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Multi-level image fusion and enhancement for target detection

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ABSTRACT

In this paper, a novel infrared-to-visible image fusion algorithm for enhancing contrast and visibility is proposed. A multi-level method based on the characteristics of images and the properties of the targets is designed to complete the image fusion process, where a contrast enhancement method is added in the low-frequency information of the layered images and the edge information is enhanced in the high-frequency information using the correlation between the low- and high-frequency components. In the experiments, three groups of infrared-to-visible images were used to demonstrate the effectiveness of the multi-level fusion method. All the evaluation indexes, such as standard deviation and information entropy, were significantly higher than other existing methods. Thus, the experimental results verified the effectiveness of the proposed image fusion methods. The quality of the fusion images was improved for better differentiability in terms of contrast and features of the targets.

1. Introduction

Image fusion was proposed in the late 1970s. Multi-sensors can be used to obtain images with different spatial, temporal, and spectral resolution, and other characteristics of the same scene. For example, infrared and visible images can be fused to find the targets hidden in a visible light image. By integrating complementary information and removing redundancy in a multi-source image, the fusion image can provide rich and enhanced information [1]. In recent years, military, commercial, and civilian demands have greatly promoted the development of fusion technology, especially for the integration of image quality and increasing algorithm speed [2]. The existing fusion algorithms can be divided into single-pixel-based weighting methods, multi-resolution analysis methods, region-based fusion methods, color fusion, etc. Some of the basic techniques of fusion methods include the pixel weighting method, the maximum selection method [3], the regional energy method [4], and the contrast method [5]. At present, the image pyramid and wavelet decomposition are the most extensive analysis methods. Both the methods are based on a multi-resolution analysis that combines the basic fusion rules and multi-resolution decomposition of the image to implement fusion. The strategy used in fusion rules can be divided into pixel-level, feature-level, and decision-level fusion. Pixel-level fusion retains the original information to a large extent. Feature-level fusion deals with feature information comprehensively and processes less data than pixel-level fusion to achieve information compression. Decision-level fusion, as the highest level of the three, takes decisions after determining and identifying image information.

The basic role of fusion is to enhance the visibility of the image and project the features of the targets. The human eyes typically pay much attention to information on image edges, gray-level changes, and structures. Therefore, the purpose of feature-level fusion is very clear. A clearer and more natural image can be obtained by combining the basic pixel-level information with feature-level information to extract meaningful feature information as feedback to pixel-level fusion. Petrović proposed a multi-level fusion method to extract image edges, which represent feature-level information, from the low-frequency information of each layered image, and added it to pixel-level fusion to improve the fusion performance [6]. However, he used only the edge information of and not the correlation between the low- or high-frequency components in the wavelet decomposition framework. High-frequency information usually contains more image details, while low-frequency information has a certain correlation with high-frequency information. Therefore, it is necessary to include the features of high-frequency components in the fusion rule. In this study, we took into account the correlation between the respective components as well as the importance of high-frequency information for target visibility. We propose an improved infrared-to-visible image multi-level fusion algorithm in a wavelet fusion framework and based on the Petrović's

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method, aimed at improving contrast and visibility of the fusion image.

2. Multi-resolution image fusion

Usually, an image can be represented with different scales, such as contours, edges and textures. The human visual system (HVS) processes information based on a multi-resolution mode that supports robustness in computing. Thus, we can decompose an image to obtain a series of sub-images of the original image at different resolutions. The wavelet transform most accurately represents multi-resolution methods [7]. The wavelet-based image fusion process (see Fig. 1) can be summarized as follows: the original input images are decomposed; sub-images are generated by the wavelet decomposition corresponding to each other; appropriate fusion rules are applied to synthesize each sub-image sequence; finally, inverse transformation of each synthetic sub-image sequence is performed to obtain the fusion results.

The wavelet decomposition of the original image gives the high-frequency component in the horizontal, vertical, and diagonal directions, and the low-frequency component in a decomposition layer. The wavelet decomposition process using orthogonal wavelet basis does not yield redundant data. In this way, we can easily analyze the frequency domain characteristics of signals in different frequency bands, and exploit these features in the fusion rules. Mallat's fast algorithm, based on the two-dimensional wavelet [8], generates three high-frequency components in the horizontal, vertical, and diagonal directions, respectively – denoted by H^k, V^k, and D^k – and a low frequency component – denoted by C^k – when the image is decomposed by the wavelet in each layer. The superscript k denotes the wavelet decomposition scales. The Mallat wavelet decomposition formula is given by

$$\begin{cases} C^k = H_m H_n C_{j-1} \\ H^k = G_m H_n C_{j-1} \\ V^k = H_m G_n C_{j-1} \\ D^k = G_m G_n C_{j-1} \end{cases} \tag{1}$$

Further, the corresponding wavelet reconstruction formula is given by

$$C^{k-1} = H_m^* H_n^* C^k + H_m^* G_n^* H^k + G_m^* H_n^* V^k + G_m^* G_n^* D^k \tag{2}$$

where matrix H is the low-pass filter and matrix G is the high-pass filter. The subscripts m and n are the rows and columns of the image, respectively. Matrix H^* is the conjugate transpose of H and matrix G^* is the conjugate transpose of G.

