Visible and Thermal image fusion using Curvelet Transform and Brain Storm Optimization

K.Madheswari[1], N.Venkateswaran[2], Member, IEEE, and V.Sowmiya[3]
[1]Department of Computer Science and Engineering
[2]Department of Electronics and Communication Engineering
[1,2]SSN College of Engineering,Chennai, India.
[3]Department of Electronics and Communication Engineering
SASTRA University,Thanjavur, India

Abstract— **In this paper, we propose a brain storm optimized image fusion framework in the curvelet transform domain that combines thermal image with the visual image to obtain a single informative fused image. The source images are decomposed using the curvelet transform and the high frequency sub-band coefficients are fused by maximum selection rule, whereas the low frequency sub-band coefficients are fused by weighted linear combination rule. The human intelligence based brain storm optimization (BSO) algorithm is employed to find the optimal weights in fusing low frequency sub-band coefficients. Simulation have been performed to compare our results with other multi resolution fusion methods such as gradient (GRAD) pyramid, shift invariant discrete wavelet transform (SIDWT) and non sub-sampled contourlet transform (NSCT). The quality of the fused image is assessed using five different quality metrics and the results indicate that the proposed method outperforms other multiresolution fusion methods in terms of both subjective and objective quality metrics.**

Keywords—image fusion; visible image; thermal image; curvelet transform; brain storm optimization.

I. Introduction

Image fusion is the process of blending the most pertinent information from multiple source images to obtain a more comprehensive fused image. The fused image contains much richer and more accurate information and thus makes it suitable for further image processing task, such as object detection, image classification, image recognition and segmentation [1]. It helps human in better interpretation of images[2]. Visual imaging is very matured and successful due to the advancement in sensor technology, however visible images are more sensitive to illumination changes [3]. On the other hand, thermal imaging is not affected by illumination changes and operable in dark environments. But, thermal images are of low resolution and sensitive to variations in the heat patterns of an object. Hence, it is advantageous to combine visible and thermal images to produce a fused image that is more informative and robust.

Recent studies [4-8] show that wavelet-based image fusion provides high-quality spectral content in fused images. However, wavelet based multi resolution transforms are working with limited directionality at all scales. The contourlet transform based image fusion method is proposed in [9] preserves edge information better than wavelet transform or pyramid transform. The contourlet transform is not shift invariant [10] due to the presence of down sampling and upsampling process. Non sub-sampled contourlet transform (NSCT) is applied to fuse multifocus images in [11], but NSCT has high computational complexity.

The authors of [12-15] presented fusion methods using the curvelet transform and showed the CT represents image edges more efficiently. The CT coefficients show less variation against noise when compared with other transforms.

Choice of the fusion rule for the image fusion process is of great importance, since, it directly affects the quality of the fused image [16]. The contemporary image fusion techniques employ the fusion rules without analyzing the content of source images and thus result in information loss, in addition to distortion in spectral characteristics of the fused image [17]. In this paper, optimized weighted average fusion rule is proposed and optimal weights are computed using BSO which makes our work different from existing curvelet based image fusion techniques.

The rest of the section is organized as follows. The proposed methodology is discussed at section 2. The results and performance evaluation of the proposed work is discussed in section 3. Finally conclusions are drawn in section 4.

II. Proposed image fusion framework

The original visible and thermal images should be geometrically registered to each other. In this paper, the source images I_1 and I_2 are registered using affine transform. The Fig.1 depicts the block diagram of the proposed approach.

The curvelet coefficients are denoted as $CI_1(x,y)$ and $CI_2(x,y)$. $CI_1^{k,l}(x,y)$ and $CI_2^{k,l}(x,y)$ denote the kth scale and l orientation of the coefficient $CI_1(x,y)$ and $CI_2(x,y)$. Where $k \in \{1,2\}$, $l=1$ when $k=1$ and $l \in \{1,\ldots,8\}$ when $k=2$. Each pair of the curvelet frequency coefficients $CI_1^{k,l}(x,y)$ and $CI_2^{k,l}(x,y)$ is fused by weighted average fusion rule based on the optimal weights chosen by BSO. Apply inverse curvelet transform to fused curvelet coefficients to get the fused image I.

A. Image decomposition using curvelet transform

The sources images I_1 and I_2 are decomposed into approximation (low frequency) and detailed (high frequency) components at the required level using curvelet transform. The coefficients of the visual and thermal images are subsequently combined using the fusion rule. The fused image F is then obtained by taking the inverse curvelet transform to the fused coefficients.

$$F = T^{-1}\left[\varphi\{T(I_1), T(I_2)\}\right] \qquad (1)$$

Where, T is the curvelet transform.

