Fusion Infrared and Visible Images Using Optimal Weights

Mehrnoosh Gholampour
Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran
mehrnosh.gholampor@birjand.ac.ir
Hassan Farsi*
Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran
hfarsi@birjand.ac.ir
Sajjad Mohamadzadeh
Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran
s.mohamadzadeh@birjand.ac.ir

Received: 20/Jan/2015 Revised: 17/Mar/2015 Accepted: 12/Apr/2015

Abstract

Image fusion is a process in which different images recorded by several sensors from one scene are combined to provide a final image with higher quality compared to each individual input image. In fact, combination of different images recorded by different sensors is one of image fusion methods. The fusion is performed based on maintaining useful features and reducing or removing useless features. The aim of fusion has to be clearly specified. In this paper we propose a new method which combines vision and infrared images by weighting average to provide better image quality. The weighting average is performed in gradient domain. The weight of each image depends on its useful features. Since these images are recorded in night vision, the useful features are related to clear scene details. For this reason, object detection is applied on the infrared image and considered as its weight. The vision image is also considered as a complementary of infrared image weight. The averaging is performed in gradient of input images, and final composed image is obtained by Gauss-Seidel method. The quality of resulted image by the proposed algorithm is compared to the obtained images by state-of-the-art algorithms using quantitative and qualitative measures. The obtained results show that the proposed algorithm provides better image quality.

Keywords: Image Fusion; Useful Features; Infrared Image; Vision Image; Weighted Averaging.

1. Introduction

Image fusion is a process of combining different images recorded from one scene to provide a final image with higher quality compared to the individual input images [1]. Image fusion algorithm has three important stages as: input images that are classified in four categories [1,2,3], image registration [4,5] and combining algorithm [1]. The image fusion is performed in three levels as: pixel-level [1], feature level [1] and decision level [1]. In this paper, the image fusion is performed in pixel level. According to the aim of fusion, definition of the quality is specified. One of image fusion methods is combination of different images recorded by different sensors. The fusion is based on maintaining useful features and reducing or removing useless features. The aim of fusion must be clearly specified. This depends on the type of images and its application. The useful and useless features depend on the aim of fusion [1]. In this paper input images have been recorded by visible and infrared sensors from same scene and in sunset time. Since visible imaging sensors are dependent to scene light image, clearness also depends on scene light. However, due to imaging time (sunset time) there is not enough light for some points of scene and therefore there is not possibility to present all scene details.

The problem can be resolved by using infrared imaging sensor. Because this performs imaging based on heat of objects and radiant heat difference is displayed as a visible image. But cold object is not clear in infrared image [1]. Therefore, it seems that combining visible and infrared images using appropriate method can resolve the shortcoming of both sensors and provide a final image with quality of day time [1]. Thus, in this case, the aim of fusion is to obtain an image with better quality such that all scene details are clear [2]. The useful features of input images are clear objects of the scene which have to retain in final image [12]. In this paper the performance of the proposed method is compared against general methods including averaging by principle component analysis [14], averaging, laplacian pyramid [5] and wavelet transform [6].

