with unpublished material.

References

Bavirisetti, D.P. and R. Dhuli, 2016. Fusion of infrared and visible sensor images based on anisotropic diffusion and karhunen-loeve transform. IEEE Sens. J., 16: 203-209. DOI: 10.1109/JSEN.2015.2478655

Burt, P.J. and E.H. Adelson, 1983. The Laplacian pyramid as a compact image code. IEEE Trans. Commun., 31: 532-540. DOI: 10.1109/TCOM.1983.1095851

Chipman, L.J., T.M. Orr and L.N. Graham, 2002. Wavelets and image fusion. Proceedings of the International Conference on Image Processing, Oct. 23-26, IEEE Xplore Press, Washington, DC, USA, USA, pp: 248-251. DOI: 10.1109/ICIP.1995.537627

Dogra, A., B. Goyal and S. Agrawal, 2017. From multi-scale decomposition to non-multi-scale decomposition methods: A comprehensive survey of image fusion techniques and its applications. IEEE Access, 5: 16040-16067. DOI: 10.1109/ACCESS.2017.2735865

Dogra, A., B. Goyal, S. Agrawal, U.J. Tanik and S. Kumar *et al*., 2019. Enhanced vascular and osseous information fusion: Disagreement of quantitative and qualitative analysis. Neural Comput. Applic. DOI: 10.1007/s00521-019-04259-w

Dogra, A., S. Kadry, B. Goyal and S. Agrawal, 2018. An efficient image integration algorithm for night mode vision applications. Multim. Tools Applic. DOI: 10.1007/s11042-018-6631-z

Ghassemian, H., 2016. A review of remote sensing image fusion methods. Inform. Fus. DOI: 10.1016/j.inffus.2016.03.003

He, K. and J. Sun, 2015. Fast guided filter. arXiv preprint arXiv: 1505.00996.

He, K., J. Sun and X. Tang, 2010. Guided image filtering. Comput. Vision-ECCV, 6311: 1-14.

https://sites.google.com/view/durgaprasadbavirisetti/datasets

Lewis, J.J., R.J. O'Callaghan, S.G. Nikolov, D.R. Bull and N. Canagarajah, 2007. Pixel- and region-based image fusion with complex wavelets. Inform. Fus., 8: 119-130. DOI: 10.1016/j.inffus.2005.09.006

Li, S., X. Kang, L. Fang, J. Hu and H. Yin, 2017. Pixel-level image fusion: A survey of the state of the art. Inform. Fus., 32: 100-112. DOI: 10.1016/j.inffus.2016.05.004

Ma, J., C. Chen, C. Li and J. Huang, 2016. Infrared and visible image fusion via gradient transfer and total variation minimization. Inform. Fus., 31: 100-109. DOI: 10.1016/j.inffus.2016.02.001

Makandar, A. and B. Halalli, 2015. Image enhancement techniques using highpass and lowpass filters. Int. J. Comput. Applic., 109: 21-27. DOI: 10.5120/19256-0999

Naidu, V.P.S., 2011. Image fusion technique using multi-resolution singular value decomposition. Def. Sci. J., 61: 479-484. DOI: 10.14429/dsj.61.705

Nencini, F., A. Garzelli, S. Baronti and L. Alparone, 2007. Remote sensing image fusion using the curvelet transform. Inform. Fus., 8: 143-156. DOI: 10.1016/j.inffus.2006.02.001

Petrović, V. and C. Xydeas, 2005. Objective image fusion performance characterisation. Proceedings of the 10th IEEE International Conference on Computer Vision, Oct. 17-21, IEEE Xplore Press, Beijing, China, pp: 1866-1871. DOI: 10.1109/ICCV.2005.175

Petrovic, V., 2001. Multisensor pixel-level image fusion. PhD Thesis, Department of Imaging Science and Biomedical Engineering Manchester School of Engineering, United Kingdom.

Rajini, K.C. and S. Roopa, 2017. A review on recent improved image fusion techniques. Proceedings of the International Conference on Wireless Communications, Signal Processing and Networking, Mar. 22-24, IEEE Xplore Press, Chennai, pp: 149-153. DOI: 10.1109/WiSPNET.2017.8299737

Shreyamsha Kumar, B.K., 2015. Image fusion based on pixel significance using cross bilateral filter. Signal Image Video Process., 9: 1193-1204. DOI: 10.1007/s11760-013-0556-9

Toet, A., 1989. Image fusion by a ration of low-pass pyramid. Patt. Recognit. Lett., 9: 245-253. DOI: 10.1016/0167-8655(89)90003-2