Indian Journal of Science and Technology, *Vol 9(31), DOI: 10.17485/ijst/2016/v9i31/92553, August 2016*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Analysis of Image Fusion Techniques based on Quality Assessment Metrics

K. Kalaivani[1,2*] and Y. Asnath Victy Phamila[2]

[1]Department of Computer Science and Engineering, VELS University, Chennai – 600117, Tamil Nadu, India; kalaivani_k@outlook.com

[2]School of Computing Science and Engineering, VIT University, Chennai – 632014, Tamil Nadu, India; phamila@outlook.com

Abstract

Objective: The objective of Image Fusion is to combine the relevant and essential information from several images into a single image, which is highly informative than any of the source images such that the resultant fused image will be more appropriate for human visual perception and for image processing tasks like segmentation, feature extraction and object recognition. **Methods:** This paper presents the basic concepts, various types and levels of fusion, literature review of non-transform and transform based image fusion techniques from the perspective of their applications, advantages and limitations. **Findings:** The performance of existing image fusion methods along with various assessment metrics that determine the quality of fused images are evaluated and theoretically analyzed. It is found that the computational complexity is considerably reduced in Discrete Cosine Transformation based methods. **Applications:** Image Fusion has been effectively applied to many fields such as Remote Sensing, Military affairs, Machine Vision, Medical imaging, and so on

Keywords: Frequency Domain, Image Fusion, Multi-Focus, Quality Assessment Metrics, Spatial Domain

1. Introduction

Image fusion is the integration of complementary information present in multiple registered images into a single image with higher reliability of interpretation and quality of data. Image fusion combines multiple source images with the help of improved image processing techniques. A single fusion methodology cannot be utilized for various applications. Based on the input data and the purpose, image fusion methods are classified as i) Multiview fusion, ii) Multitemporal fusion, iii) Multifocus fusion and iv) Multimodal fusion. Multiview fusion combines the images taken by a sensor from different view- points at the same time. Multiview fusion provides an image with higher resolution and also recovers the 3d representation of a scene. Multimodal fusion refers the combination of images from different sensors and is often referred as multisensor fusion which is widely used in applications like Medical diagnosis, Security, Surveillance, etc. Multitemporal fusion integrates several images taken at various intervals to detect changes among them or to produce accurate images of objects.

It is impossible for the optical lens to capture all the objects at various focal lengths. Multi focus image fusion integrates the images of various focal lengths from the imaging equipment into a single image of better quality. This fusion methodology is widely used in Visual Sensor Networks (VSN), which refers to a spatially distributed system with vast number of sensors installed at various locations for monitoring. Sensors are cameras, which records the video sequences or still images. In VSN, images are compressed before they are transmitted to other nodes, the large amount of data is acquired at each monitoring points, which drastically occupies the memory, so an extensive research and study were required on image fusion. The objective of an image fusion technique is to effectively minimize the volume and maximize the quality and relevant information of a scene in terms of its application. The liter-

**Author for correspondence*

Table 1. Studies on various tasks of image fusion methodology

Ref	Task
[1]	Image Sharpening
[2,3]	Context Enhancement
[4],[5]	Improved classification
[6–9]	Stereo-viewing capabilities
[10–12]	Change detection
[13,14]	Object recognition and Retrieval
[15]	3D Scene reconstruction
[16]	Emotion Recognition

ature shows that the image fusion rule is applied to digital images for various tasks as shown in table 1.

The importance of fusion is increasing because of different image acquisition techniques[17] which make the resultant image features enabling improved detection and localization of the target[18]. The paper mainly addresses the multifocus image fusion and organized as follows: in Section 2, the processing levels of fusion are described. Section 3 addresses the various non-transform and transform based fusion methodologies adopted by various researchers. Section 4 describes different quality measures that are used to verify the performance of the fusion algorithm. Section 5 focuses the issues in various fusion techniques and Section 6 provides the conclusion.

2. Levels of Fusion

Image fusion is carried at three processing levels based on the stage in which the fusion needs to be performed. The different levels of fusion are pixel, feature and decision level[19].