* Corresponding Author

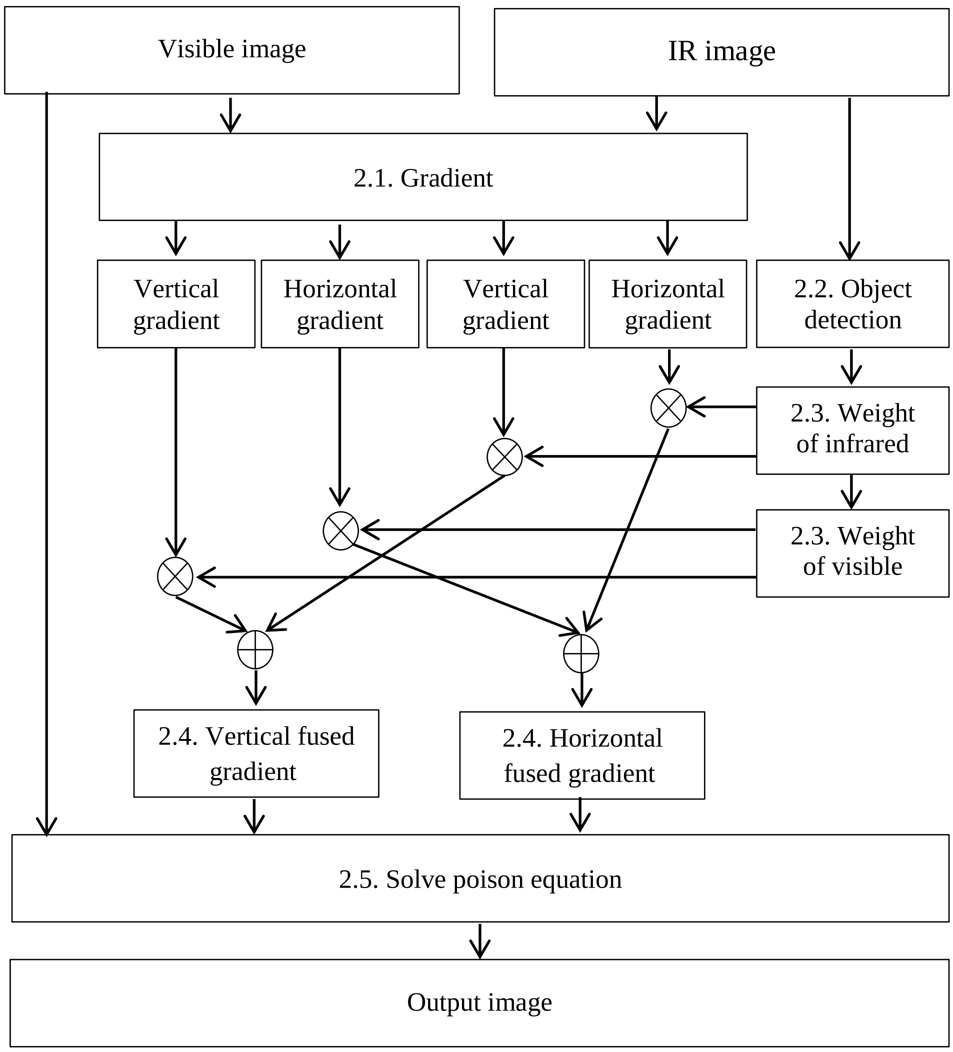

Fig. 1. Block diagram of the proposed algorithm

In averaging by principle component analysis method, the weight of each image is the normalized weight proportional to its principle component [14]. In averaging method, pixels of the output image are obtained by averaging on pixels of input image. In Laplacian method, each input image is decomposed into its Laplacian pyramid surfaces, then fusion is performed by combination of pyramid surfaces and final image is obtained using inverse pyramid transform [15]. In wavelet method, each input image is decomposed by wavelet transform and then the wavelet coefficients of the final image is calculated by maximization of high frequency coefficients and averaging on low frequency coefficients. The final image is obtained by using inverse wavelet transform [16]. In these methods, there are two problems: reduction in final image contrast and reduction in clarity of final image background, compared to visible input image. These problems occur because firstly low frequency components are blurred by averaging in whole image and so the contrast of final image reduces. Secondly, the weight of each image is not proportional to useful features. This causes that the useful information to be useless. In following section, we propose a new method which provides optimum weights and prevents contrast reduction in the final image.

2. The Proposed Method

An effective method to prevent contrast reduction is to apply averaging on gradient of each image. Because the gradient represents sudden changes or in other words high frequency image components and so low frequency image components remain without any changes. This results in the contrast reduction to be removed and low frequency information remains without any changes. To retain the useful information, we find the optimal weight of each image. The optimum weight includes only useful image features.

