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Fast mutual modulation fusion for multi-sensor images

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ABSTRACT

Multiresolution analysis based image fusion methods have become a hot research area. However, these methods may not suitable for the real-time applications due to their complex and time-consuming analysis process. Therefore, a fast mutual modulation fusion (FMMF) algorithm for multi-sensor images is proposed. First, two source images are magnified by factors that derive from the ratio of the corresponding pixel energy respectively; then an offset term obtained by computing statistical parameters of source images is added; finally, the fused image is obtained by multiplying the previous results. The proposed method concerns only addition and multiplication, and thus is effective. 'Experiments' shows that FMMF algorithm has superior performance and efficiency, compared with some algorithms based on multiresolution analysis.

1. Introduction

Due to the different physical properties of the image sensor, multi-sensor images contain abundant complementary information; some features of the scene can be seen in one image, while invisible or not obvious in the others. Therefore, the fusion algorithm should integrate the complementary information from multiple images into the fused image that better describes the scene than single source image and thus are more suitable for the visual perception and computer processing tasks such as segmentation, feature extraction, and object recognition [1]. According to the stage where the fusion is performed, Pohl prompted that image fusion can be classified into pixel-, feature- and decision-level [2].

For pixel-level image fusion, multiresolution analysis (MRA) based fusion method is extensively investigated. The representative MRAs include pyramid decomposition such as Laplacian pyramid (LP) [3], morphological pyramid (MP) [4], gradient pyramid (GP) [5], wavelet analysis such as discrete wavelet transform (DWT) [6], shift-invariant discrete wavelet transform (SIDWT) [7], and dual-tree complex wavelet transform (DTCWT) [8], and multiscale geometry analysis such as curvelet transform (CVT) [9], contourlet transform (CT) [10], and non-subsampled contourlet transform (NSCT) [11]. All MRA based image fusion methods need three steps: (i) perform an MRA transform on each source image; (ii) construct a composite MRA representation according to some fusion rules; (iii) obtain the fused image by applying the inverse transform on the composite MRA representation. Since MRA can effectively extract the salient information of the source image at different decomposition levels, MRA based image fusion can improve the fusion performance. However, the process of MRA transform is complex and time-consuming, for example, non-subsampled MRA needs more computation time to yield a redundant representation with the same size as the original image. In many cases, image fusion is only a component of an image-based application system that, before and/or after fusion, needs to process many other complex works, such as de-noising, registration, target detection. Although MRA based image fusion can produce good fusion quality, it may not be applied to the real-time system. In this paper, we propose a fast mutual modulation fusion (FMMF) algorithm, which is not only efficient due to its concerning only addition and multiplication operations, but also effective due to its reasonable fusion rules. The proposed method can be used to fuse multi-sensor images such as infrared and visible images, and multimodal medical images.

The rest of this paper is organized as follows. Section 2 describes the framework of the fast mutual modulation fusion (FMMF) algorithm and presents the fusion parameters. Section 3 analyzes the fusion mechanism of FMMF. Section 4 shows our experimental results and compares the effectiveness and efficiency with other fusion schemes. Section 5 concludes this paper.

2. Fusion algorithm

2.1. The description of fusion algorithm

Modulation is a common technique for signal processing. For example, carrier signal can vary with the amplitude of an input

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0030-4026/

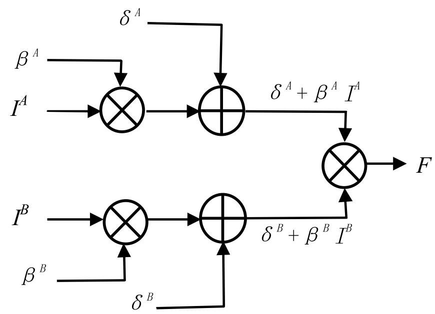

Fig. 1. Flowchart of FMMF algorithm.

signal by multiplying the input signal. This technique is also employed to synthesize the complementary information from different source images. Brovey transform [12] is an example of the modulation principle and is successfully used for remote sensing image fusion. For multi-sensor image fusion, since some pixels value may be close or equal to 0, the product of source images may result in loss of complementary information. Therefore, the simple multiplication modulation may not suitable for multi-senor images. Fortunately, according to Eckhon's research, the shunting induced modulation coupling simultaneously chooses both additive coupling and multiplicative coupling and can achieve a nonlinear enhancement effect among closely spaced synaptic inputs along a dendrite [13]. Following this idea, we propose the fast mutual modulation fusion (FMMF) algorithm in this paper. The algorithm workflow is illustrated in Fig. 1. First, two source images are magnified by a multiplication factor respectively; next, an offset term is added to the magnified images; then, previous results are multiplied; finally, the product is normalized to [0,1] to obtain the fused image.

