International Journal of Advances in Image Processing Techniques– IJIPT
Volume 3 : Issue 1 [ISSN : 2372-3998]
Publication Date: 18 April, 2016

Regional Weight Optimization Based Multi-Sensor Image Fusion in Spatial Domain

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Abstract— **In this paper, a new multi-sensor image fusion method that combines the source images by optimally weighting in terms of predetermined regions is proposed. The Artificial bee colony algorithm is employed to determine weights. The regions are produced by K-Means algorithm. The experiments are conducted with images for different applications. The proposed method is objectively and subjectively compared with well-known image fusion methods from the literature. Experimental results show that the method outperforms the other methods.**

Keywords— **Image fusion, Multi-sensor fusion, ABC, K-Means.**

I. Introduction

Todays, various imaging sensors developed for different purposes like military, industrial robotic etc. Each sensor individually presents very important information. In addition to that, combination of them can be more comfortable for human cognition. Combining complementary data from input images, which taken from different sensors, into one image to provide more meaningful and detectable information is called multi-sensor image fusion.

Multi-sensor image fusion has been increasing interest due to improvement of the sensor technologies. Consequently, many image fusion methods for different areas like enhanced night vision (ENV) [1], concealed weapon detection (CWD) [2], remote sensing (RS) [3] and medicine (M) [4] has been encountered over the last decade.

One of the main problems for image fusion techniques is detecting content and amount of information to be provided by input images. Typically, this is conducted by a multi-scale transform techniques like discrete wavelet transform (DWT), Laplacian transform (LP) or morphological transform. These techniques are frequently used in multi-sensor image fusion methods [5-8]. However, operating translation processes increase computational load of fusion operations. Moreover, since more than one pixel values are affected from modification of coefficient in the transform domain, combination process could produce unpredictable side effects like artefact [9].

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Combination of source image data is employed by fusion rules. A typical implementation of it depends on average of source images data or choosing data from a source image that has bigger value than other source image. These rules are deficient for yielding optimum fusion results. Weighted average approach can be solution for this problem. On the other hand, in this approach, the weights must be determined optimally. In addition that, for solution of this optimization problem, a suitable objective function must be determined.

In this paper, a new multi-sensor image fusion method is proposed. The proposed method uses weighted average fusion rules for predetermined region. The weights are optimized by artificial bee colony algorithms. The regions are produced by K-Means algorithm.

The rest of the paper is organized as: in section 2, general structure of the proposed method is introduced. The experimental results are presented in section 3 and the conclusions are discussed in section 4.

II. Regional Optimization Based Image Fusion

A. *K-Means*

The K-Means algorithm is used as the segmentation algorithm in this work. It is one of the simplest and well-known unsupervised clustering methods. After setting the number of clusters (n), the algorithm proceeds by selecting random initial cluster centers and then iteratively tuning them as follows:.

- Repeat step 1-2 until there is no further change in assignment of pixels to clusters
    1. Each pixel is assigned to a cluster whose center is nearest to the pixel.
    2. Update the center by averaging the intensity value of pixels belonging to the cluster.

B. *Artifical Bee Colony Algorithm (ABC)*

Artificial Bee Colony (ABC) is one of the well-known swarm based meta-heuristic algorithms introduced by Dervis Karaboga in 2005 [10]. It is motivated by the intelligent foraging behavior of honey bees.

A solution is called as food positions. For an optimisation task consisting of *D* parameters, a food position can be expressed as follows:

$$x = (x_1, x_2, \ldots, x_D) \qquad (1)$$

The population of ABC consists of foods positions modified by three different types of artificial bees conduct search operations. Bees are separated according to their duties. The first type of bees is employed bee going to the food source visited by itself previously. There is only one employed bee for each food source. The second group is called onlooker bees waiting in the hive to choose a food position to search for richer food sources. Consequently, more than one onlooker bees can be found in a food source. At the initial stage of ABC, number of employed and onlooker bees are the same as number of population. The last type of bee is the scout bee carrying out random search. An employed bee that cannot find a better food source during predetermined period of iterations becomes a scout. This period is determined by limit parameter. The main steps of the algorithm are given as follows:

- Define the initial parameters.
- Create an initial population randomly
- Repeat each phase until stopping condition is reached
  - I. Employed bee phase
  - II. Onlooker bee phase
  - III. Scout bee phase

Before starting iteration of ABC, some algorithm parameters like limit (L), maximum iteration (N), population size (P) must be determined. Also, a fitness function that identifies the quality of food sources must be defined. The initial population is created by determining random P food positions. After that, the iteration can be start. At the each iteration, phases for employed, onlooker and scout bees are conducted respectively.

An employed bee search for new food source having better quality within neighborhood of her food source as follows:

$$v_{i,j} = x_{i,j} + \phi_{i,j}(x_{i,j} - x_{k,j}) \tag{2}$$

Where i=1, … , P, j=1, … , D and $\Phi_{i,j}$ is a random parameter valued between [-1, 1].

In the onlooker phase, onlooker bees probabilistically choose their position based on the quality of food position of employed bees. The probability of being selected for the position of i^{th} employed bee can be calculated as follows:

$$p_i = \frac{f_i}{\sum_{n=1}^{P} f_n} \tag{3}$$

Where f is quality of food sources determine by fitness function.

In the scout bee phase, if there is any scout bee in iteration, all scout bees choose their food sources randomly and become an employed bee.

C. *ABC Based Optimization for Regional Image Fusion*

In the proposed method, the source images are fused by weighted average fusion rules in spatial domain without any transformation. The weights are produced by artificial bee colony algorithm (ABC). Rather than determining weights for all pixels independently, a weight is used for a group of pixels. Thus, amount of weight that must be determined is decreased and optimization problem become easier to solve.

First of all, the region map (R) must be produced by K-Means algorithm. In the fusion of thermal and visible images, the thermal image is segmented since the main purpose of fusing these images is to enhance the visible image with the complementary information transferred from the thermal image. For medical image set, the CT image is segmented, because MR image contain more complex intensity values. In remote sensing image set, no matter which source image is segmented.

In the fusion rules, image data are combined by using the weights produced by ABC in terms of regions. The pixels of source images in the same corresponding region are scaled by the same weight. By this way, more meaningful fusion is conducted. Because, the pixels with the same content have the same effects on the fused image.

The quality measure that used as fitness value in ABC is yielded by *SCD* metric. *SCD* computes the quality by considering the source images and their impact on the fused image. Therefore it is convenient to use in optimization.

The basic steps of the proposed method can be described as follows:

1. The region map R that contains K regions is produced by K-Means algorithm.
2. By grouping each pixel of source images with respect to R, $I_{1,k}$ and $I_{2,k}$ are determined (k=1, 2, … ,K)
3. until the optimum fused image is produced, the following steps are repeated:
   - i. By using the w coefficients produced by ABC, the regions of the source images are combined as follow:

$$I_{f,k} = w_k \cdot I_{1,k} + (1 - w_k) \cdot I_{1,k} \tag{4}$$

   - ii. Each fused region $I_{f,k}$ together constitute the fused image I_f.
   - iii. I_f is evaluated by *SCD* to produce fitness values.
   - *iv.* New weights are generated by *ABC.*

The schematic diagram of the proposed image is given in Figure 1.

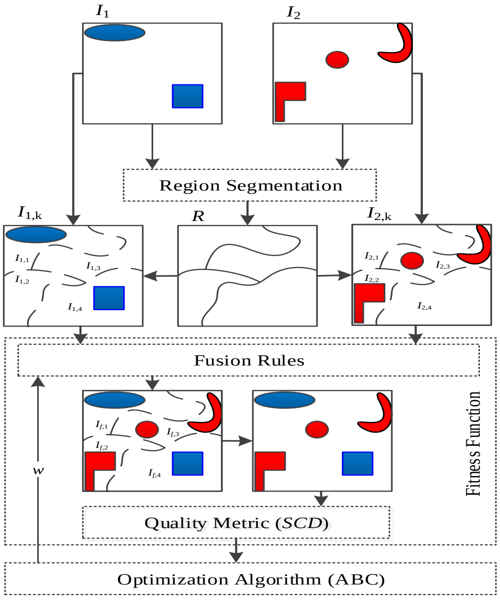

Figure 1. Schematic diagram of the proposed metric

III. Quality Evaluations

Quality evaluation is very important step in image fusion to quantitatively analyze the success of fusion methods. Four different image quality metrics are used to compare result of the fusion methods quantitatively.

