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A fusion algorithm for infrared and low light level images based on edge information and support value transform

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HIGHLIGHTS

- The technology of edge detection is used to extract the edge information.
- Support value transform is used to obtain the sequences of approximations and support values.
- Different fusion strategies based on the different characteristics of different frequency components are proposed.
- Three experiments are performed to compare the proposed method with other current methods.
- Subjective and objective evaluations are given.

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ABSTRACT

In this paper, a fusion algorithm for infrared and LLL images based on edge information and support value transform is proposed. Firstly, the infrared and LLL images are combined after edge detection to obtain the first fused image. Secondly, the infrared, LLL and the first fused images are decomposed respectively by using the support value transform (SVT) to obtain the sequences of their approximations and support values. Thirdly, the multiple sets of sequences of approximations and support values are combined together. Finally, the fused images are recovered by using the inverse support value transform (ISVT). The experiments and results demonstrate that the fused image which uses the algorithm presented in this paper has the advantage of better visual effect. It has preserved the detailed information effectively and has extracted more edge information from source images compared with the conventional fusion algorithms.

1. Introduction

Single infrared or low light level imaging technology, due to different principles, each has advantages and disadvantages. LLL images have high resolution, good image quality and rich details of background, while they cannot detect the objects in hidden conditions. Infrared images are capable of showing the concealed objects in some poor environment, while they are insensitive to the changes of the brightness in the scene which results in poor image quality and lacking details about the scene. The technology of image fusion with infrared and LLL images can enhance the understanding of the scene, highlight the target, and is conducive to detecting object faster and more accurate in hidden and confused military background. Considering the complementary roles of infrared and low light level images, fusing the LLL and infrared images for better observed effect has become one of the hot topics in the field of current night vision technology.

As is known to all, there are a lot of fusion algorithms for infrared and LLL images. The easiest method is based on weighted average, which takes the same weight for the pixel values of the original images and then the fused image is obtained by adding the pixel values. But this algorithm has an obvious shortcoming, which the contrast of the fusion image will become lower than the source images, if you use this algorithm to fuse source images. In order to solve this problem, several image fusion algorithms based on Pyramid have been put forward and improved in recent years, such as Gaussian Pyramid [1], Laplacian Pyramid [2,3] and Gradient Pyramid [4]. The basic idea is to construct the Pyramid structure of the input image firstly, then to select the feature value according to a certain method to obtain the fusion Pyramid, at last to obtain the fused image by using the inverse transform. Wavelet transform [5–7] is regarded as a breakthrough of Fourier analysis method, and has also been applied in image fusion. Compared with

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the Pyramid method, the main change is using wavelet transform instead of Pyramid.

In 2007, Sheng et al. [8] proposed a new image fusion method using the support value transform, which uses the support value to represent the salient features of image. This is based on the fact that, in support vector machines (SVMS), the data with larger support values have a physical meaning in the sense that they reveal relative more importance of the data points for contributing to the SVM model. The mapped least squares SVM (mapped LS-SVM) is used to efficiently compute the support values of image. The support value analysis is developed by using a series of multiscale support value filters, which are obtained by filling zeros in the basic support value filter deduced from the mapped LS-SVM to match the resolution of the desired level. Compared with the widely used image fusion methods, such as the Laplacian Pyramid, DWT, the results demonstrate that it is effective and superior.

These algorithms mentioned above can successfully fuse the source images, and all the fused images contain the target information and background information. But in terms of the preservation of detailed information of source images, they perform not well. On this issue, the paper proposes a fusion algorithm based on edge information and support value transform, which preserves the detailed information effectively and it has extracted more edge information from source images. Compared with existing technology, it has significant advantages. Firstly, it uses the technology of edge detection to extract the edge information of source images for later use, which makes the ultimate fused image with more distinctive edge details. Secondly, it uses SVT as multiresolution transform. Unlike the wavelet transform, the support value transform directly provides the salient features of original image. It is an undecimated dyadic transform and is isotropic and shift-invariant and does not create artifacts. Thirdly, in terms of the fusion strategy of low-frequency component images (sequences of approximations in this paper), we propose an improved method based on weighted average, and the weights are determined by the mean deviation of gray. Lastly, In terms of the fusion of support values sequences, there are two fusion operations and the strategy is the mix which is based on region energy and weighted average.