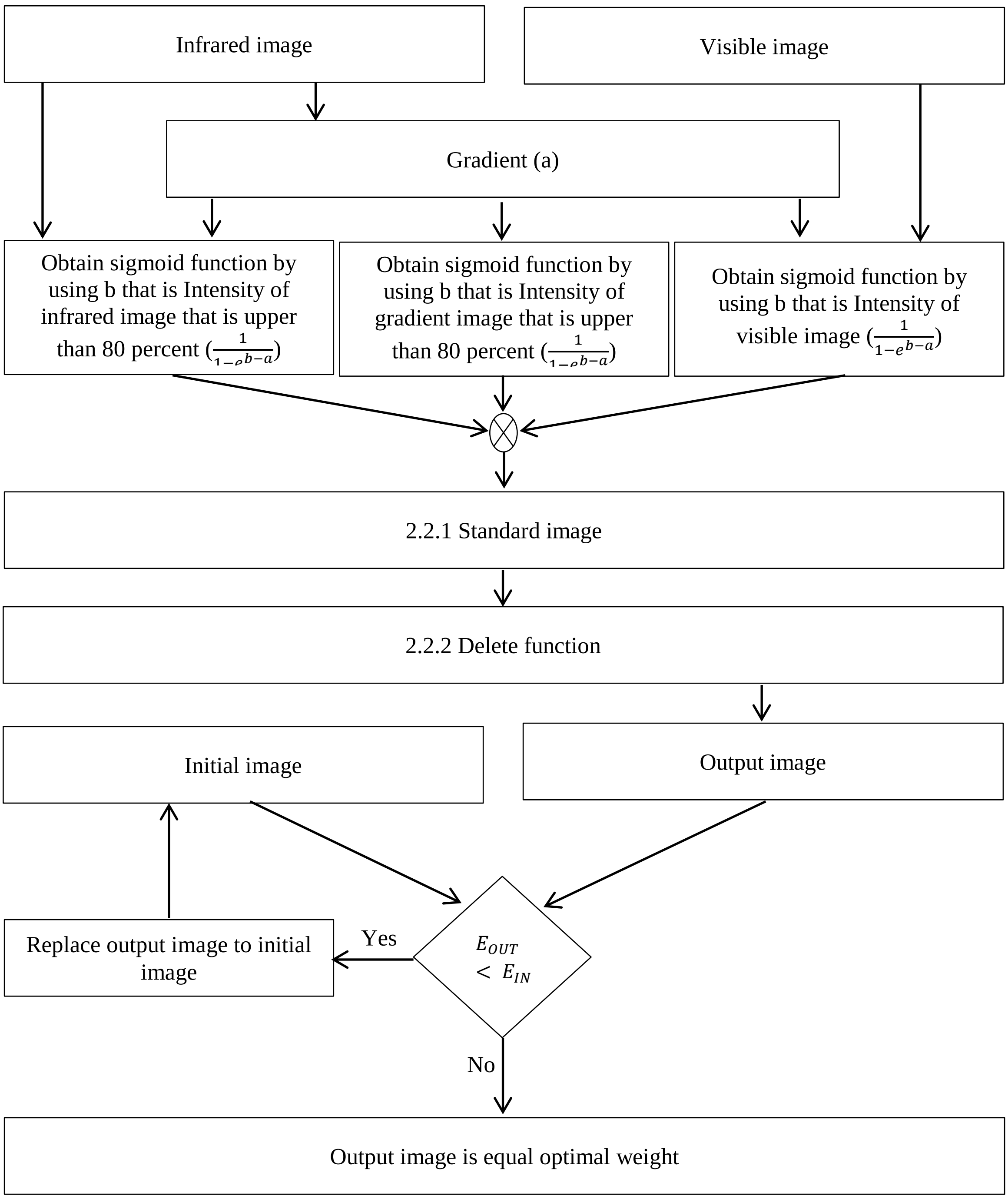

Fig. 2. Block diagram of the proposed object detection

The useful features are background information and hidden objects for the visible image and infrared image, respectively. Note that we use the term of "hidden objects" for infrared images because these objects cannot be observed in visible images. Therefore, the weight of infrared image is complementary of the weight of visible image. The aim of fusion is to detect the hidden objects existed in infrared image and to display them in a same background as existed in visible image. The block diagram of the proposed method is shown in Figure 1 which is detailed on following subsections.

2.1 Gradient Block

The inputs to the gradient block are the input images and the outputs are horizontal and vertical gradient of each image. The image gradient is obtained by convolution of input image with a vector of [-1/2, 0, 1/2] in row and column directions [17]. The gradient is used to extract the required information from images for instance, the edges and the changes in intensity. After computation of the gradient images, the pixels with large gradient values will be considered as possible edge pixels. The pixels with the largest gradient values in the direction of the gradient are considered as edge pixels, and the edges may be traced in the direction perpendicular to the gradient direction. One example of edge detection algorithm based on gradient is the Canny edge detector.

2.2 Object Detection

In order to find the optimum weight of the infrared image, or in other words, hidden objects, it is applied as an input to the object detection block. For more classification, the process of object detection is shown as a block diagram in Figure 2. The main criterion for object detection is to exist higher intensity of object area compared to the background image. During the detection of high density areas in the image, undesired and additional areas will be also detected. Thus, it requires to use an effective method to remove undesired areas and maintain target area. This can be achieved by detection of target area borders, detailed in following section.

2.2.1 To Obtain Standard Image

Standard image includes the borders of the target area. This image is a multiplication of three threshold images. The threshold image is obtained by sigmoid function which is applied on gradient image. The gradient image is compared to three threshold levels. These thresholds are: (a) visible image intensities, (b) intensity upper than 80 percent of infrared image and (c) intensity upper than 80 percent of infrared gradient image.

2.2.2 To Execute Delete Function

Gamut of input and output of delete function is zero and one. For detection of target area completely, equality of neighbor pixels is used as a criterion. The delete function is given by:

$$F_{OUT}(i,j) = |f_{in}(i,j)) - IM(i,j)_{base}| + 0.7*(\left|\sum_{(p,q)\in N(x,y)} L - f_{in}(i,j))\right| \quad (1)$$

Where N is quartette neighborhood of current pixel located in position of (i, j) from input image. This function is executed twice for each pixel (for L=0, and L=1). The value of L corresponding to lower function value is selected and the lower function value is considered for output pixel. In first step, this function is executed on initial image. In next step, this function is applied on output image of the previous step and it is repeated until output image energy is less than input image energy. The energy of each image is obtained by:

$$E(i,j) = |f_{OUT}(i,j)) - IM(i,j)_{base}| + 0.7*(\left|\sum_{(p,q)\in N(x,y)} N - f_{OUT}(i,j))\right| \quad (2)$$

Where N is quartette neighborhood of current pixel located in position of (i, j) from input image. Note that the coefficient of 0.7 has been obtained in simulation by manual changing to get the best performance in the proposed method. By repeating the execution of delete function, we obtain an image which satisfies the criterion as mentioned in block diagram of Figure 2 which is $E_{out}<E_{in}$. Therefore the target area is detected and weight of infrared image is calculated. Since useful information of two images are complementary, we consider the weight of infrared and visible images complementary as well.

2.3 To Obtain Weight of Input Images

The weight of infrared and visible images are multiplied in gradient infrared and visible images, respectively.

2.4 To Obtain Fused Image Gradients

The horizontal and vertical gradients of two images are independently added together. The obtained horizontal and vertical gradients are considered as fused gradients in same direction.

$$I_{F'x} = (1-w)*I_{A_x} + (w)*I_{B_x} \quad (3)$$

$$I_{F'y} = (1-w)*I_{A_y} + (w)*I_{B_y} \quad (4)$$

Where W is the optimum fused weight.