A. *Sum of the Correlation of Differences (SCD)*

Amount of information that transferred from source images is an important measure for image fusion. To provide this information, *SCD* make use of correlation between the source image and their impact on the fused image [11]. *SCD* metric expressed as:

$$SCD = r(F_1, I_1) + r(F_2, I_2) \tag{6}$$

where *r* refers correlation between two images. F_1 and F_2 are pixel by pixel difference of fused image and the source images.

B. *Quality of Edge (QE)*

QE measures the quality by using edge information that transferred from source images to the fused image [12]. *QE* is calculated as:

$$QE = \frac{\sum_{i=1}^{n}\sum_{j=1}^{m} k^a(i,j)w^a(i,j) + k^b(i,j)w^b(i,j)}{\sum_{i=1}^{n}\sum_{j=1}^{m} w^a(i,j) + w^b(i,j)} \tag{7}$$

where w^a and w^b are weighting coefficients based on sobel edge strength of the input images, k^a ve k^b edge preservation coefficients.

C. *Mutual Information (MI)*

Mutual information (MI) is metric takes input images and fusion image to calculate shared information between the source images and the fused image. Consequently, *MI* can be defined as a metric that calculate how much information transferred to fused image from all input images. *MI* can be expressed as:

$$MI = S_{1,f} + S_{2,f} \tag{8}$$

where, *S*, which is shared information between two images, calculates as.

$$S_{a,b} = \sum_{i,j} P_{a,b}(i,j)\log\frac{P_{a,b}(i,j)}{P_a(i)P_b(j)} \tag{9}$$

where $P_{a,b}$ is the normalized joint gray level histogram of images *a* and *b*, P_a and P_b are the normalized marginal histograms of the two images.

D. *Structural Similarity (SSIM)*

The *SSIM* is used for calculating the similarity between two images. SSIM is calculated on consequent windows of an image. The similarity between window *R* and *F* of a common window size (e.g. 8x8) is:

$$SSIM(R,F) = \frac{(2\mu_R\mu_F + c_1)(2\sigma_{RF} + c_2)}{(\mu_R^2 + \mu_F^2 + c_1)(\sigma_R^2 + \sigma_F^2 + c_2)} \tag{10}$$

where; μ_R is the average of *R*, μ_F is the average of *F*, σ^2_R is the variance of *R*, σ^2_F is the variance of *F*, σ_{RF} is the covariance of *R* and *F*, $c_1=(k_1L)^2$ and $c_2=(k_2L)^2$ are the two variables to stabilize the division, *L* is the dynamic range (typically 255 for 8-bit gray level images), k_1=0.01 and k_2=0.03 [17]. SSIM index produces a value between -1 and 1.

IV. Experimetns

The experiments are conducted for different multi-sensor image fusion applications. The proposed fusion method is compared with Laplacian pyramid (LP) [13], morphologic pyramid (MP) [14], discrete wavelet transform (DWT) [15] and The optimized region based multi sensor image fusion (ORMSIF) [5] in the experiments. All these methods use a transform technique on fusion process.