The concept of different processing levels of fusion is illustrated in figure 1. The pixel level fusion takes place at the lowest level with the integration of measured physical parameters. In the feature level fusion, the features i.e. characteristics of the individual images are extracted and then a fusion rule is employed. Feature Fusion either uses the statistical approach or Artificial Neural Network for combining the extractions of individual source images. In decision approach, the individual images are processed for feature extraction and classification. The local decisions are then made before the fusion rule is employed to form a resultant image.

3. Image Fusion Techniques

The generic image fusion process involves four stages which includes spatial and temporal alignment, decision

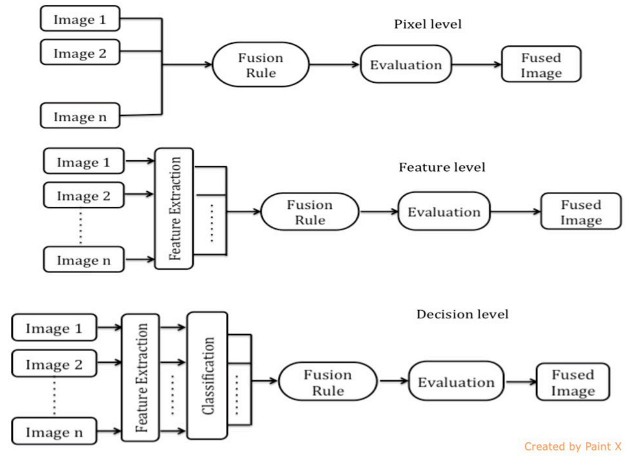


Figure 1. Levels of Fusion.

labeling and radiometric calibration[20]. The images to be fused are spatially aligned into a similar geometric base (image registration), which is a pre requisite for fusion without which the spatial information among the different input images cannot be associated. In some cases the images are then resampled and the gray levels are interpolated[21]. The temporal alignment is required when the input images are changing over time. Feature maps are then generated with the identified characteristics of all input images. Decision map is constructed once the pixels or feature maps are labeled based on the criteria. Semantic equivalence is done by linking different inputs to a common phenomenon[22].

The fusion methods are generally classified into spatial and frequency domain methods[23,24]. The spatial domain method works directly on the pixel gray level and color space of the input images and hence they are referred as single scale fusion methods or non-transform based fusion techniques. The frequency domain method decomposes the source images into sequence of images by mathematical transformation and employs the combination rules to obtain the fused coefficients. The inverse transformation is then employed to get the resultant fused image, hence this kind of fusion is referred as multi-scale fusion or transform based fusion.

3.1 Non Transform based Fusion

Non-transform based fusion techniques fuse the images by directly computing on the pixel intensity values. The simplest pixel level fusion can be done based on the average or maximum or minimum of the pixel intensities of source images. The simplest spatial based averaging method results in undesirable side effects like reduced contrast[25] and features are superimposed like photographic double exposure effect[26]. The pixel averaging approach is good at eliminating the Gaussian noise at the cost of compromising the contrast information. The maximum pixel intensity approach produces the image with full contrast but results in sensor noise[27].

Some of the spatial based methods like Brovey Transform, Intensity Hue Saturation, Principal Component Analysis[28] suffer from spectral distortion whereas the methods such as High Pass Modulation and High Pass Filtering produces less spectral distortion. The performance of non-transform based fusion technique proposed by various researchers is better when compared to some of the transform based fusion techniques, and the list is shown in Table 2. Shutao Li et al.[29] suggested a method which fuses the images of diverse focuses by decomposing them into several blocks and then integrating them by the use of spatial frequency.