2.5 Final Image Construction Using Fused Gradient

In order to construct fused image using fused gradients, we use solving Poisson equation [8]. Suppose final fused image and the gradient fused image are presented by ∇F and $\nabla F'$, respectively. It requires minimizing following equation:

$$\int abs\ (\nabla F - \nabla F')d\emptyset \quad (5)$$

Where $\emptyset$ is image area and equation (5) should be zero. To solve final fused problem, it requires solving Poisson equation:

$$\Delta F = div\ (\nabla F') \quad (6)$$

This implies that following equation is solved in terms of F(i,j):

$$F(i,j+1) + F(i,j-1) - 2*F(i,j) + F(i-1,j)+F(i+1,j) - 2*F(i,j) = div(\nabla F') \quad (7)$$

Thus, it requires to find the image pixel located in (i,j). Equation (7) can be rewritten as:

$$F(i,j) = 0.25*(F(i,j+1) + F(i,j-1) + F(i-1,j) + F(i+1,j) - div(\nabla F') \quad (8)$$

This equation is used for all image pixels. Thus, the number of unknown quantities is equal to all fused image pixels. Iterative method is used to solve Eq. (8). We use Gauss-seidel method due to having high speed convergence. According to the aim of fusion, visible image pixels are considered as initial values.

3. Output of the Proposed Object Detection Method

As an example, we apply the proposed object detection algorithm on three groups of input images named: Nato Camp, Duine and Trees. The obtained results are shown in Figures 3, 4 and 5. In these Figures, (a) shows infrared image that is the input of the object detection, (b) shows the infrared image that is the output of first step of the object detection, (c) shows initial image that is the input of the delete function and (d) shows weight of infrared image that is the output of the object detection. As observed, the proposed method detects the hidden object (which is a person) and therefore it considers the hidden object as a weight of the infrared image. Figures 3(b) through 5(b) and 3(d) through 5(d) contain difference features. For instance, Figures 3(b) through 5(b) extract only the edges of the hidden object, but Figures 3(d) through 5(d) detect the hidden object. Meanwhile, Figures 3(b) through 5(b) consists of a lot of noise, and the proposed detection method removes the noise of Figures 3(b) through 5(b) and the obtained results are shown in the Figures 3(d) through 5(d).

4. Evaluation of the Proposed Algorithm

The proposed algorithm is evaluated using qualitative and quantitative measures. Visual comparison and numerical comparison are used as quantitative and qualitative measures, respectively.

4.1 Visual Comparison

Figures 6, 7 and 8 show the obtained images by different fusion algorithms. Visual and infrared images are shown in figures (a) and (b), respectively. The resulted image by using PCA [18,19], averaging [6], Laplacian pyramid [20], Wavelet [21] and the proposed algorithms are presented in Figures (c), (d), (e), (f) and (g), respectively.

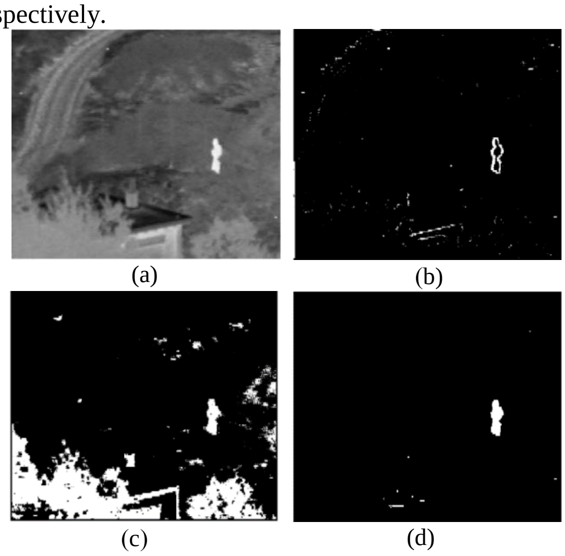

Fig. 3. Object detection on Nato Camp: (a) Infrared image (b) Standard image (c) Initial image (d) Weight of infrared image.

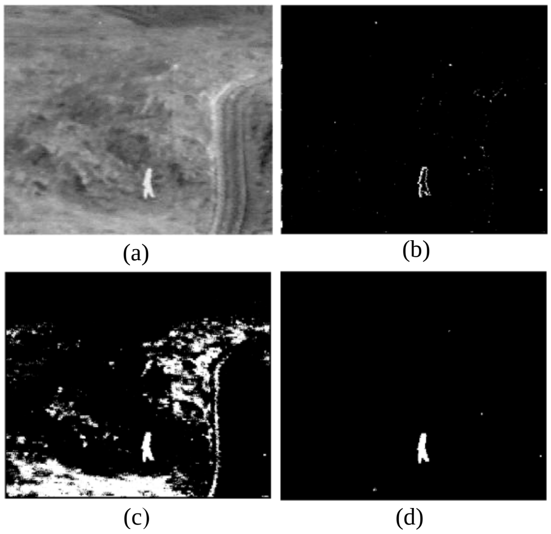

Fig. 4. Object detection on Duine: (a) Infrared image (b) Standard image (c) Initial image (d) Weight of infrared image.

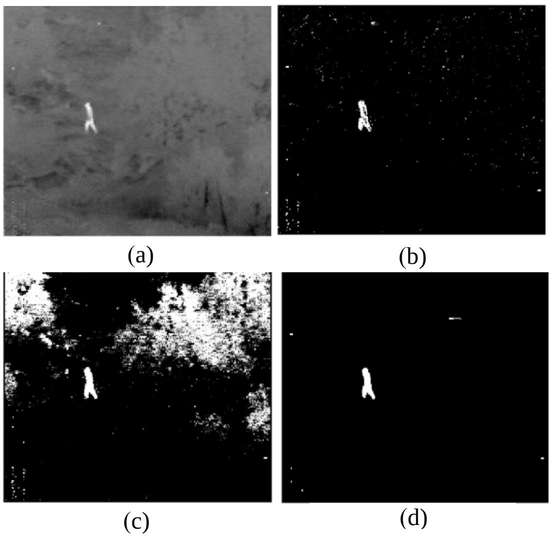

Fig. 5. Object detection Trees: (a) Infrared image (b) Standard image (c) Initial image (d) Weight of infrared image.