In the Figure 2-5, the fused images are given to clearly confirm the perceptual evaluation. In these figures, the first two images are source images and the other images are fusion results of LP, MP, DWT, ORMSIF and the proposed method respectively. The image set and the fusion results for enhanced night vision (ENV) are given in Figure 2. For this image set, the sign board cannot be read in the thermal image, while it is clearly perceptible in the visible image. In addition to that, the thermal image contains a man that cannot be seen in the visible image. In the image set for concealed weapon detection (CWD) seen in Figure 3. A weapon in envelop is detected by thermal sensor without the detail of the scene. The opposite situations are occurs in visible image. The image set in Figure 4 is given as an example of medical (M) applications. The CT image is best suited for viewing bone tissue while examining soft tissue is available via the MR image. Fusion of CT and MR images generates an image containing both soft and bone tissues. The last image set that is example of remote sensing (RS) application is seen in Figure 5.

It can be seen from the fusion results that the proposed method has successfully transferred the complementary information from the source image. Quality of the fused images produced by the proposed method and the ORMSIF are very close to each other. On the other hand the proposed method yields this quality with lesser computational load, since there is no transformation. The other methods that do not contain optimization have worse performance than the proposed method

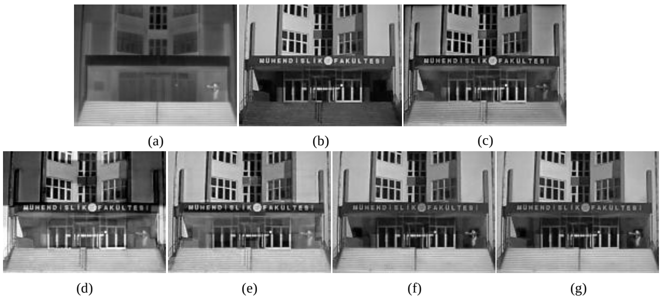

Figure 2. Fusion results of image set for enhanced night vision (ENV) aplication. Source images: (a) thermal image, (b) visible image. Fused images: (c) LP, (d) MP, (e) DWT, (f) ORMSIF, (g) Proposed.

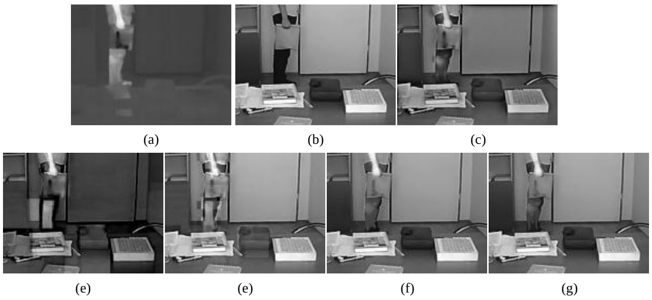

Figure 3. Fusion results of image set for concealed weapon detection (CWD) aplication. Source images: (a) thermal image, (b) visible image. Fused images: (c) LP, (d) MP, (e) DWT, (f) ORMSIF, (g) Proposed.

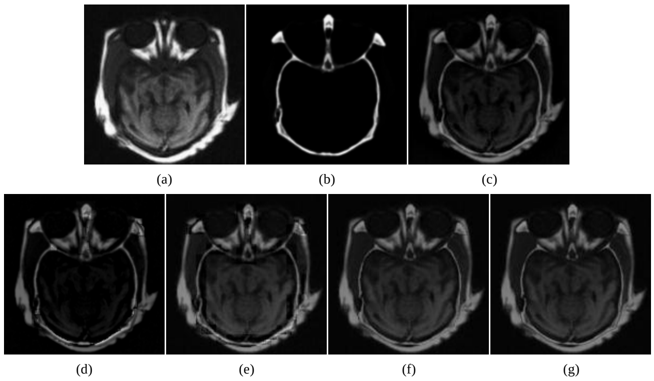

Figure 4. Fusion results of image set for medical (M) aplication. Source images: (a) MR image, (b) CT image. Fused images: (c) LP, (d) MP, (e) DWT, (f) ORMSIF, (g) Proposed.