Table 2. Studies on Non- Transform based fusion techniques

Ref	Proposed Technique	Techniques Compared
[29]	Spatial Frequency (SF) + Threshold	Wavelet: Db4, Db 10, Sym 8, Bior 3.5
[30]	Avg + Segmentation by Normalized cuts + SF	Discrete Wavelet Transform
[31]	Spatial Frequency + Genetic Algorithm	Haar Wavelet, Morphological Wavelet
[32]	Sparse representation + Choose Max	Spatial Gradient, Wavelet Transform, Curvelet Transform, Non Sub Sampled Contourlet Transform
[33]	Modified Pulse Coupled Neural Network	Conventional Pulse Coupled Neural Network

3.2 Transform based Fusion

Transform based fusion technique applies mathematical transformation on images before a fusion rule is employed. There are various transform based techniques such as Discrete Cosine Transformation (DCT), Discrete Wavelet Transformation (DWT), Shift Invariant Discrete Wavelet Transform (SIDWT), Contourlet Transform (CT), Non-Subsampled Contourlet Transform (NSCT), Standard Deviation Weighted Average (SDWV), Simple Weighted Average (SWV), Entropy Metrics Weighted Average (EMWV) and so on. Discrete Cosine Transformation is widely used in various image compression applications[34] such as still image JPEG, Motion JPEG, H263 video and MPEG[35]. For JPEG standard images in VSN, the application of Spatial Frequency (SF) or Averaging (Avg) or Variance or Consistency Verification (CV) or any combination of these in DCT domain is outstanding in terms of visual perception and the qualitative parameters compared to the conventional DCT, DWT and NSCT. Researchers proposed different fusion techniques whose performance is comparatively better than some of the techniques, which are listed in table 3.

Liquiang et al.[43] proposed a method integrating the quaternion with traditional curvelet transformation to address the blurring of an image. Zang et al.[44] proposed the Multi resolution Analysis based Intensity Modulation method for high resolution fused image.

Table 3. Studies on Transform based fusion techniques

Ref	Proposed Technique	Techniques Compared
[36]	DCT + Contrast, DCT + Average	WT
[37]	DCT + Variance, DCT + Variance + CV	DCT + Avg, DCT+ Contrast, DWT, SIDWT
[38]	DCT + AC_Max + CV	DCT + Avg, DCT + Variance, DCT + Variance + CV, DWT, SIDWT (Haar)
[39]	DCT + SF	DCT + Avg, DCT + Contrast, DCT + Variance, DCT + Variance + CV, DWT
[40]	DWT + Adaptive Local Energy Metrics + Fast Continuous Linearized Augmented Lagrangian Method	Maximum Selection, SWV, SDWV, EMWV
[41]	Segmentation + DWT	WT
[42]	NSCT	DWT

4. Fusion Metrics

The performance of the fused image can be accessed by the objective evaluation of the metrics based on reference and non-reference images[45]. RMSE (Root Mean Squared Error), SSIM (Structured Similarity Index Measure), PSNR (Peak Signal to Noise Ratio), Petrovic, SF (Spatial

Frequency), MG (Mean Gradient), LMI (Localized Mutual Information), FMI (Feature Mutual Information), Correlation Coefficient (CORR) and Piella are some of the metrics used by the researchers to evaluate the quality of the fused image for the source images taken from the image dataset[46-49]

4.1 Root Mean Squared Error[50,51] is used to find the dissimilarity between the reference image and the fused image. Low RMSE values indicate that the test image is close to the reference image.

$$RMSE = \sqrt{\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}((\ A(m,n) - B\ (m,n))^2}$$

4.2 Peak Signal to Noise Ratio measures the quality and the value will be high if the fused image is more identical to the reference image.

$$PSNR = 10\log_{10}\frac{r^2}{MSE}$$

where MSE refers the Mean Squared Error and r is the peak value of the reference image. The metrics MSE and PSNR are used to measure the perceived errors of the fused image.

4.3 Petrovic ($Q^{AB/F}$)[52,53] metric is a pixel wise measure of information preservation in the resultant image(F) from the source images (A, B).

$$Q^{AB/F} = \left(\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}[Q^{AF}(m,n)W^{A}(m,n) + \ Q^{BF}(m,n)W^{B}(m,n)]}{\sum_{m=1}^{M}\sum_{n=1}^{N}[W^{A}(m,n) + W^{B}(m,n)]}\right)$$

where Q^{AF} and Q^{BF} are calculated from the edge values and W^A and W^B are the weight factors. The value may lie between 0 & 1, where the value 0 implies the complete loss of information and 1 refers the ideal fusion. Performance of various techniques based on Petrovic values of test image "Pepsi" is shown in Table 4.

