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Multi-focus image fusion based on window empirical mode decomposition

Xinqiang Qin *, Jiaoyue Zheng, Gang Hu, Jiao Wang

School of Science, Xian University of Technology, Xian 710054, China

HIGHLIGHTS

- A novel fusion algorithm based on window empirical mode decomposition is proposed.
- The WEMD is an improved form of bidimensional empirical mode decomposition.
- A scheme based on the visual feature contrast and the local visibility is presented, respectively.
- Experimental results indicate that the proposed method provides superior performance over those of related methods.

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ABSTRACT

In order to improve multi-focus image fusion quality, a novel fusion algorithm based on window empirical mode decomposition (WEMD) is proposed. This WEMD is an improved form of bidimensional empirical mode decomposition (BEMD), due to its decomposition process using the adding window principle, effectively resolving the signal concealment problem. We used WEMD for multi-focus image fusion, and formulated different fusion rules for bidimensional intrinsic mode function (BIMF) components and the residue component. For fusion of the BIMF components, the concept of the Sum-modified-Laplacian was used and a scheme based on the visual feature contrast adopted; when choosing the residue coefficients, a pixel value based on the local visibility was selected. We carried out four groups of multi-focus image fusion experiments and compared objective evaluation criteria with other three fusion methods. The experimental results show that the proposed fusion approach is effective and performs better at fusing multi-focus images than some traditional methods.

1. Introduction

In recent years, with the rapid development of image fusion technology into many fields such as computer vision, medical imaging, military applications and remote sensing, there has been a good deal of research into image fusion [1–5]. Multi-focus image fusion is an important branch of image fusion. Due to the limited depth of field of optical lenses used in cameras, it is often not possible to obtain an image that contains all the relevant objects in focus. One way to overcome this problem is by using a multi-focus image fusion technique, where several images with different focus points are combined to form a single image with all objects fully in focus.

In general, the image fusion algorithm can be divided into two categories: one based on the spatial domain and the other based on the transform domain. The spatial domain algorithm is based on the pixel-by-pixel gray values of the source image, using fusion algorithms such as weighted averaging, principle component analysis and false color transform method [6–8]. The benefits of this algorithm are that it is fast and convenient, but the downside is that the fusion process itself determines the precision of the resultant fused image. The transform domain algorithm is mainly based on a multi-scale analysis method, using fusion algorithms including the pyramid transform, wavelet transform, ridgelet transform, curvelet transform and so on [9–12]. The benefit of this algorithm is that it has good fusion performance, but it is too complex and has poor efficiency.

In order to expand the multi-scale analysis method, American scientist Norden Huang proposed the empirical mode decomposition (EMD) in 1998. EMD is a novel multi-scale signal processing tool, which is excellent for analyzing data that are non-linear and non-stationary [13]. EMD is well-established and widely used for the processing of one-dimensional signals. Nunes et al. proposed the bidimensional empirical mode decomposition (BEMD) in 2003, a further development of EMD [14]. BEMD is a novel

* Corresponding author.
E-mail address: xqqin2007@163.com (X. Qin).

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decomposition tool based on the data itself. It can decompose the source image into a finite number of bidimensional intrinsic mode functions (BIMF) and a residual component, allowing the different frequency characteristics of the image to be analyzed [15].

Currently, there are a variety of bidimensional empirical mode decomposition algorithms that have been developed, some of which are EMD based on direction (DEMD) [16], EMD based on bidimensional interpolation (BIEMD) [17], EMD based on complex (CEMD) [18]and EMD based on a window function (WEMD) [19].

At present, there are many methods for the fusion of multi-focus images. For example, in 2014, Zhang proposed a multi-focus image fusion algorithm based focus detection, experimental results have shown that the proposed fusion algorithm retains good ratings by human visual system and objective measures compared to other multi-focus fusion algorithms [20]. In 2015, Yang proposed a multi-focus image fusion method, which is based on BEMD and improved local energy algorithm, simulation shows that the proposed algorithm significantly outperforms traditional methods such as the maximum criterion, weighted average, and wavelet fusion rules [21]. In 2016, Xiao proposed an algorithm of multi-focus image fusion based on the depth extraction, theoretical analysis and experimental results show that the proposed algorithm can avoid the blocking artifacts, and outperform the state-of-the-art methods both subjectively and objectively in most cases [22]. In 2017, Luo proposed a multi-focus image fusion using HOSVD and edge intensity, several experiments are conducted to verify the superiority of the proposed fusion framework in terms of visual and statistical analyses, the fusion results show that the proposed multi-focus image fusion method is robust to noise interference and is flexible to combine various fusion strategies [23].