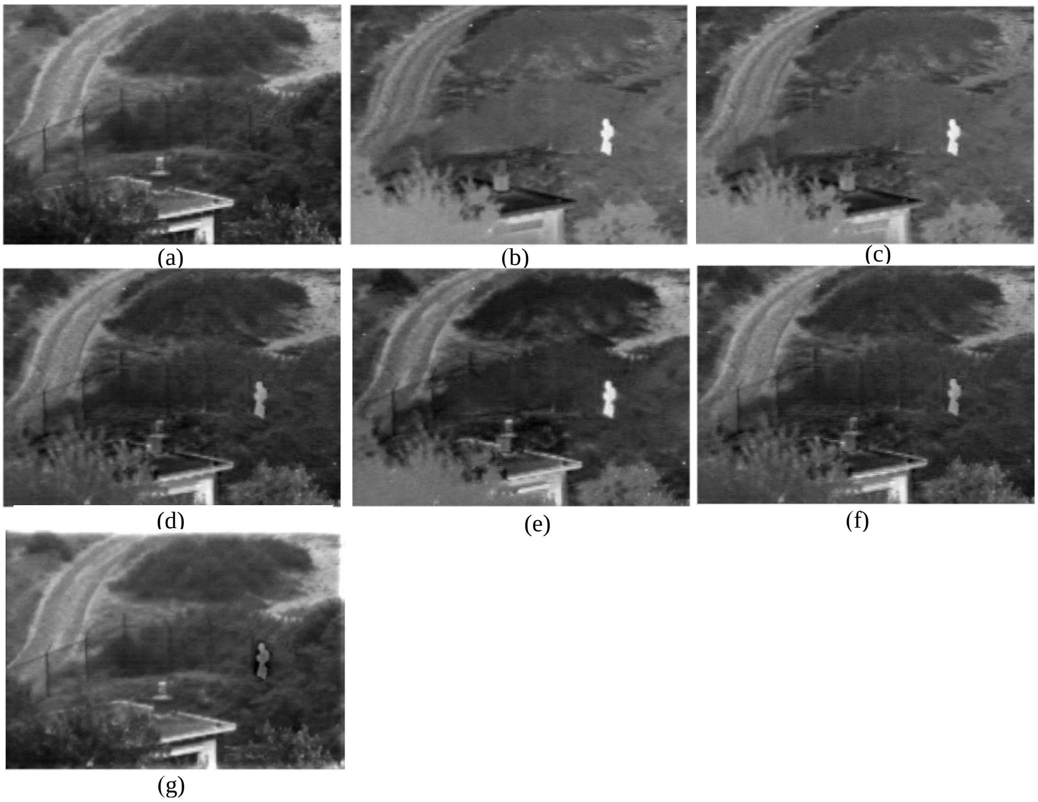

Fig. 6. Input and output of different methods on Nato Camp: (a) visible image (b) infrared image (c) output of PCA (d) Output of averaging method (e) Output of laplacian pyramid (f) output of wavelet (g) Output of the proposed algorithm.