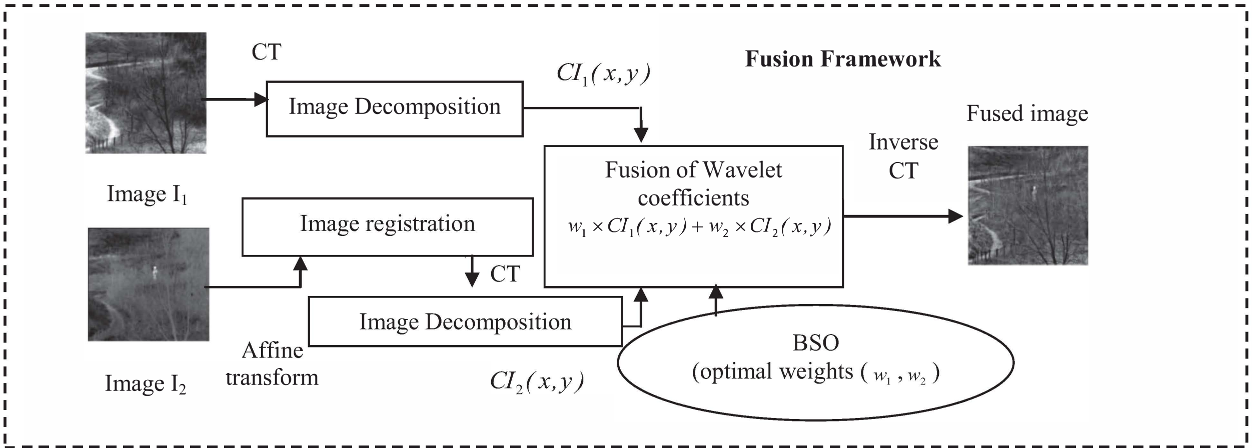


Fig 1. Proposed Image Fusion Framework

B. Optimized image fusion rule

In this paper image fusion is formulated as a multi-objective optimization problem as given below: The set of values (weights) is defined as a group of N ideas

$$w = \begin{Bmatrix} w_{11}, w_{12}, \ldots, w_{1N} \\ w_{21}, w_{22}, \ldots, w_{2N} \end{Bmatrix}$$

Where, $w = (w_1, w_2)^T \in A$ which maximizes the one of the objective namely the entropy of the fused image.

$$H = -\sum_{i=0}^{255} p(i) \times \log_2(p(i)) \qquad (2)$$

Where, $p(i)$ is the probability of occurrence of i^{th} intensity of the fused image. As a second objective the group of N ideas, W should also minimize the RMSE value computed using

$$RMSE = \frac{1}{2}[\,P + Q\,] \quad where$$

$$\begin{bmatrix} P = \sqrt{\dfrac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[F(i,j) - I_1(i,j)]^2} \quad and \\ Q = \sqrt{\dfrac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[F(i,j) - I_2(i,j)]^2} \end{bmatrix} \qquad (3)$$

$F(i,j)$, $I_1(i,j)$, $I_2(i,j)$ are fused, visible and thermal images respectively. One of the simple ways to handle the multi-objective optimization problem is to construct an overall objective function as a linear combination of the multiple conflicting objective functions and the overall objective function is defined as follows:

$$f(x) = \alpha_1\left[-\sum_{i=0}^{255} p(i) \times \log_2(p(i))\right] + \alpha_2 A$$

$$A = \left[\frac{1}{\frac{1}{2}\left[\sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[F(i,j) - I_1(i,j)]^2} + \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[F(i,j) - I_2(i,j)]^2}\right]}\right]$$

Where α_1 and α_2 are constants whose values indicates the relative significance of one objective function relative to other. In our case, we chosen $\alpha_1 = \alpha_2$ =0.5.Each row in the idea set is substituted in Eq. (1) and the fused image is obtained. The solution set that maximizes the multi objective function will be stored as global best idea (gbest). After the maximum number of iterations is reached the gbest value is the optimal weight to obtain the final fused image.