4.4 Structural Similarity Index Measure (SSIM) [55] measures the structural resemblance between two images and this reference metric considers image degradation as a modification in structural information.

$$SSIM\ (A,B) = \frac{2\ \mu_A\mu_B + c_1}{\mu_A^2 + \mu_B^2 + c_1}\ \frac{2\sigma_{AB} + c_2}{\sigma_A^2 + \sigma_B^2 + c_2}$$

where μ_A, μ_B refers the mean, σ_{AB} refers the cross co-variance and c_1, c_2 are constants.

4.5 Spatial Frequency (SF) finds the clarity of the resultant fused image with the edge information computed using the row and column frequency. Higher Spatial Frequency indicates the higher clarity of the image.

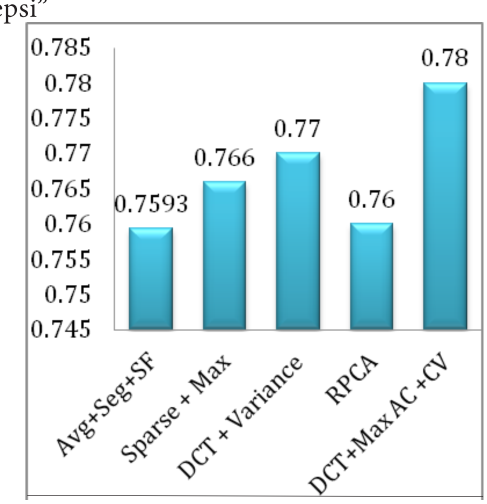
$$RF = \sqrt{\frac{1}{MN}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1}((B(m,n) - B\ (m,n-1))^2}$$

$$CF = \sqrt{\frac{1}{MN}\sum_{n=0}^{N-1}\sum_{m=0}^{M-1}((B(m,n) - B\ (m-1,n))^2}$$

$$SF = \sqrt{RF^2 + CF^2}$$

Table 4. Performance report of the various techniques on test image "Pepsi"

Ref	Technique Used	Petrovic ($Q^{AB/F}$)
[30]	Avg + Segmentation + SF	0.7593
[32]	Sparse representation + Choose Max	0.7660
[37]	DCT + Variance	0.7700
[54]	RPCA	0.7600
[38]	DCT+AC_Max +CV	0.7800



4.6 Piella (Q^{w}_{t}) [56] metric finds the quantity of information captured from the input images to the fused image.

$$Q^{w_t} = \sum_{w_t \in W} c(w_t)(\lambda\,(w_t)Q_0(A, F(w_t) + (1 - \lambda(w_t)\,Q_0(B, F(w_t)))$$

where Q_0 refers the Wang-Bovik image quality index[57] and $\lambda(w_t)$ represents the local weight referring the relative importance of the source image A compared to B.

4.7 Mean Gradient (MG)[58] estimates the edge details of the resultant image. Higher values denote the maximum preservation of edge details in the fused image. LMI[59] and FMI[60] metrics calculates the amount of mutual information between the resultant fused image and the source images. These values are computed by the application of normalization of the joint and the marginal histogram of the source and resultant image. Performance of various techniques based on Mutual Information (MI) is shown in table 5. CORR is used to find the degree of correlation between the standard reference image and the fused image.

W. Huang et al.[62] suggested a focus measure on the basis of Sum-Modified-Laplacian (SML) method which differentiates the focused from defocused image blocks. To access the quality of multi-exposure multi-focus images, Rania Hassen et al. proposed FQI (Fusion Quality Index) based on three key factors i) Preserving Contrast, ii) Preserving Structure and iii) Sharpness[63].