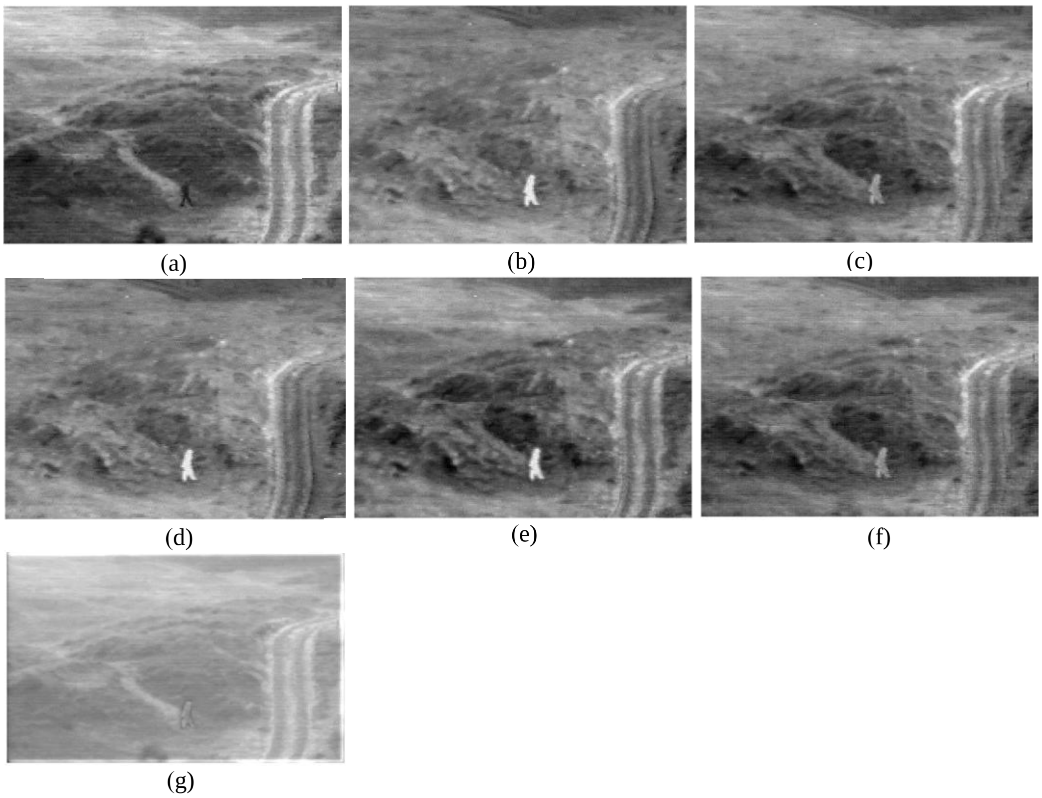

Fig. 7. Input and output of different methods on Duin: (a) visible image (b) infrared image (c) output of PCA (d) Output of averaging method (e) Output of laplacian pyramid (f) output of wavelet (g) Output of the proposed algorithm.

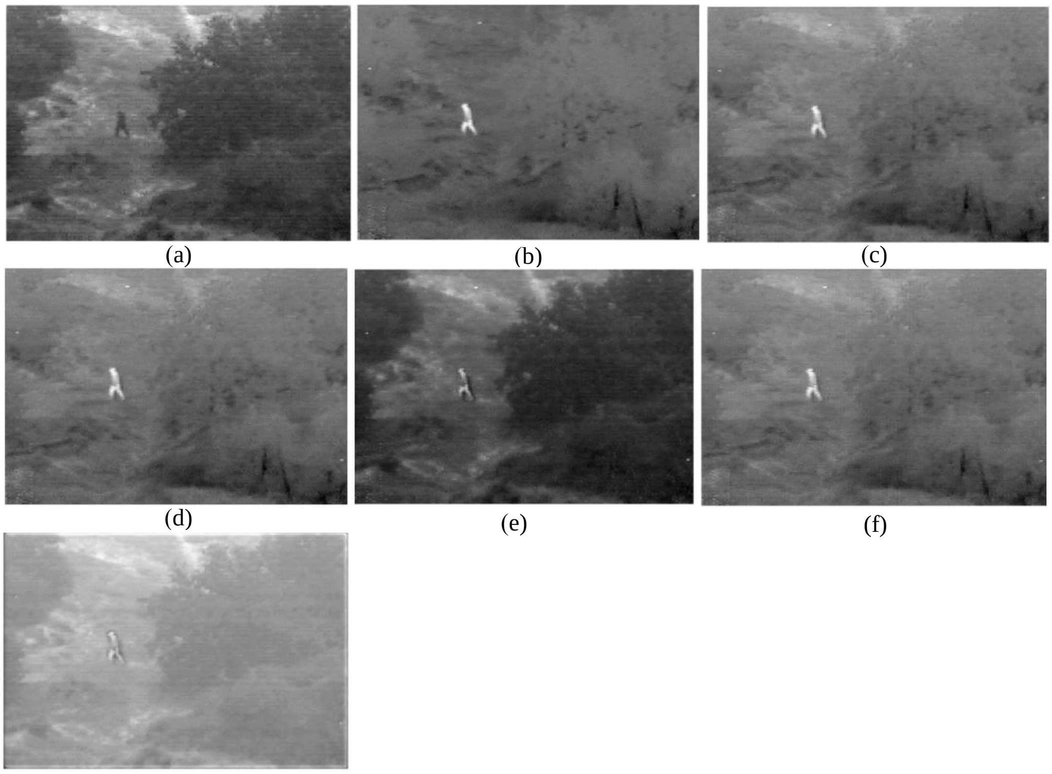

Fig. 8. Input and output of different methods on Trees: (a) visible image (b) infrared image (c) output of PCA (d) Output of averaging method (e) Output of Laplacian pyramid (f) output of wavelet (g) Output of the proposed algorithm.

As observed, the output image provided by the proposed method maintains useful features of the infrared image which is hidden person and also maintains the background of visible image better than other fusion algorithms. Therefore, the proposed algorithm provides more effective fusion compared to the other algorithms.

4.2 Quantitative Comparison

Quantitative comparisons are performed by using two criteria named structural similarity [22] and maintain edge [23,24].

4.2.1 Structural Similarity

Structural similarity is given by:

$$SSIM\ (A,B) = [I(A,B)][C(A,B)][S(A,B)] \qquad (9)$$

Where I(A,B), C(A,B) and S(A,B) are intensity, contrast and intensity correlation of A and B images given by:

$$I(A,B) = \frac{2\mu_A\mu_B}{\mu_A^2+\mu_B^2}\ ;\ C(A,B) = \frac{2\sigma_A\sigma_B}{\sigma_A^2+\sigma_B^2};\ S(A,B) = \frac{\sigma_{AB}}{\sigma_A\sigma_B} \qquad (10)$$

Where σ is standard deviation and μ is mean of image.

This criterion must have low value for infrared images and high value for visible images because in infrared images the only useful information is the hidden object (the hidden person) whereas all background information related to visible images is reflected to fusion image and therefore the structural similarity between the visible image and final image will be high. The obtained structural similarity of PCA, Averaging, Laplacian pyramid, Wavelet and the proposed method are given in Table 1, Table 2 and Table 3 for Nato Camp, Duine and Trees images, respectively. As observed, the proposed method provides lower value for infrared images and higher values for visible images. This means that the proposed method results in higher performance compared to other methods.