C. Evaluation of fusion performance

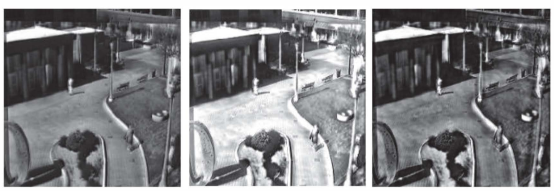
In our proposed system we have adapted seven quality metrics to quantitatively evaluate the performance of the fusion method. The metrics are Nonlinear Correlation Information Entropy (QNCIE), Gradient based Fusion performance (Q_G), Phase Congruency based image fusion metric (Q_P), Piella's metric (QW) and Chen-Blum Metric (Q_{CB}). The large value of all metrics denotes the better fusion result [18].

III. EXPERIMENTAL RESULTS AND DISCUSSION

The proposed image fusion framework is compared with several other state-of-the-art multi resolution image fusion methods namely GRAD, SIDWT, and NSCT. The proposed fusion method is implemented using MatLab 2015. The number of decomposition level is set to 5 for CT. The decomposition level for GRAD and SIDWT is set to 2.

Number of decomposition level is set to 4 for NSCT and the direction in each level is set to 2,3,3,4. The high frequency components are fused by maximum selection rule whereas low frequency coefficients are fused using average fusion rule for GRAD, SIDWT and NSCT.

a) Visible image b) Thermal image c) GRAD



d) SIDWT e) NSCT f) Proposed

Figure 2. Fusion result of street image

a) Visible image b) Thermal image c) GRAD

d) SIDWT e) NSCT f) Proposed

Figure 3. Fusion result of sandpath image

The fusion results of street image is depicted in Fig 2. The street visible image gives the clear structure of building, trees, benches, street lamp and boundary of street line. On the other hand thermal image provides clear information about location of objects of the same scene. When integrating these two images using SIDWT the visual information of the person standing nearer to park is not effectively combined in the fused image. The result of GRAD is also not satisfactory because of low contrast resultant image. The NSCT fused image having more number of saturated pixel due to its redundancy property, therefore performance of NSCT also not satisfactory. The proposed method effectively combines the background structure and objects from visible and thermal images. Shadow of the man and the benches are clearly visible. Moreover, the contours of the building, trees, lamp and street path are more visible compared with other approaches.

Table 1. Comparison of fusion performance with quality metrics

Methods/Metrics	Q_{NCIE}	Q_G	Q_P	Q_W	Q_{CB}	E	RMSE
Result of street Image							
Proposed	0.8204	0.5301	0.4220	0.7209	0.6020	7.6863	9.3251
NSCT	0.8112	0.4101	0.4012	0.7105	0.5043	7.6431	13.9366
SIDWT	0.8069	0.3670	0.3572	0.7020	0.4301	6.9025	10.9087
GRAD	0.8136	0.3000	0.3980	0.6560	0.4065	6.7865	11.9870
Result of sandpath Image							
Proposed	0.8126	0.5933	0.4545	0.7891	0.6105	7.2722	9.4614
NSCT	0.8058	0.5905	0.3863	0.7443	0.5576	6.9998	14.8960
SIDWT	0.8031	0.3184	0.1959	0.7205	0.5075	6.1201	9.3962
GRAD	0.8030	0.2553	0.1900	0.6696	0.3897	6.0096	10.9847

The sandpath visible image conatins the information about the structure of sandpath and trees while the thermal image gives the information of man. The man is not visible in the GRAD fused image as well as the contour of the sandpath is not clear. Moreover, due to low contrast resultant image, there is no differentiation of objects and background in the GRAD fused image. The result of NSCT is better than SIDWT, but the original brightness of trees are lost in the NSCT fused image. The proposed method effectively combines structure of tree and man in the fused image and compared with other methods the proposed method gives highly contrasted image. The result of sandpath image is given in fig 3. The value of QG from table 1 indicates that the proposed method transfers more features such as edges and boundaries to the fused image compared with state-of-art methods. The value (0.6020) of QCB indicates that the proposed fused image is highly contrasted and preserved more edge information. The phase congruency metric QP indicates that the proposed method transfers more information about corners and edges from the input images while the GRAD method have less information about corners and edges in the fused image.

IV. CONCLUSION

In this paper, a brain storm optimized image fusion framework to combine thermal and visible images to produce a single informative fused image is presented. The proposed method uses the curvelet transform for image decomposition and human intelligence based brain storm optimization (BSO) for finding the optimal weights using an objective function based on entropy and RMSE. The experimental results demonstrates that the proposed methodology has higher entropy index which confirms that information from source images are well combined into the fused image. The subjective and objective assessment of the fused image shows that the proposed method is superior to the state of art fusion techniques.