5. Discussion

The selection of a fusion technique and the level of fusion is application dependent. Feature and decision level fusion

Table 5. Mutual Information metric values of various techniques on test image "Clock"

Ref	Technique Used	MI
[61]	NSCT + Focused Area Detection	8.65
[54]	RPCA	8.57
[38]	DCT + Max AC + CV	9.04

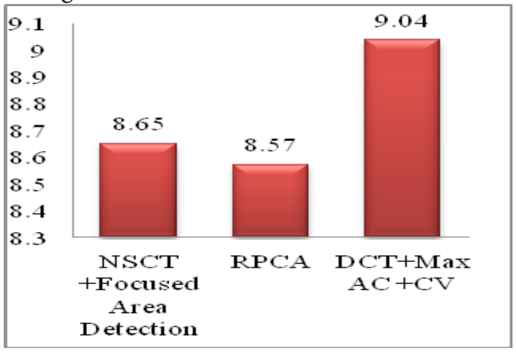


Table 6. Advantages and Limitations of different fusion methodology

Method / Ref	Advantages	Limitations
Spatial based method	Simple	Reduced Contrast
Block based method[65]	Improves the convergence between pixels	Block effect due to difficulty in finding sub block size
Evolution algorithm[66] and quad tree structure	Determines the Sub block size	Inaccurate in finding sub block size
Bilateral gradient based method [67] & Artificial Neural Network[68]	Improves the accuracy in finding the size of sub blocks	Unable to completely eliminate "block effect" for the sub-blocks which has clear and blurred area.
Wavelet Packet[69] & Frame Transform[70]	Overcomes the problem of Single Scale based transform methods	Ineffective representation of plane as well as line singularities of images. Inaccurate representation of image edge directions
Contourlet Transform[71]	Overcomes the limitations of wavelet transform and provides an asymptotic optimal representation of contours	Lacking of shift invariance and presence of pseudo Gibbs phenomena
Non Subsampled Contourlet Transform[72]	Retains shift invariance and effectually suppresses Pseudo Gibbs phenomena	Time Consuming
Transformation with Sparse representation[32]	Excellent Performance on both clean and noisy images	Time consuming and Complicated

schemes are employed for applications like emotion recognition, pattern classification[64], gaming environment, etc.

In general, many of the spatial based methods are time consuming and inappropriate for any real time application. The block-based method improves the convergence across pixels in the resultant image; it degrades the image quality due to the presence of block effect. If the source images are not registered well, the Spatial Gradient method, which is based on single pixel, leads to artifacts in the resultant fused image. Various fusion methodology adopted by various researchers is illustrated in table 6.

The popular multi-scale transform techniques such as DWT, SIDWT, NSCT are time consuming and complex, hence they cannot be used in an environment like resource constrained VSN. The usage of various methods in DCT domain considerably reduces the computational complexity and makes it easy to implement especially for multi-focused images. Limitation of the multi scale transform based methods can be addressed and minimized by the integration of spatial and transform based methods. A Single image fusion metric cannot validate the performance of fusion algorithm. Various metrics were studied and quality measures such as SSIM, PSNR, CORR and MSE are used for assessing the fusion when there are reference images, whereas the other metrics such as Petrovic, SF, MG, MI and FMI are used for non-reference images[73].

6. Conclusion

This paper has presented an overview of various image fusion techniques in non-transform and transform based fusion methods like Pixel Averaging, Select Minima or Maxima, Brovey, Principal Component Analysis, DCT, DWT, SIDWT, NSCT and various integrations with the objective of combining the several source images into a single image of better quality and information, which cannot be achieved otherwise. The analysis and usage of different fusion schemes are elaborated. The various performance metrics, which are used to measure the quality of the fused image were reviewed and analyzed.