2. The proposed algorithm

The total flow chart of the algorithm is shown in Fig. 1. Firstly, the infrared and LLL images are combined after edge detection to obtain the first fused image. Secondly, the infrared, LLL and the first fused images are decomposed respectively by using the support value transform (SVT) to obtain the sequences of their approximations and support values. Thirdly, the multiple sets of sequences of approximations and support values are combined together. By the way we propose a new strategy for the sequences of approximations, which called the improved fusion strategy based on weighted average, where the weights are determined by the mean deviation of gray. And for the support values sequences, we choose the mixed fusion strategy based on region energy and weighted average. Finally, the fused image is recovered by using the inverse support value transform (ISVT). The theories of each point are introduced in detail in the remaining of this section.

2.1. Edge detection

As is shown in the flow chart, the technology of edge detection is used firstly. Edge detection is a basic problem in the field of image processing and computer vision, with the purpose of marking the points whose brightness values change obviously in digital image. Here we use this technique to obtain the detail information which interests us. And Classic Sobel [9] operator is commonly used as a gradient amplitude detection operator, because of the simple principle, small amount of calculation, and fast running speed. The mathematical expression of the operator is:

$$\begin{cases} \Delta_x f(x,y) = [f(x-1,y+1) + 2f(x,y+1) + f(x+1,y+1)] - [f(x-1,y-1) + 2f(x,y-1) + f(x+1,y-1)] \\ \Delta_y f(x,y) = [f(x-1,y-1) + 2f(x-1,y) + f(x-1,y+1)] - [f(x+1,y-1) + 2f(x+1,y) + f(x+1,y+1)] \end{cases} \tag{1}$$

where $\Delta_x f(x,y)$ refers to the edge information of the horizontal direction of the image, while $\Delta_y f(x,y)$ refers to the vertical direction. And we finally get the results:

$$f_1 = \sqrt{\Delta_x fa(x,y)^2 + \Delta_y fa(x,y)^2} \tag{2}$$

$$f_2 = \sqrt{\Delta_x fb(x,y)^2 + \Delta_y fb(x,y)^2} \tag{3}$$

where f_1 refers to the result of the infrared image after edge detection; f_a refers to the infrared image; f_2 refers to the result of the LLL image after edge detection; f_b refers to the LLL image.

Then we use the fusion strategy based on weighted average to obtain the first fused image. And its fusion strategy can be described as:

$$f_t = \alpha \times f_1 + (1-\alpha) \times f_2 \tag{4}$$

where f_t refers to the first fused image. The weights are α and $1-\alpha$, and the value of α is 0.5.

2.2. Support value transform (SVT) [8,10]

Similar to the wavelet transform, the SVT is a multiresolution transform with frame elements indexed by scale and location parameters based on least squares support vectormachine, LS-SVM. Unlike the wavelet transform, however, the support value transform directly provides the salient features of original image. It is an undecimated dyadic transform and is isotropic and shift-invariant and does not create artifacts.

In LS-SVM [11–13], the optimized conditions can be written as the linear equation:

$$\begin{pmatrix} 0 & \vec{1} \\ \vec{1} & \Omega \end{pmatrix} \begin{pmatrix} b \\ \alpha \end{pmatrix} = \begin{pmatrix} 0 \\ Y \end{pmatrix} \tag{5}$$

where $\Omega = K + I\gamma^{-1}$, $k_{ij} = K(x_i, x_j)$, $Y = [y_1, \ldots, y_N]^T$, $\vec{1} = [1, \ldots, 1]^T$, $\alpha = [\alpha_1, \ldots, \alpha_N]^T$, $Y = [y_1, \cdots, y_N]^T$, K is the kernel function and α_i is the support value of support vector x_i.

Similar to the standard LS-SVM, the solution of the mapped LS-SVM is to solve a set of linear equations in (5). The explicit solution of (5) is

$$b = \frac{\vec{1}\Omega^{-1}Y}{\vec{1}\Omega^{-1}\vec{1}}, \alpha = \Omega^{-1}(Y - b\vec{1}) \tag{6}$$

And matrices A and B can be defined as constants and are pre-calculated by

$$A = \Omega^{-1}, \quad B = \frac{\vec{1}^T\Omega^{-1}}{\vec{1}^T\Omega^{-1}\vec{1}} \tag{7}$$