4.2.2 Maintain Edge

Maintain edge is a measure for evaluation of fused algorithms and its value is between zeros to one. The value of zero means that the edge information has been lost whereas the value of one indicates all edge information has completely maintained. Therefore, higher value of maintain edge indicates the fusion algorithm is more appropriate and edge information is maintained.

Table 1. Comparison of similarity structural that is related to Nato Camp input

Fusion algorithms	**Sum of structural similarity**	**structural similarity with visible image**	**structural similarity with infrared image**
PCA	12.8484	1.7531	11.954
Averaging	16.5413	10.4168	6.1245
Laplacian pyramid	16.6348	7.9466	8.6881
Wavelet	16.5742	10.4180	6.1562
The proposed method	**17.3109**	**15.7363**	**1.5742**

Table 2. Comparison structural similarity that is related to Duine input images

Fusion algorithms	Sum of structural similarity	structural similarity with visible image	structural similarity with infrared image
PCA	31.9668	14.4797	17.4871
Averaging	47.9530	17.1848	30.7692
Laplacian pyramid	36.3190	14.8922	21.2468
Wavelet	48.1597	17.2093	30.9504
The proposed method	**17.9357**	**17.2586**	**0.6771**

Table 3. Comparison structural similarity that is related to Trees input images

Fusion algorithms	Sum of structural similarity	structural similarity with visible image	structural similarity with infrared image
PCA	31.9668	14.4797	17.4871
Averaging	31.9884	15.2024	16.7860
Laplacian pyramid	19.7236	15.4598	4.2638
Wavelet	31.9886	15.2176	16.7711
The proposed method	**19.7086**	**16.210**	**3.8675**

As an example, we calculate the maintain edge resulted by averaging with PCA, averaging, Laplacian pyramid, wavelet and the proposed algorithms for three different images: Nato Camp, Duin and Trees. The obtained results are presented in Table 4. As observed, the proposed algorithm provides higher value compared to other methods. This means that the proposed method is more capable to maintain the information of input image edges.

Table 4. Maintain edge of Nato Camp, Duin, Trees

Fusion algorithms	Nato Camp	Duin	Trees
Averaging with PCA	0.3626	0.3137	0.3137
Averaging	0.4153	0.3500	0.3183
Laplacian pyramid	0.2958	0.2706	0.2703
Wavelet	0.4144	0.3500	0.3176
The proposed method	**0.6806**	**0.6955**	**0.5757**

4.2.3 Running Time

A running time of the averaging PCA, averaging, Laplacian pyramid, wavelet and the proposed method has been computed by using MATLAB on the computer (Intel, CPU 2.0, 2GB memory) and has been represented in Table 5. The size of three images is 1280*960. As observed, the running time of the proposed method is lower than other methods.

Table 5. Time duration of Nato Camp, Duin, Trees

Fusion algorithms	Nato Camp	Duin	Trees
Averaging with PCA	287.345 s	279.344 s	291.478 s
Averaging	250.073 s	246.691 s	251.679 s
Laplacian pyramid	257.867 s	249.675 s	259.213 s
Wavelet	256.355 s	247.543 s	258.467 s
The proposed method	**203.578 s**	**245.468 s**	**232.741 s**

5. Conclusions

In this paper, we proposed a fusion algorithm based on infrared and visible images by averaging on gradients of input images. The gradient of image includes high frequency features of the image and therefore low frequency components maintain and prevent blending in output image. By obtaining the optimum weights of the infrared and visible images for fusion, we ensure that useful features are used in final image. The useful features are hidden objects and background for the infrared and visible images, respectively. In order to evaluate the proposed method, the obtained results are compared to averaging by PCA, averaging, Laplacian pyramid and wavelet methods for three different images named: Nato Camp, Duin and Trees. The evaluation is performed by using qualitative and quantitative measures. Visual comparison is used as qualitative measure and numerical comparison including structural similarity and maintain edge is used as quantitative measure.

In visual comparison, the obtain results show that the proposed method maintains the background information (useful information related to visible image) and hidden objects (useful information related to infrared image) more effectively compared to other methods.

In numerical comparison, the resulted structural similarity has lower value for infrared and higher value for visible image by applying the proposed method compared to other methods. This means that the proposed method maintains the useful information for both infrared and visible images in fused image. Also, the obtained results for maintain edge using the proposed method have higher values compared to other methods. This indicates that the proposed method maintains edge information belonging to both infrared and visible images better than other methods. Thus, the obtaining results show that the proposed algorithm results in higher quality in the fused image compared to other methods.

References

[1] H. B. Mitchel, *Image Fusion: Theories, Techniques and Applications*, Springer, 2010.

[2] R.S. Blum, Z. Liu, *Multi- Sensor Image Fusion and Its Applications*, Taylor and Francis Group, New York, 2005.

[3] S. Li, B. Yang, H. Jianwen, "Performance Comparison of Different Multi-Resolution Transforms for Image Fusion", *International Journal on Multi-Sensor, Multi-Source Information Fusion*, Vol. 3, No. 2, pp. 741-746, 2011.

[4] M. Gong, Z. Zhou, J. Ma, "Change Detection in Synthetic Aperture Radar based on Image fusion and Fuzzy Clustering", *IEEE transaction on Image Processing*, Vol.: 21, No. 4, pp. 2141-2151, 2012.