In Fig. 1, $I^A(i, j)$ and $I^B(i, j)$ are the source images; $F(i, j)$ is the fused result; (i, j) is the pixel coordinate. The FMMF algorithm can be described as

$$F(i,j) = \left(\delta^A + \beta^A I^A(i,j)\right) \times \left(\delta^B + \beta^B I^B(i,j)\right) \tag{1}$$

where β^A and β^B are the multiplication factors; δ^A and δ^B are the offset. The expanded form of (1) is

$$\begin{aligned} F(i,j) &= (\delta^A + \beta^A I^A(i,j)) \times (\delta^B + \beta^B I^B(i,j)) \\ &= \delta^A\delta^B + \left(\delta^B\beta^A I^A(i,j) + \delta^A\beta^B I^B(i,j)\right) + \beta^A\beta^B I^A(i,j) I^B(i,j) \end{aligned} \tag{2}$$

where $\delta^A\delta^B$ is the offset term; $(\delta^B\beta^A I^A(i,j) + \delta^A\beta^B I^B(i,j))$ is the addition term; $\beta^A\beta^B I^A(i,j) I^B(i,j)$ is the product term. From Eqs. (1) and (2), one can see that this fusion scheme is a nonlinear mutual modulation model and has the advantages of both addition and multiplication modulation.

2.2. Fusion parameters

The parameters β^A and β^B control the weights of the addition term and the product term. Since the salient information or the target features in the source images have higher intensity, we determine β^A and β^B according to the energy at each pixel location (i, j)

$$\begin{cases} \beta^A(i,j) = \dfrac{\left(I^A(i,j)\right)^2}{\left(I^A(i,j)\right)^2 + \left(I^B(i,j)\right)^2} \\ \beta^B(i,j) = 1 - \beta^A(i,j) \end{cases} \tag{3}$$

The parameters δ^A and δ^B have more influence on the dynamic range (contrast) and brightness of the fused image. The equivalent number of looks (ENL) [14] is defined on mean and standard deviation, which characterizes the whole brightness and contrast of an image, and can describe the smoothness, detail and texture information of an image. *ENL* is computed as follows:

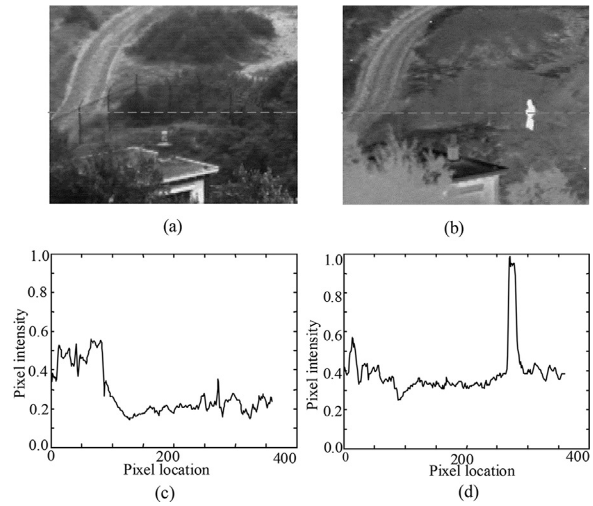

Fig. 2. 1-D signals of infrared and visible image. The profile curves (c), (d) of visual and infrared in the dash line.

$$\mathrm{ENL} = \frac{\mu^2}{\sigma^2} \tag{4}$$

where μ is the mean of the image, σ is the standard deviation of the image. By using ENL, δ^A and δ^B can be defined as global parameters

$$\delta^A = \delta^B = \begin{cases} e^{(d-10.0)} & \text{if } d \geq 1.0 \\ \dfrac{2}{1+d^{4.0}} & \text{if } d < 1.0 \end{cases} \tag{5}$$

where

$$d = \begin{cases} \dfrac{\mathrm{ENL}^A}{\mathrm{ENL}^B} & \text{if } \mu^A \geq \mu^B \\ \dfrac{\mathrm{ENL}^B}{\mathrm{ENL}^A} & \textit{if } \mu^A < \mu^B \end{cases} \tag{6}$$

For improving the compatibility of the fusion algorithm, we set $\delta^A = \delta^B$, thus the order has no limit to the source images in the fusion process.

3. Analysis of the fusion mechanism

We experimentally analyze the fusion mechanism of FMMF algorithm. The concrete method is as follows:

(i) Sample a row of pixels from the visible image A and the infrared image B respectively as shown in Fig. 2(a) and (b); then denote these pixels as $f^A(i)$ and $f^B(i)$. Fig. 2(c) and (d) shows the variation of the intensity. It can be seen that the infrared signal has less detail than the visible one and that the intensity of the target (pedestrian) in the infrared signal is closely saturated.

(ii) Use our method to fuse $f^A(i)$ and $f^B(i)$; δ^A and δ^B are manually adjusted in the range of [0, 1000]; β^A and β^B are calculated according to Eq. (3). The fusion results are illustrated in Fig. 3 in which each curve describes the variation of the energy. Compared with the original signal, one can find that the intensity become weak in the fused signal when $\delta^A = \delta^B = 0$. Especially, the intensity of the infrared target largely degrades because β^A is too small. With the increase of δ^A and δ^B, the fused results