

FUSION OF INFRARED AND VISIBLE IMAGES BASED ON TARGET REGION DETECTION METHODS: REVIEW

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Abstract: The infrared image is the result of the infrared thermal imaging sensors detecting the outside temperature difference. The visible image is suitable for human visual characteristics, but it is constrained by lighting and environmental conditions. We test fusion of near infrared images (IR) with visible images (Vi) for detail enhancement and contrast using several quality metrics. Fusion experiments on IR and Vi images, indicate that the proposed methods is effective and efficient, which achieves better performance than the ordinary fusion methods.

Keywords: Infrared Images (IR), Visible Images (Vi), PCA, ICA, NN.

I. INTRODUCTION

With the recent advancement in sensor imaging technology, an unmanned aerial vehicle (UAVs) having multiple infrared (IR) and visible light sensors can work in both the timings either day or night. These UAVs are autonomous, but it can be controlled via remote or it may be semiautonomous [1]. The UAVs are mostly used in the application of defense, target localization, forest fire control, etc.

With the infrared and visible sensors, individually, lots of difficulties are involved in target detection because the color, and texture information of the target in visible images are large abundant. However, it fails to detect the target information that can be easily identified in the infrared images. Therefore, there is need to develop an efficient approach to merge both types of information to merge

into a single image for detection the target region, properly. Now, the role of fusion comes in the picture to fuse both the information available in the images captured by visible and infrared camera.

The main objective of the image fusion is to merge all credential information extracted from the visible and infrared images without any spatial and spectral distortion. So that, the resultant fused images have more amount of information. This will improve the image resolution and enhance the details for the human visualization and next higher order processing tasks.

Several computationally light weight approaches are tested for the fusion and the results are compared using several fusion metrics.

II. METHODS

1. Based on Wavelet Transform:

French scientist Morlet and Grossman had developed the method of Wavelet Transform in the early 1980s [6].

Yifeng Niu et al. in [2] has proposed an Airborne Infrared and Visible Image Fusion for Target Perception based on Target Region Segmentation and Discrete Wavelet Transform. In this paper, a new approach to infrared and visible image fusion based on target regions detected in DWT domain, which can help UAV to realize environment perception. Other than the conventional fusion methods based on region segmentation. The fusion experiments are done on condition that the target is unmoving and observable both in visible and infrared images, targets are moving and observable

both in visible and infrared images, and the target is observable only in an infrared image.

Lingchao Zhan et al. in [3] has given Infrared and Visible image fusion method based on three stages of Discrete Wavelet Transform. The method has three stages, in the first two stages, the infrared and visible images are fused using different wavelet fusion rules, the two fusion results from the first and the second stage are fused again using another wavelet fusion rule, and then get the final fusion result.

Yujia Zuo et al. in [4] proposed an infrared (IR) and visible image fusion method introducing region segmentation into the dual-tree complex wavelet transform region. The method involves segmenting the region in an IR image by significance, and identifying the target region and the background region; then, fusing the low-frequency components in the DTCWT region according to the region segmentation result. For high-frequency components, the region weights need to be assigned by the information richness of region details to conduct fusion based on both weights and adaptive phases, and then introducing a shrinkage function to suppress noise; Finally, the fused low-frequency and high-frequency components are reconstructed to obtain the fusion image.

2. Based on Principal component analysis:

Principal component analysis (PCA) is another powerful tool used for merging remotely sensed images. This statistical technique transforms a set of correlated variables into a set of uncorrelated linear combinations of the original variables. Evaluation of principal components (PCs) of an image involves computing the covariance matrix and eigen-values. In this fusion, PCA transforms the input images to their eigen space. The weighting for each source image are obtained from the eigen vector corresponding to the largest eigen value of the covariance matrix of each source image. Using the weights fusion is performed in the eigen space.

The main advantage of PCA is dimensionality reduction without much loss of information. PCA is superior in performance to the simple averaging technique.

3. Based on Independent component analysis:

Yin LU et al. in [5] has proposed a novel infrared and visible image fusion method based on independent component analysis. The disadvantage of the traditional fusion method based on independent component analysis (ICA) is that the primary feature information that describes the IR objects and the secondary feature information in the IR image are fused into the fused image. Secondary feature information can depress the visual effect of the fused image. A novel ICA-based IR and visible image fusion scheme is proposed in this paper.

ICA is employed to extract features from the infrared image, and then the primary and secondary features are distinguished by the kurtosis information of the ICA base coefficients. The secondary features of the IR image are discarded during fusion. The fused image is obtained by fusing primary features into the visible image.