7. References

1. Vivone G, Alparone L, Chanussot J, Mura MD, Garzelli A, Member S et al. A Critical Comparison Among Pansharpening Algorithms. IEEE Transactions on Geoscience and Remote Sensing. 2015; 53(5):2565–86.
2. Leckie DG. Synergism of synthetic aperture radar and visible/infrared data for forest type discrimination. PE&RS, Photogrammetric Engineering and Remote Sensing. 1990; 56(9):1237–46.
3. Raskar R, Ilie A, Yu J. Image fusion for context enhancement and video surrealism. In: ACM SIGGRAPH 2005 Courses. ACM. 2005; 4 pp.
4. Sheoran A, Haack B. Classification of California agriculture using quad polarization radar data and Landsat Thematic Mapper data. GIScience and Remote Sensing. 2013; 50(1):50–63.
5. Zhu Z, Woodcock CE, Rogan J, Kellndorfer J. Assessment of spectral, polarimetric, temporal, and spatial dimensions for urban and peri-urban land cover classification using Landsat and SAR data. Remote Sensing of Environment. 2012; 117:72–82.
6. Bloom AL, Fielding EJ, Fu X-Y. A demonstration of stereophotogrammetry with combined SIR-B and Landsat TM images. International Journal of Remote Sensing. 1988; 9(5):1023–38.
7. Toutin T. SPOT and Landsat stereo fusion for data extraction over mountainous areas. Photogrammetric Engineering and Remote Sensing. 1998; 64(2):109–13.
8. Gudmundsson SA, Aanaes H, Larsen R. Fusion of stereo vision and time-of-flight imaging for improved 3D estimation. International Journal of Intelligent Systems Technologies and Applications. 2008; 5(3-4):425–33.
9. Franke U, Rabe C, Badino H, Gehrig S. 6d-vision: Fusion of stereo and motion for robust environment perception. In: Pattern Recognition Letters, Elsevier. Springer. 2005; 216–23.
10. Thamarai M, Mohanbabu K. An Improved Image Fusion and Segmentation using FLICM with GA for Medical Diagonosis. Indian Journal of Science and Technology. 2016; 9(12).
11. Nichol J, Wong MS. Satellite remote sensing for detailed landslide inventories using change detection and image fusion. International Journal of Remote Sensing. 2005; 26(9):1913–26.
12. Gong M, Zhou Z, Ma J. Change detection in synthetic aperture radar images based on image fusion and fuzzy clustering. IEEE Transactions on Image Processing. 2012; 21(4):2141–51.
13. Bu S, Cheng S, Liu Z, Han J. Multimodal Feature Fusion for 3D Shape Recognition and Retrieval. IEEE MultiMedia. 2014; 21(4):38–46.
14. Annabattula J, Koteswara Rao S, Sampath Dakshina Murthy A, Srikanth KS, Das RP. Multi-sensor submarine surveillance system using MGBEKF. Indian Journal of Science and Technology. 2015; 8(35):1–5.
15. Li Z, Wang K, Meng D, Xu C. Multi-view stereo via depth map fusion: A coordinate decent optimization method. Neurocomputing. 2016; 178:46–61.
16. Sun B, Li L, Wu X, Zuo T, Chen Y, Zhou G et al. Combining feature-level and decision-level fusion in a hierarchical