[5] J. Black, "Multi View Image Surveillance and Tracking", *Motion and Video Computing*, Vol. 32, pp. 169-174, 2002.

[6] B. Zitova, J. Flusser, "Image Registration Methods: A Survey ", *Image and Vision Computing*, Vol. 21, pp. 977–1000, 2003.

[7] L. Zagorchev, A. Goshtasby, "A Comparative Study of Transformation Functions for Non-Rigid Image Registration", *IEEE Transactions on Image Processing*, Vol. 15, pp. 529-538, 2006.

[8] R. G. Radke, S. Andra, O. Al-Kofahi, B. Roysam, "Image Change Detection Algorithms: A Systematic Survey", IEEE Trans. Image Process., Vol. 14, No. 3, pp. 294 -307 2005

[9] S. Zheng, "Pixel-Level Image Fusion Algorithms for Multi Camera Imaging System", *M.Sc. thesis, University of Tennessee, Knoxville, United States*, 2010.

[10] R. Wong, F. Bu, H. Jin, L. Li, "A Feature Level Image Fusion Algorithm Based on Neural Network", *International Conference on IEEE Bioinformatics and Biomedical Engineering*, pp. 821-824, 2007.

[11] Y. Zhao, Y. Yin, D. Fu, "Decision Level Fusion of Infrared and Visible Images for Face Detection", *IEEE Conference on Control and Decision*, pp. 2411-2414, 2008.

[12] J. B. Priestly, "Night Vision Devices", *Defense Scientific Information & Documentation Centre*, Vol. 18, No. 1, 1985.

[13] T. Neo, "Fusion of Night Vision and Thermal Images", *M.Sc. Thesis, Science, Naval Postgraduate School Montary, California, United Stats*, 2006.

[14] V. Nadio, and J. Raol, "Pixel-Level Image Fusion Using Wavelet and Principle Component Analysis", *Defense science journal*, Vol. 58, pp. 338-352, 2008.

[15] S. M. Mukane, Y. S. Ghodake, P. S. Khandagle, "Image Enhancement Using Fusion by Wavelet and Laplacian Pyramid", *IJCSI International Journal of Computer Science*, Vol. 10, pp. 1694-0814, 2013.

[16] G. Pajares, and J. Cruz, "A Wavelet-Based Image Fusion Tutorial", *Pattern Recognition*, Vol. 37, pp. 1855 – 1872, 2004.

[17] R. C. Gonzalez, and R. E. Woods, *Digital Image Processing*, Second Edition, Prentice Hall, U.S.A, 1987.

[18] V. Nadio and J. Raol, "Pixel-Level Image Fusion Using Wavelet and Principle Component Analysis", *Defense science journal*, Vol. 8, pp. 338-352, 2008.

[19] S. K. Sadhasivam and et al, "Implementation of Max Principle with PCA in Image Fusion for Surveillance and Navigation", *Electronic letters on Computer Vision and Image Analysis*, Vol. 10, No. 1, pp. 1-10, 2011.

[20] R. Chandrakantha, J. Saibabaa, Geeta Varadana & P. Ananth Raj, "A Novel Image Fusion System for Multi-sensor and Multiband Remote Sensing Data", *IETE Journal of Research*, Vol. 60, No. 2, pp. 168-182, 2014.

[21] G.Pajares and J.M.Cruz, "A Wavelet-based Image Fusion tutorial", *Pattern Recognition*, Vol. 37, pp. 1855-1872, 2004.

[22] Z. Liu, E. Blasch, Z. Xue, J. Zhao, "Objective Assessment of Multi-resolution Image Fusion Algorithms for Context Enhancement in Night Vision: A Comparative Study", *IEEE Transaction on Pattern Analysis and Machine Intelligence*, Vol. 34, No. 1, pp. 94-109, 2012.

[23] V. Petrovic, and C. Xydeas, "Objective Evaluation of Signal-Level Image Fusion performance", *Optical engineering*, Vol. 44, pp. 1-8, 2005.

[24] V. Tsagaris, and V. Anastassopoulos, "Global Measure for Assessing Image Fusion Methods", *Optical Engineering*, Vol. 45, pp. 1-8, 2006.

Mehrnoosh Gholampour received his B.Sc. and M.Sc. degrees from University of Birjand, Birjand, Iran in 2012 and 2014 respectively, all in Communication Engineering. Her research interest and contributions are in image processing, image fusion and signal processing with a focus on image and speech coding. She is also interested in applications signal processing Biomedical with a focus on image fusion.

Hassan Farsi received the B.Sc. and M.Sc. degrees from Sharif University of Technology, Tehran, Iran, in 1992 and 1995, respectively. Since 2000, he started his Ph.D. in the Centre of Communications Systems Research (CCSR), University of Surrey, Guildford, UK, and received the Ph.D. degree in 2004. He is interested in speech, image and video processing on wireless communications. Now, he works as associate professor in communication engineering in department of Electrical and Computer Eng., university of Birjand, Birjand, IRAN.

Sajjad Mohammadzadeh received the B.Sc. degree in electrical engineering from Sistan & Baloochestan, University of Zahedan, Iran, in 2010. He received the M.Sc. degree in communication engineering from South of Khorasan, University of Birjand, Birjand, Iran, in 2012. He is currently Ph.D. student in Department of Electrical and Computer Engineering, University of Birjand, Birjand, Iran. His area research interests include Image Processing and retrieval, Pattern recognition, Digital Signal Processing and Sparse representation.