A Novel Automatic Weighted Image Fusion Algorithm

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***Abstract*—A new automatic weighted image fusion algorithm is proposed. The current weighted averaging image fusion algorithm has good rapidity, but its fusion quality depends on the choice of weight values to a great extent. In order to choose weight values more reasonably, K-L transform is adopted, which has advantages in multi-component information reduction. The available information in source images is concentrated to new independent principal component matrixes. The redundant information from different source images is decreased and the weighted coefficients are thereby determined. Comparison experiment is performed with infrared and visible images. Experimental results of subjective and objective evaluation show that, the fused images based on the new algorithm have improvements in image clarity, information amount and so on. Furthermore, the algorithm maintains the characteristic of simplicity and practicability of existing algorithms and can be applied in the situation when high speed image fusion is required.**

Keywords- infrared image; visible; K-L transform; image fusion; automatic weighted

I. INTRODUCTION

Image fusion algorithms based on spatial transform is the most widely used methods of image fusion. Rather than processing any image transformation towards the source images and considering the correlation between the pixels, such methods put forward the source images directly by selecting, averaging or weighted averaging the corresponding pixels, so that a new fused image can be obtained simply and rapidly [1]. However, due to the simplicity of the algorithm, the image fusion performance sometimes cannot meet the requirements. The characteristics from the original images are hardly expressed and the details of texture are missed seriously. It is important to optimize existing algorithms. In other words, the quality of the image fusion should be upgraded without influencing the calculating complexity significantly.

II. WEIGHTED AVERAGING IMAGE FUSION

The weighted averaging image fusion method comes from the direct averaging method, which is one of the most basic fusion algorithms [2]. This method gives different weights to the involved source images, which means that the gray value of the corresponding pixels are multiplied by various factors, and then sum up in order to obtain the fusion results. In order to facilitate and simplify the description, this paper uses two source images as an example to illustrate the image fusing process and methods. For the situation of three or more source images fusion, the results can be deduced accordingly.

Suppose the involved source images as A and B which has the size of $M \times N$. The fused image is described as F. The image fusion process can be indicated as following:

$$F(m,n) = \omega_1 A(m,n) + \omega_2 B(m,n) \tag{1}$$

where m is the line number of the image pixels, n is the row number of the image pixels.

The selection of weighted factor values ω_1 and ω_2 is the crucial issue in the algorithm. They can be set up with human experience or dynamic calculation. Under normal circumstances, the weighted factors are deduced with the following equation:

$$\omega_1 = \frac{A(m,n)}{A(m,n)+B(m,n)}\ ,\ \omega_2 = 1-\omega_1 \tag{2}$$

If $\omega_1 = \omega_2 = 0.5$, the fusion method is called direct average image fusion. By means of adopting redundant information provided by each source images, the weighted average fusion method can improve the detection reliability. At the same time, it can increase the SNR (signal to noise ratio) of the fused image when used in multi-frame image fusion. Suppose there are M images which contain noises:

$$g_i(m,n) = f(m,n) + \eta_i(m,n) \tag{3}$$

where $i = 1,2,...,M$, $f(m,n)$ is the source image without noise, $\eta_i(m,n)$ is the noise of the pixel (m,n) which is supposed as irrelative and zero-averaged random noises.

After the image fusion, the result image $\bar{g}(m,n)$ is:

$$\bar{g}(m,n) = \frac{1}{M}\sum_{i=1}^{M} g_i(m,n) \tag{4}$$

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Obviously, $$E\{\bar{g}(m,n)\} = f(m,n) \tag{5}$$

$$\sigma^2_{\bar{g}(m,n)} = \frac{1}{M}\sigma^2_{\eta(m,n)} \tag{6}$$

where $E\{\bar{g}(m,n)\}$ is the average value of $\bar{g}$, $\sigma^2_{\bar{g}(m,n)}$ and $\sigma^2_{\eta(m,n)}$ are the variances of $\bar{g}$ and η at (m,n) relatively.

The standard variance of the fused image is:

$$\sigma_{\bar{g}(m,n)} = \frac{1}{\sqrt{M}}\sigma_{\eta(m,n)} \tag{7}$$

Equation (7) shows that the standard variance of the fused image is reduced to $1/\sqrt{M}$ of the original after the averaging fusion method. In fact, the averaging image fusion method is a type of smoothing process which not only reduces the image noises but also weakens the image contrast [3]. The edges and the outlines of the images are blurred to some extent. Moreover, there would be obvious signs of stitching if the gray-scales of source images vary greatly. It is not conducive to the human identification and the follow-up target identifying process [4]. In most applications, this image fusion method is difficult to obtain satisfactory fusion results.

III. Automatic weighted fusion optimization based on K-L transform

As described in last section, the weighted average fusion method is simple and has a good effect, but the key problem to determine the fused image quality is the choice of weight values. Current weighted methods make a second-time superposition to the repeated parts (redundant information) of different source images, which may lead to spatial information and spectral information confusion and cause unclear physical meaning [5]. To solve this problem, the common compositions among the weighed images must be few, that is, reduce the mutual-correlation and redundant between images, so it will make its physical meaning and geometric meaning clear [6]. In order to eliminate the correlation among the weighting source images, K-L transform is used in this paper to do with them and the available information is concentrated to new independent principal component matrixes which are fewer and non-correlated. In the following, details will be introduced.