classifier for emotion recognition in the wild. Journal on Multimodal User Interfaces. 2015; 1–13.
17. Jiang Y, Wang M. Image fusion with morphological component analysis. Information Fusion. 2014; 18:107–18.
18. Toet A, Franken EM. Perceptual evaluation of different image fusion schemes. Displays, Elsevier. 2003; 24(1):25–37.
19. Pohl C, Van Genderen JL. Multisensor image fusion in remote sensing: Concepts, methods and applications. International Journal of Remote Sensing. 1998; 19(5):823–54.
20. Mitchell HB. Image fusion: Theories, techniques and applications. Springer, 2010.
21. Ludusan C, Lavialle O. Multifocus image fusion and denoising: a variational approach. Pattern Recognition Letters. 2012; 33(10):1388–96.
22. Hong G. Image Fusion, Image Registration, and Radiometric Normalization for High Resolution Image Processing. 2007.
23. Mitianoudis N, Stathaki T. Optimal contrast correction for ICA-based fusion of multimodal images. Sensors Journal. 2008; 8(12):2016–26.
24. Li H, Manjunath BS, Mitra SK. Multisensor image fusion using the wavelet transform. Graphical models and image processing. 1995; 57(3):235–45.
25. Zhang Z, Blum RS. A categorization of multiscale-decomposition-based image fusion schemes with a performance study for a digital camera application. Proceedings of the IEEE. 1999; 87(8):1315–26.
26. Burt PJ, Kolczynski RJ. Enhanced image capture through fusion. Proceedings of IEEE Fourth International Conference on Computer Vision. 1993. p. 173–82.
27. Sharma RK, Leen TK, Pavel M. Probabilistic Image Sensor Fusion. Image (Rochester, NY). 1999; 1.
28. Amro I, Mateos J, Vega M, Molina R, Katsaggelos AK. A survey of classical methods and new trends in pansharpening of multispectral images. EURASIP Journal on Advances in Signal Processing. 2011; 2011(1):79.
29. Li S, Kwok JT, Wang Y. Combination of images with diverse focuses using the spatial frequency. Information Fusion, Elsevier. 2001; 2(3):169–76.
30. Li S, Yang B. Multifocus image fusion using region segmentation and spatial frequency. Image and Vision Computing, Elsevier. 2008; 26(7):971–9.
31. Kong J, Zheng K, Zhang J, Feng X. Multi-focus image fusion using spatial frequency and genetic algorithm. International Journal of Computer Science and Network Security. 2008; 8(2):220.
32. Yang B, Li S. Multifocus Image Fusion and Restoration with Sparse Representation. IEEE Transactions on Instrumentation and Measurement. 2010; 59(4):884–92.
33. Singhai DAJ. Multifocus image fusion using modified pulse coupled neural network for improved image quality. IET Image Processing. 2010; 4(March):443–51.
34. Djamel S, Mouldi B. Image compression via embedded coder in the transform domain. Asian Journal of Information Technology. 2006; 5(6):633–9.
35. Wallace GK. The Jpeg Still Picture Compression Standard. IEEE Transactions on Consumer Electronics. 1992; 38(1).
36. Tang J. A contrast based image fusion technique in the DCT domain. Digital Signal Processing, Elsevier. 2004; 14(3):218–26.
37. Haghighat MBA, Aghagolzadeh A, Seyedarabi H. Multi-focus image fusion for visual sensor networks in DCT domain. Computers and Electrical Engineering. 2011; 37(5):789–97.
38. Phamila YAV, Amutha R. Discrete Cosine Transform based fusion of multi-focus images for visual sensor networks. Signal Processing, Elsevier. 2014; 95:161–70.
39. Liu C, Longxu J, Hongjiang T, Guoning L. Multi-focus image fusion based on spatial frequency in discrete cosine transform domain. IEEE Signal Processing Letters. 2015; 22(2):220–4.
40. Yang Z-Z, Yang Z. Novel multifocus image fusion and reconstruction framework based on compressed sensing. IET Image Processing. 2013; 7(9):837–47.
41. Jia-zheng Y, Qing L, Bo-xuan S. Multifocus Image Fusion Based on Region Selection. TELKOMNIKA Indonesian Journal of Electrical Engineering. 2013; 11(11):400–4.
42. Zhang Q, Guo B long. Multifocus image fusion using the nonsubsampled contourlet transform. Signal Processing, Elsevier. 2009; 89(7):1334–46.
43. Guo L, Dai M, Zhu M. Multifocus color image fusion based on quaternion curvelet transform. Optics Express. 2012; 20(17):18846.
44. Wang Z, Ziou D, Armenakis C, Li D, Li Q. A Comparative Analysis of Image Fusion Methods. IEEE Transactions on Geoscience and Remote Sensing. 2005; 43(6):1391–402.
45. Phamila YAV, Amutha R. Low complexity multifocus image fusion in discrete cosine transform domain. Optica Applicata. 2013; 43(4).
46. Dataset of Standard Gray scale test images, Computer Vision Group, University of Granada. 2003. Available from: http://decsai.ugr.es/cvg/CG/base.htm
47. Image Repository, Fractal Coding and Analysis Group. University of Waterloo. 2009. Available from: http://links.uwaterloo.ca/Repository.html
48. Test Images, University of Southern California, 1981. Available from: http://sipi.usc.edu/database.
49. Naidu VPS. Multi focus image fusion using the measure of focus. Journal of Optics. Springer. 2012; 41(2):117–25.
50. Rockinger O. Image Sequence Fusion Using a Shift-Invariant Wavelet Transform. Proceedings of International Conference on Image Processing. 1997; 3. p. 288–91.
51. Wang Z, Bovik AC. A universal image quality index. IEEE Signal Processing Letters. 2002; 9(3):81–4.
52. Drajic D, Cvejic N. Adaptive fusion of multimodal surveillance image sequences in visual sensor networks.