REFERENCES

[1] Myungjin Choi, Rae Young Kim, Myeong-Ryong Nam, and Hong Oh Kim, " Fusion of Multispectral and Panchromatic Satellite Images Using the Curvelet Transform" IEEE GEOSCIENCE AND REMOTE SENSING LETTERS, vol. 2, no. 2, pp.136-140, April. 2005.

[2] Tumpa Dey ,"A Survey on Different Fusion Techniques of Visual and Thermal Images for Human Face Recognition", International Journal of Electronics Communication and Computer Engineering, vol.4, no.6, pp10-15, 2013

[3] Rajiv Singh, Ashish Khare, Rajiv Singh, Ashish Khare," Fusion of multimodal medical images using Daubechies complex wavelet transform – A multi-resolution approach", Information Fusion, vol.19, pp. 49–60, 2014

[4] S.M. Mahbubur Rahman, M.Omair Ahmad and M.N.S. Swamy, "Contrast-based Fusion of noisy images using discrete wavelet transform. IET image Processing, vol.4, no.5, pp374-384.

[5]H. Li, B.S. Manjunath, and S.K. Mitra, "Multi-sensor image fusion using the wavelet transform", Graphical Models and Image Processing, vol.57, pp. 235–245, 1995.

[6] X. Li, M.He and M.Roux, "Multifocus image fusion based on redundant wavelet transform", IET Image Processing. vol.4 no.5 pp.283-293, 2010.

[7]Andreas Ellmauthaler, Carla L. Pagliari and Eduardo A.B. da Silva," Multi-scale Image Fusion Using the Undecimated Wavelet Transform with Spectral Factorization and Non-orthogonal Filter Banks", IEEE TRANSACTIONS ON IMAGE PROCESSING, vol.22, no. 3, pp.1005-1017, 2013.

[8] Sajad Farokhi , Mariyam Shamsuddin , U.U. Sheikh , Jan Flusser, Mohammad Khansari , and Kourosh Jafari-Khouzani "Near infrared face recognition by combining Zernike moments and undecimated discrete wavelet transform", Digital Signal Processing vol.31, pp.13–27, 2014.

[9] Kishor P. Upla, Manjunath V. Joshi and Prakash P. Gajjar, "An Edge Preserving Multiresolution Fusion: Use of Contourlet Transform and MRF Prior", IEEE TRANSACTIONS ON GEOSCIENCE AND REMOTE SENSING, vol. 53, no. 6, pp. 3210-3220, 2015.

[10] Shutao Li and Bin Yang, " Hybrid Multiresolution Method for Multisensor Multimodal Image Fusion", IEEE SENSORS JOURNAL, vol.10, no. 9, pp.151-156, 2010.

[11] Yong Yang, Song Tong, Shuying Huang, and Pan Lin, " Multifocal Image Fusion Based on NSCT and Focused Area Detection ", IEEE SENSORS JOURNAL, vol.15,no.5, pp. 2015.

[12]Filippo Nencini, Andrea Garzelli, Stefano Baronti and Luciano Alparone, " Remote sensing image fusion using the curvelet transform ", Information Fusion vol.8, pp.143–156, 2007.

[13] Limin Dong , Qingxiang Yang , Haiyong Wu , Huachao Xiao , Mingliang Xu , "High quality multi-spectral and panchromatic image fusion technologies based on Curvelet transform". Neurocomputing vol. 159, 268–274,2015.

[14]H.S. Bhadauria , M.L. Dewal, "Medical image denoising using adaptive fusion of curvelet transform and total variation", Computers and Electrical Engineering ,vol.39, pp.1451–1460,2013.

[15]S. Sulochana, R. Vidhya, R. Manonmani," Optical image fusion using support value transform (SVT) and curvelets", Optik vol.126, pp.1672–1675, 2015.

[16]George Bebis, Aglika Gyaourova, Saurabh Singh, Ioannis Pavlidis, "Face recognition by fusing thermal infrared and visible imagery", Image and Vision Computing Journal, vol. 24, pp. 727–742, 2006.

[17]Zheng Liu, Erik Blasch, Zhiyun Xue, Jiying Zhao, Robert Laganiere and Wei Wu," Objective Assessment of Multi-resolution Image Fusion algorithms for Context enhancement in Night Vision: A Comparative Study", IEEE transactions on Pattern Analysis and Machine intelligence. vol.34 no.1, pp. 94-109,2012.