4. Fusion using Neural Networks:

Li et al. (2002) proposed a pixel level multi-focus image fusion method using artificial neural networks. The algorithm first divides the source images into blocks. Features signifying the clarity of an image block are extracted and fed into the ANN, which then learns to determine which source image is clearer at a particular pixel location. Two neural network models, namely the Probabilistic Neural Network (PNN) and Radial Basis Function Network (RBFN), have been considered for fusion. This ANN based approach is found to outperform the DWT-based approaches, particularly when there is object movement or registration problems in the source images.

Zhang et al. (2008) proposed a fusion scheme using Radial Basis Function (RBF) neural network combined with nearest

neighbor clustering method. Experiments show this method can improve fusion performance with proper width parameter. As RBF network training requires no iteration, few training parameters, and has high training speed, the authors concluded that RBF network is very much suitable for fusion.

Although ANN offers good generalization performance, the robustness of ANN methods is limited by the quality of the training data and the accuracy of convergence of the training algorithm.

5. Fusion Quality Assessment

Fusion quality was estimated using several different metrics. These were Q_x , edge preservation value [7], universal image quality index based values: Q_p considering the inputs saliency, Q_w weighting salient image areas, and Q_e the edge dependent measure [8]. Q_c is universal quality index measure that has been extended to take into account the similarity between inputs and resulting images [9]. As different type of quality values, the human perception based measures were calculated.

The same contrast sensitivity filters were used as in [10], namely Mannos-Skarison resulting Q_M , Daly's filter for Q_D and Ahumada's filter for Q_A . Also the combined mutual information MI with fusion symmetry FS were calculated [11].

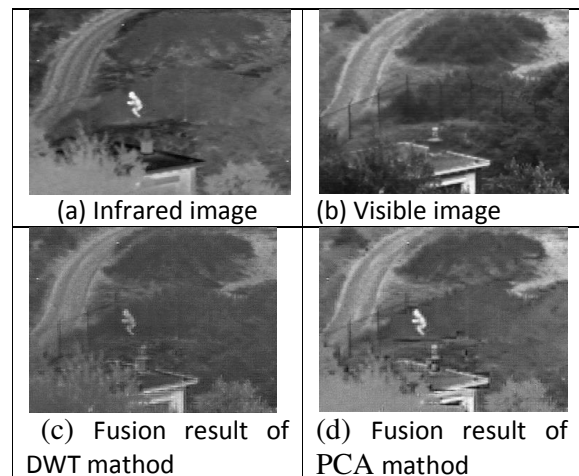


Visible Images Infrared Images
Fig. 1: Examples of Visible Images and Infrared Images.

III. RESULTS

Review on various pixel and feature-level fusion methods reveals that the combination of a multi-resolution transform with a decision making algorithm yields better fusion results.

The infrared and visible images in the experiment have been matched exactly, they were shot in the same scene and at the same time. Figure 2 shows a group of images in the experiment, figure 2(a) is an infrared image, figure 2(b) is a visible image. We can see a person in the infrared image, but we can't see the person in the visible image.



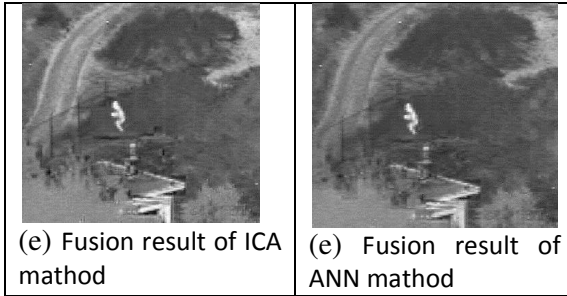


Fig.2 Experiments Results

Evaluation Criteria:

In order to evaluate the performance of the methods, adopt the mean, information entropy (IE), standard deviation (SD) and average gradient (AG) as objective evaluation criteria to evaluate the results of fusion methods.

(1) The mean is the mean value of the image pixel values. It reflects the average brightness of an image. The calculation formula is shown in equation (1)

$$I^- = \frac{1}{mn} \sum_{x=1}^m \sum_{y=1}^n I(x, y) \quad \dots(1)$$

$I(x, y)$ is the pixel value of an image, $m \times n$ is the size of an image.

(2) Information entropy is an important indicator of the evaluation of images. The calculation formula is shown in equation (2)

$$H = - \sum_{i=0}^{L-1} P_i \log_2 P_i \quad \dots(2)$$

P_i the distribution probability of the gray value i , L is the total number of the gray level.

(3) Standard deviation reflects the image texture information. The larger the standard deviation, the more dispersed distribution of the gray levels of an image, the sharper textures. The calculation formula is shown in (3)

$$SD = \sqrt{\frac{1}{mn} \sum_{x=1}^m \sum_{y=1}^n (I(x, y) - I^-)^2} \dots(3)$$

$I(x, y)$ is the pixel value of an image, I^- is the mean value of an image pixel values, $m \times n$ is the size of an image.