3. Multi-level fusion method

Feature-level and pixel-level fusions have their particular advantages, so we combine the two. In order to improve the fusion quality, layered images are fused using the multi-level fusion method proposed in this paper, and are then reconstructed through the inverse wavelet transform to obtain the final fusion image in the wavelet fusion framework. Fig. 2 shows the entire fusion process.

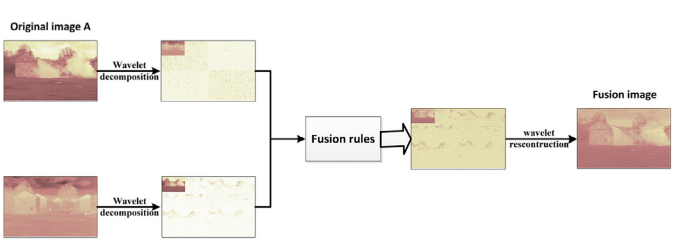

Fig. 1. Schematic diagram of wavelet decomposition and reconstruction.

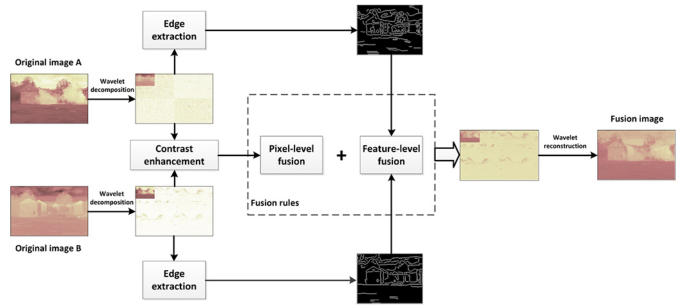

Fig. 2. Schematic diagram of a multi-level fusion process based on contrast enhancement.

3.1. Contrast enhancement

Targets in an infrared image are usually colder or hotter than the background and are specifically marked as a dark or light region in the image. Hence, the contrast of the targets should be enhanced after the fusion. The general methods based on wavelet transform only use the average or weighted average method for the low-frequency component [9], without taking into account the information of the original image contrast. We improve the contrast of the low-frequency components to improve the visibility of the targets in the fusion image corresponding to the characteristics of the targets in the input images. The bright–dark degree of the target in the image can be characterized by the region mean, and therefore, we define the contrast of a target area relative to its peripheral region as the ratio of the average gray value of the two parts:

$$R = \frac{\mu_T}{\mu_B} \tag{3}$$

where μ_T is the average gray value of the target areas, and μ_B is the average gray value of the background areas.

Let the current pixel in the image be at the center and take an area size $m_T \times n_T$ as the target area. Then, we take a large area $m \times n (m > m_T, \quad n > n_T)$, which is the background region of the target area (see Fig. 3). If the target is very different from the background (regardless of the brightness of the background), the value $|R-1|$ is relatively large. Consider an input image A, which is an infrared image, and another input image B, which is a visible image. C_A^k and C_B^k are the low-frequency components in the decomposition of the wavelet layer k of images A and B, respectively. First, the two parts of the low-frequency components are averaged to obtain a low-frequency component C_F^k of the fusion. Therefore, we have

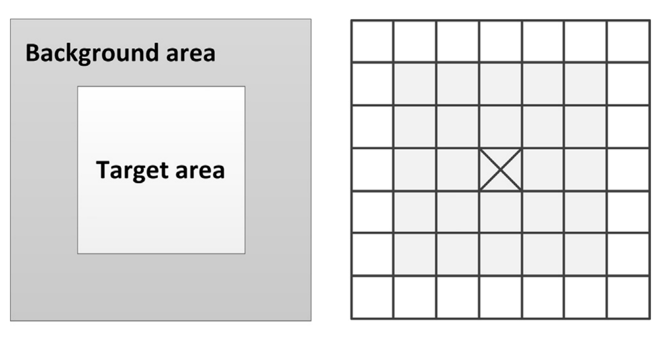

Fig. 3. Target and background areas: (a) target and background areas; (b) region selection.