A. Principle of K-L transform

The source image is defined as matrix X:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & & & \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} = [x_{ik}]_{m\times n} \tag{8}$$

where m indicates the number of the source images, n indicates the number of the pixels in each source images. Each row vector stands for one source image and i、k represent the line number and row number of each corresponding pixel.

The linear transform of the image can be presented with the following equation:

$$Y = TX \tag{9}$$

where X is the data matrix of the source image and Y is the data matrix of the transformed image. T is the transform matrix that accomplishes the linear transform. If T is an orthogonal matrix that composed from the covariance matrix C of source matrix X, the linear transform in equation (9) is called K-L transform. Each row vector of the data matrix resulted from K-L transform is known as a principle component.

B. Image transform based on K-L algorithm

The K-L transform procedures to the source image are as follows:

1) Compute the covariance matrix C according to the source image matrix X, that is:

$$C = \frac{1}{n}[X - \bar{X}][X - l\bar{X}] = [c_{ij}]_{m\times n} \tag{10}$$

where $\bar{X} = [\bar{x}_1, \bar{x}_2, ..., \bar{x}_m]^T$, $\bar{x}_i = \sum_{k=1}^{n} x_{ik} \Big/ n$, $l = [1,1,...,1]_{1\times n}$, $c_{ij} = \sum_{k=1}^{n}(x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j) \Big/ n$.

Here, C is a symmetric matrix.

2) Deduce the characteristic value λ and the feature vector U of the covariance matrix C and compose the transform matrix T. The characteristic equation is:

$$(\lambda I - C) = 0 \tag{11}$$

where I stands for unit matrix.

The characteristic value $\lambda_j (j = 1,2,...,m)$ of C can be calculated from (11) and sequenced with the order of $\lambda_1 \geq \lambda_2 \geq \cdots \lambda_{\mathrm{m}}$. Then the corresponding unit feature vector U_j of each characteristic value can be obtained, that is, $U_j = [u_{1j}, u_{1j}, \cdots u_{mj}]^T$.

3) Acquire the transform matrix T: $T = U^T$, $U = [U_1, U_2, ..., U_m] = [u_{ij}]_{m\times m}$, whose rows are composed with

feature vectors. Matrix U is a orthogonal matrix that meets $U^T U = UU^T = 1$.

4) Substitute transform matrix T to (9) and complete K-L transform.

$$Y = \begin{bmatrix} u_{11} & u_{21} & \cdots & u_{m1} \\ u_{12} & u_{22} & \cdots & u_{m2} \\ \cdots & & & \\ u_{1m} & u_{2m} & \cdots & u_{mm} \end{bmatrix} X = U^T X \qquad (12)$$

The row vector $Y_j = [y_{j1}, y_{j1}, \cdots y_{jn}]$ of matrix is called principle component j. Through the K-L transform, a group of new principle component variables are acquired [7].

C. Image transform based on K-L algorithm

In order to confirm the weight values in weighted averaging fusion method, the covariance matrixes of the source images are firstly computed. Their characteristic values are thereby be deduced. The maximal characteristic value λ_i and its corresponding feature vector u_i can be obtained respectively. Each weighted factor ω_i of the source image is composed with λ_i, as equation (13) shows.

$$\omega_i = \lambda_i \Big/ \sum_{i=1}^{m} \lambda_i \qquad (13)$$

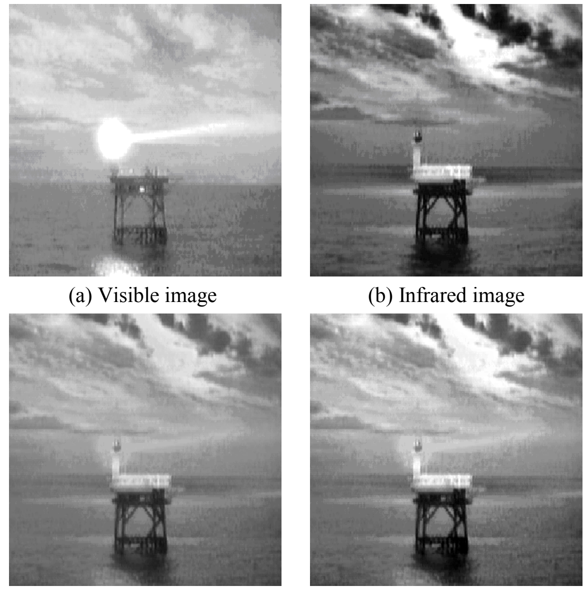
The fused image $F(m,n)$ is deduced from ω_i and u_i, that is

$$F(m,n) = \sum_{i=1}^{m} \omega_i u_i \qquad (14)$$

Here, scaling factor method is used for the computation of weight values, which is confirmed dynamically. In this way, the cross correlation and the redundancy rate between each source image is reduced. The physical meaning and the geometrical meaning are also specified. The result of the weighted averaging fusion can be enhanced.