(4) Average gradient reflects the tiny details of variance, texture variation and image resolution. The greater the average gradient, the better the image resolution. The calculation formula is shown in (4)

$$AG = \frac{1}{mn} \sum_{x=1}^m \sum_{y=1}^n \sqrt{\frac{[I(x+1,y)-I(x,y)]^2 + [I(x,y+1)-I(x,y)]^2}{2}} \dots(4)$$

$I(x,y)$ is the pixel value of an image, $m \times n$ is the size of an image.

Analysis: The fusion results are evaluated by the evaluation criteria i.e.

| Method | the mean | IE | SD | AG |
|------------|-------------|-----------|------------|-----------|
| Figure2(c) | 89.34 2 | 5.56 7 | 21.76 6 | 6.09 7 |
| Figure2(d) | 105.0 11 | 4.78 6 | 29.89 7 | 9.43 2 |
| Figure2(e) | 90.87 6 | 7.76 5 | 31.76 5 | 6.76 8 |
| Figure2(f) | 103.1 27 | 7.34 2 | 31.24 3 | 8.82 1 |

IV. CONCLUSION

In this paper, image fusion methods for infrared and visible images based on region target detection are proposed. Target detection technique is employed to segment the source images into target and background regions. Different fusion rules are adopted respectively in target and background regions. Fusion experiments on real world image sequences indicate that the proposed method is effective and efficient, which achieves better performance than the general fusion methods.

REFERENCES

[1] W. Jian and Z. Shaofeng, "Visible and Infrared Image Fusion Method Based on

Wavelet Transform and YUV”, *Journal of Northwestern Polytechnical University*, vol. 3, no. 33, 2013.

[2] Yifeng Niu, Shengtao Xu, Lizhen Wu and Weidong Hu, “Airborne Infrared and Visible image fusion for target perception based on target region segmentation and Discrete Wavelet Transform” *Hindawi Publishing Corporation Mathematical Problems in Engineering*, Volume 2012 pp. 1-10, October 2012.

[3] Lingchao Zhan, Yi Zhung, “Infrared and Visible image fusion method based on three stages of Discrete Wavelet Transform”, *International Journal of Hybrid Information Technology*, Vol.9 No.5, pp. 407-418, 2016.

[4] Yujia Zuo, Jinghong Liu, Guanbing Bai, Xuan Wang and Mingchao Sun, “Airborne Infrared and Visible image fusion combined with region segmentation ” *MDPI Journal of Sensors*, pp.1-15, May 2017.

[5] Yin Lu , Fuxiang Wang, Xiaoyan Luo, Feng Liu, “Novel infrared and visible image fusion method based on independent component analysis” *Front. Computer Science*, Vol.8, No.2, pp. 243- 254, 2014.

[6] L. Fan, Y. Zhang, Z. Zhou, D.P. Semanek, S. Wang, and L. Wu, “An Improved Image Fusion Algorithm Based on Wavelet Decomposition”, *Journal of Convergence Information Technology*, vol. 10, no. 5.

[7] C. Xydeas and V. Petrovic, “Objective image fusion performance measure,” *Electronics Letters*, vol. 36, pp. 308–309, 2000.

[8] G. Piella and H. Heijmans, “A new quality metric for image fusion,” in *International Conference on Image Processing, ICIP Proceedings.*, vol. 3, 2003, pp. III – 173–6 vol.2.

[9] N. Cvejic, A. Loza, D. Bull, and N. Canagarajah, “A similarity metric for

assessment of image fusion algorithms,” *International Journal of Information and Communication Engineering*, pp. 178–182, 2005.

[10] H. Chen and P. K. Varshney, “A human perception inspired quality metric for image fusion based on regional,” *Information Fusion*, vol. 8, pp. 193 – 207, 2007.

[11] C. Ramesh and T. Ranjith, “Fusion performance measures and a lifting wavelet transform based algorithm for image fusion,” in *Proc. Of the 5th International Conference on Information Fusion*, vol. 1, 2002, pp.317–320.

[12] J. Li, J. Sun and X. Mao, “Multi Resolution Fusion of Remote Sensing Images Based on Resolution Degradation Model”, *Geo-Spatial Information Science*, vol.1, no.8.

[13] G. Piella, “New Quality Measures for Image Fusion”, *Proceedings of International Conference on Information Fusion*, Stockholm, Sweden, pp. 542-546.

[14] J. Zhuqing, “Study of Multi-Source Image Fusion Method in Transform Domain”, Ph D.Thesis, Jiangnan University, Wuxi.