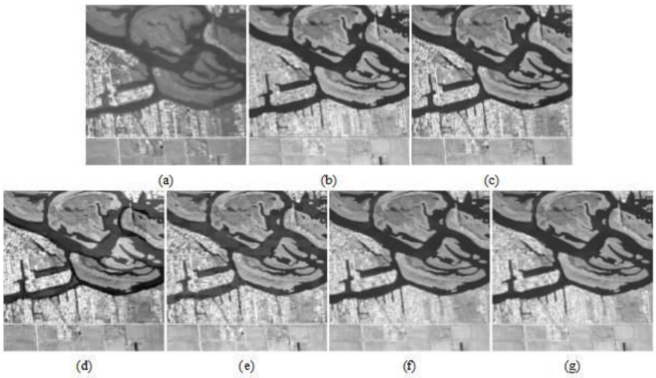

Figure 5. Fusion results of image set for remote sensing (RS) aplication. Source images: (a) the first source image, (b) the second source image. Fused images: (c) LP, (d) MP, (e) DWT, (f) ORMSIF, (g) Proposed.

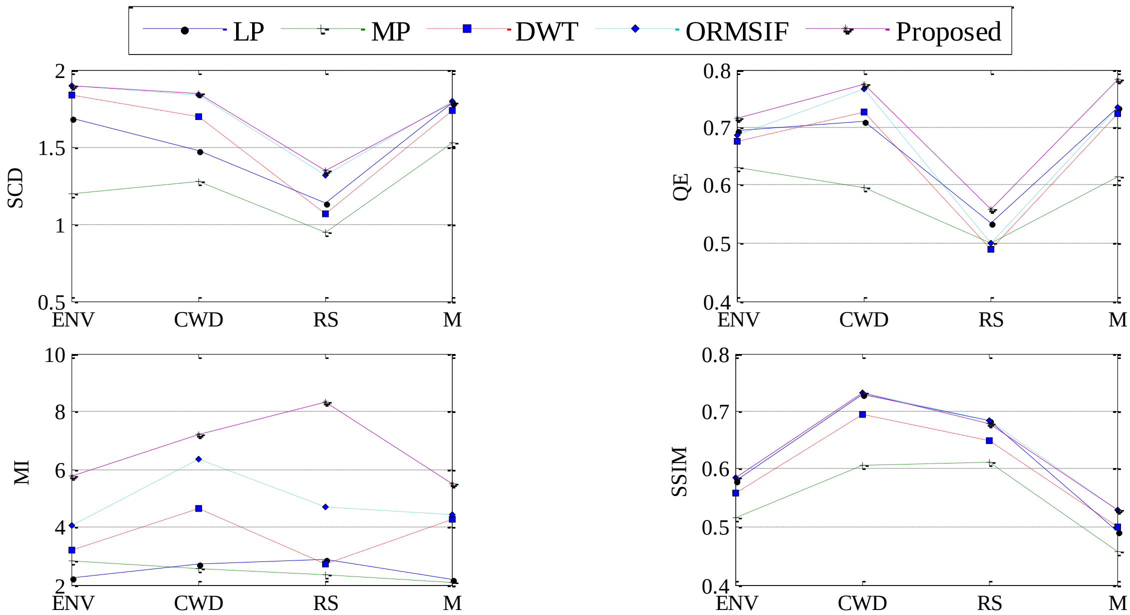

Figure 6. Quantitative comparison of the image fusion methods in terms of the quality metrics.

In Figure 6, quantitative results of fusion methods are given for evaluation of each quality metric used in experiments. In the figure, there are four graphics in which the metric values are shown in vertical axis and the images are illustrated in horizontal axis. As can be seen from the figure, the proposed method outperforms the other method in terms of each quality metrics.

V. Conclusions

In this study, a new image fusion method that based on weight optimization for predetermined region is presented. K-Means algorithm used on segmentation stage and artificial bee colony algorithm is used on optimization stage. The fusion process is implemented in spatial domain. The fusion result of the method and several well-known methods are compared visually and quantitatively. The fused images are evaluated by four different quality metrics in quantitative comparison.

The experimental results show that the proposed method give better performance than the other method frequently used in the literature for different multi-sensor image fusion application such as enhanced night vision, concealed weapon detection, remote sensing and medical imaging. The ORMSIF, which is another optimization based image fusion method, gives similar results. On the other hand result of the proposed method produces these results with lesser effort.

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