This work proposes a novel multi-focused image fusion method based on the WEMD method. The experimental results show that the proposed fusion method fully utilizes the decomposition characteristics of the WEMD method and the local regional visibility, to obtain a better fusion result than either the NSCT method, the CEMD method or the wavelet method.

2. Window empirical mode decomposition

The DEMD method is multi-resolution, multi-scale and adaptive, but it lacks directionality and the decomposition quality is poorer. Due to the BIEMD method needing to be carried out as a bidimensional plane interpolation operation, the resultant decomposition is quite time-consuming, so such a method is not suitable for image processing. The CEMD method needs to operate on the image matrix line by line and so, coupled with a time-consuming EMD process, it requires a good deal of time and a great number of calculations.

WEMD is an improved BEMD, proposed by Liang et al. [24]. It uses the adding window principle for its decomposition process, effectively resolving the signal concealment problem. In the window adaptive adjustment method, the window size is determined by the number of pixels with either the maximum value or minimum value in the window. From its center, the window expands equally on all sides until the number of pixels with the maximum value in the window equals the number of pixels with the minimum value. The principle behind this method is that for the low frequency information, the maximum and minimum values of the image are concentrated in a relatively larger area while for the high frequency information, the maximum and minimum values are concentrated in a relatively smaller area. As the size of the window is determined by the local scale characteristic of the signal itself, it is adaptively adjusted in the window translation process, with the window larger for low frequency information and smaller for high frequency information. So the steps of the WEMD algorithm can be summarized as follows [19]:

(1) Initialization, $r_0 = I$ (I is the source image), $i = 1$.
(2) Identify all the local extrema points of r_{i-1}, and form the maximum and the minimum point sets.
(3) For the decomposition layers i:
   a. Set the current maximum window size to $N \times N$, the initial window size to $M \times M$, and the window size to $K = M$.
   b. Set the current pixel as the center of window K where the number of the maximum value pixels is equal to the number of the minimum value pixels. Calculate the pixel average of the window K (mean), then go to step d.
   c. $K = K + 2$. If $K < N$, go to step b; if $K \geqslant N$, calculate the pixel average of the window K (mean) directly.
   d. Let mean be the local average of the current pixel. Move to the next pixel, When $K = M$, go to step b until all the pixels of the entire image have been processed.
(4) The h_{i-1} is formed with all the mean points, and $imf_{i-1} = r_{i-1} - h_{i-1}, r_i = h_{i-1}, i = i + 1$.
(5) Repeat steps 2–4 until the specified number of decomposition layers. The decomposition process is shown in Fig. 1.

The WEMD algorithm does not use a stop criterion based on standard deviation or a bidimensional envelope surface interpolation as the traditional BEMD method does, but uses the mean value of all elements in the window directly as the center point value of the current window, thus speeding up the processing.

Fig. 2 shows the four decomposition layers that result for a group of multi-focus images processed using the WEMD method. Source image 1 has its left half in focus, source image 2 its right half. From the multi-focus decomposed images of this group, we can see that the WEMD algorithm can extract detailed information, with the details and background clear in the BIMF images. The first layer BIMF component preserves most of the high frequency detail information from the image, including edges, texture, etc. The second layer BIMF component also retains some details, but is obviously not as clear and distinct as the first layer. The level of detail in the third and fourth layer BIMF components gradually decreases. The residual component retains more low frequency information, and is similar to the source imageit mainly carries

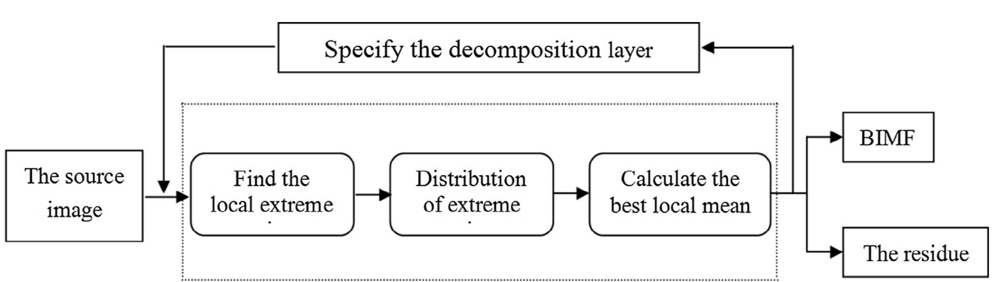

Fig. 1. The decomposition process.