IV. EXPERIMENTS AND ANALYSIS

Figure 1 gives the fused image results from the approaches above. The experimental objects are a different-source image pair of a lighthouse on the sea that was pictured at the same time and the same scene. Figure 1(a) is the visible image which can clearly express the structure of the lighthouse but the definition of the tower basis part is not good. Figure 1(b) presents an infrared source image which can clearly identify the light and the tower basis that has high surface thermal radiation but lighthouse cannot be seen easily. It is shown that these two source images have significantly different characteristics and details. Figure 1(c) is the fused image that based on the weighted average method. Here, the weighted average factor value is designated by equation (2). Figure 1(d) proposes the result from the newly developed auto-weighted image fusion algorithm which based on K-L transform.



(a) Visible image (b) Infrared image

(c) Weighted averaging fusion result (d) Automatic weighted averaging fusion result

Figure 1. Lighthouse fusion experiment

Figure 1 shows that the fusion of the visible and infrared images can acquire more accurate and more comprehensive information of the object. As for the subjective evaluation, the entire brightness of the common weighted averaging image is moderate and the visual effect is relatively mellowing, but the definition is slightly unsharp. The fused image based on K-L transform has a better quality in definition. The overall image clarity, the gray level and the outlines improves notability. The temperature discrepancy inside the scene can be easily identified.

Table 1 lists the objective evaluation results of different methods. Five factors are chosen, including entropy (E), cross entropy (CE), standard deviation (SD), spatial frequency (SF) and deviation index (DI). E and CE focus on the amount of information, SD and SF focus on clarity, while DI reflects the changes before and after the fusion.

TABLE I. OBJECTIVE EVALUATION FOR LIGHTHOUSE FUSION

Image type	E	CE	SD	SF	DI
Visible image	7.443		30.163	0.006	
Infrared image	7.246		26.281	0.004	
Weighted averaging	7.661	0.341	30.149	0.007	0.121
Optimized weighted averaging	7.673	0.330	28.155	0.008	0.109

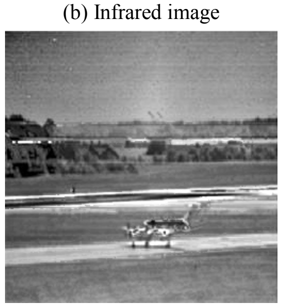
Table 1 indicates that although weighted average method effectively eliminates the noise of source image, the standard deviation is lower, because the essence of weighted average fusion method is a smoothing process to image pixels. It can eliminate the noise of image but the image contrast is reduced. Improved algorithm makes a balance between cross entropy and deviation index comparing with common weighted average method, but has a great advance in standard deviation and spatial frequency, which is consistent to subjective evaluation. Meanwhile, image entropy is lifted, which proves its information has a great increase compared with original image.

Figure 2 shows a group of different source image pairs of airplane on the airstrip. Figure 2(a) is the visible source image, in which we could see the shape of airplane and the mountain forest appearance of background, but can not acquire the thermal energy information of the plane and can not determine whether there are hidden building in the mountain forest. Figure 2(b) is the infrared source image, where strong or weak part of thermal radiation and a suspected building can be seen, but the details of plane contour, texture and background are not clear. Figure 2(c) is a fusion image based on weighted average fusion method. Here, weight values in figure 2(d) are determined by equation (2). Figure 2(d) is the fusion image acquired by the K-L transform based method.

(a) Visible image

(b) Infrared image

(c) Weighted averaging fusion result



(d) Automatic weighted averaging fusion result

Figure 2. Airplane fusion experiment

From the experimental results, we can see that the effect of the image fusion is basically the same as the conclusion of the previous experiments. Comparing with the common weighted average fusion method based on the equation (2), we can get a higher degree of image clarity by the method used in this article. We can not only recognize the thermal parts of the aircraft and the suspected houses in the background, but can also clearly identify the aircraft casters, the projection of airframe, and other information such as the textures of hills, two flying cannonballs in distance.

Table 2 gives the objective evaluation of image fusion algorithms. The fused image based on optimized weighted averaging has a better performance in SD and SF. Optimized weighted averaging method has a lower CE than the common one, indicating the information in the source image is preferably maintained. Its DI was slightly higher than the weighted average fusion, which means the resolution is increased but the spectral characteristics are less maintained. In general, the optimized method has improvements in many aspects, especially on the visual effects.

TABLE II. OBJECTIVE EVALUATION FOR AIRPLANE FUSION

Image type	E	CE	SD	SF	DI
Visible image	7.189		25.238	0.005	
Infrared image	7.376		21.387	0.004	
Weighted averaging	7.622	0.333	24.523	0.006	0.139
Optimized weighted averaging	7.698	0.314	29.235	0.007	0.142

V. CONCLUSION

This paper introduces a novel automatic image fusion algorithm. In order to choose weight values reasonably, K-L transform is adopted to concentrate the available information of source image into new independent principal component matrixes. Comparing with the common weighted fusion method, fused image obtained by this new method has a better visual quality and provides more useful information.

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