IEEE Transactions on Consumer Electronics. 2007; 53(4):1456–62.

53. Xydeas CS. Objective Image Fusion Performance Measure. Electronic Letters. 2000; 36(4):308–9.
54. Wan T, Zhu C, Qin Z. Multifocus image fusion based on robust principal component analysis. Pattern Recognition Letters, Elsevier. 2013; 34(9):1001–8.
55. Wang Z, Bovik AC, Simoncelli EP. Image quality assessment: From error visibility to structural similarity. IEEE Transactions on Image Processing. 2004; 13(4):600–12.
56. Piella G, Heijmans H. A new quality metric for image fusion. Proceedings of IEEE International Conference on Image Processing. 2003.
57. Piella G. A general framework for multiresolution image fusion: from pixels to regions. Information fusion. 2003; 4(4):259–80.
58. Bai X, Zhou F, Xue B. Edge preserved image fusion based on multiscale toggle contrast operator. Image and Vision Computing. 2011; 29(12):829–39.
59. Hossny M, Nahavandi S, Creighton D, Bhatti A. Image fusion performance metric based on mutual information and entropy driven quadtree decomposition. Electronics letters. 2010; 46(18):1266–8.
60. Haghighat MBA, Aghagolzadeh A, Seyedarabi H. A non-reference image fusion metric based on mutual information of image features. Computers and Electrical Engineering. 2011; 37(5):744–56.
61. Yang Y, Tong S, Huang S, Lin P. Multifocus Image Fusion Based on NSCT and Focused Area Detection. IEEE Sensors Journal. 2015; 15(5):2824–38.
62. Huang W, Jing Z. Evaluation of focus measures in multi-focus image fusion. Pattern Recognition Letters. 2007; 28(4):493–500.
63. Hassen R, Wang Z, Salama MMA. Objective Quality Assessment for Multiexposure Multifocus Image Fusion. IEEE Transactions on Image Processing. 2015; 24(9):2712–24.
64. Mangai UG, Samanta S, Das S, Chowdhury PR. A survey of decision fusion and feature fusion strategies for pattern classification. IETE Technical Review. 2010; 27(4):293–307.
65. De I, Chanda B. Multi-focus image fusion using a morphology-based focus measure in a quad-tree structure. Information Fusion. 2013; 14(2):136–46.
66. Aslantas V, Kurban R. Fusion of multi-focus images using differential evolution algorithm. Expert Systems with Applications. 2010; 37(12):8861–70.
67. Tian J, Chen L, Ma L, Yu W. Multi-focus image fusion using a bilateral gradient-based sharpness criterion. Optics communications. 2011; 284(1):80–7.
68. Li S, Kwok J, Wang Y. Multifocus image fusion using artificial neural networks. Pattern Recognition Letters, Elsevier. 2002; 23(8):985–97.
69. Kannan K, Perumal SA, Arulmozhi K. Area level fusion of multi-focused images using multi-stationary wavelet packet transform. International Journal of Computer Applications. 2010; 2(1):88–95.
70. Li S, Kwok JT, Wang Y. Using the discrete wavelet frame transform to merge Landsat TM and SPOT panchromatic images. Information Fusion. 2002; 3(1):17–23.
71. Do MN, Vetterli M. The contourlet transform: an efficient directional multiresolution image representation. IEEE Transactions on Image Processing. 2005; 14(12):2091–106.
72. Da Cunha AL, Zhou J, Do MN. The nonsubsampled contourlet transform: theory, design, and applications. IEEE Transactions on Image Processing. 2006; 15(10):3089–101.
73. Qu G, Zhang D, Yan P. Information measure for performance of image fusion. Electronics letters. 2002; 38(7):1.