Multifocus Image Fusion Based on Empirical Mode Decomposition

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Abstract

When scene contains objects that are on different depth of focus, display all areas of the picture very well isn't possible. Combining information from multiple images of the same scene into image with better description of the scene than any of the individual source images, the technique of multifocus image fusion has been attracting more attention in the field of digital image processing in last decade. In this paper, novel multifocus image fusion algorithm based on complex Empirical Mode Decomposition is proposed. Experimental results show that the proposed novel method for image fusion is more effective then other multifocus image fusion methods based on EMD.

1 Introduction

Multifocus image fusion is challenging task in the area of digital image processing and as a result has *„all-in-focus“* image that integrate complementary and redundant information from multiple images. Important applications of image fusion include medical imaging, remote sensing, computer vision, and robotics. Also, image fusion is of particular importance in modern microscopy where the resolution is compromised by the limited depth of focus.

Image fusion is the process of combining information of two or more images of a scene into a highly informative image that contains more information then any other orginal image. That image contains all significant informations from multfocus images that are result of compatibile sensors or diferent depth of focus the same sensor. The actual fusion process can be performed at different levels of information representation [2]. A common categorization is to distinguish between:

1) pixel level,
2) feature level,
3) symbol level.

Image fusion at pixel level means fusion at the lowest processing level referring to the merging of measured physical parameters. This fusion method is also known as nonlinear fusion method. Fusion at feature level requires feature extraction prior, to identify characteristics such as size, shape, contrast and texture. The fusion is thus based on those extracted features and enables the detection of useful features with higher confidence. Fusion at simbol level allows the information to be effectively combined at the highest level of abstraction. The choice of the appropriate level depends on many different factors such as data soures, application and available tools.

Image fusion is becoming very popular in digital image processing, so numerous multifocus image fusion algorithms have been proposed in recent years. There are many aplications that as results have better or worse *„all-in-focus“* image today. An image fusion method based on segmetation region using DWT is proposed by authors [2]. Multifocus image fusion sheme based on wavelet packet transform (WPT) that generalizes the discrete wavelet transform and provides a more flexibile tool for the time-scale analysis of data is proposed in [3]. Also, there are algorithms that uses spatial frequency and genetic algorithm and they combines image fusion at pixel and feature level [4]. A spatial domain and frequency domain integrated approach to fusion multifocus images is proposed in [5].

Contrast to the many methods for image fusion, Empirical Mode Decomposition (EMD) is intuitive and direct method for signal decomposition. It is natural to consider EMD with more or less modifications for the problem of heterogeneous image fusion. Existing solutions that use complex EMD for complex signal decomposition on Intrinstic Mode Functions (IMFs) and make multifocus image fusion is proposed by authors in [1], [6]. In this paper, the modification of the described image fusion algorithm in [1] is made to increase its efficientcy, speed of execution, simplicity and robustness of the parameters is proposed. Effectiveness of the proposed algorithm is tested and compared with other methods on set of grayscale and color images.

This paper is organized as follows. In section 2 a brief description of the Empirical Mode Decomposition is given, while section 3 describes its applications on 2D signals. Also, in section 3 the fusion of multifocus images using EMD in order to create *„all-in-focus“* image is described. Section 4 provides a comparative analysis of the proposed algorithm with other algorithms that use EMD, while section 5 is conclusion.

2 Empirical Mode Decomposition

Empirical Mode Decomposition is a fully adaptive method for decomposing nonlinear and nonstacionary signals. EMD adaptively decomposes a signal into a finite set of AM/FM modulated components called Intrinsic Mode Functions. By definition, an IMF is a function of which the number of extrema and the number of zero crossings differ by at most one, and the mean of the two envelopes associated with the local maxima and local minima is approximately zero. The EMD algorithm decomposes the signal $z(t)$ as follows:

Step 0: Initialize: $r_0 = z$, $i = 1$.

Step 1: Extract the n-th IMF as follows:
1) Set $h_{j-i} = r_{j-i}$, $j = 1$,

2) Identify all local maxima and minima of r_{j-i}, and construct upper envelope u_{max} of the maxima and lower envelope u_{min} of the minima of h_{j-i}.

3) Calculate a mean value of upper and lower envelope as $m = (u_{max} + u_{min})/2$, and establish the candidate for IMF as $h_j = h_{j-i} - m$.

4) If resulting signal h_j is in accord with IMF criteria, it becomes an IMF. Otherwise, set $j = j + 1$, and repeat the process 2) and 3) as long as h_j becomes IMF, ie. $IMF_i = h_j$.

5) Calculate residuum $r_i = r_{i-1} - IMF_i$, $i = i + 1$, and the procedure b) – d) is applied iteratively to obtain all the IMFs.

EMF results with $mIMF$ and residuum r_m, and decompose signal $z(t)$ as:

$$z = \sum_{i=1}^{m} IMFi + r_m \tag{1}$$

Fig. 1 shows decomposition signal X on IMFs, where X denotes input signal, IMF_{1-3} denotes IMFs, and IMF_4 is residuum of EMD process.

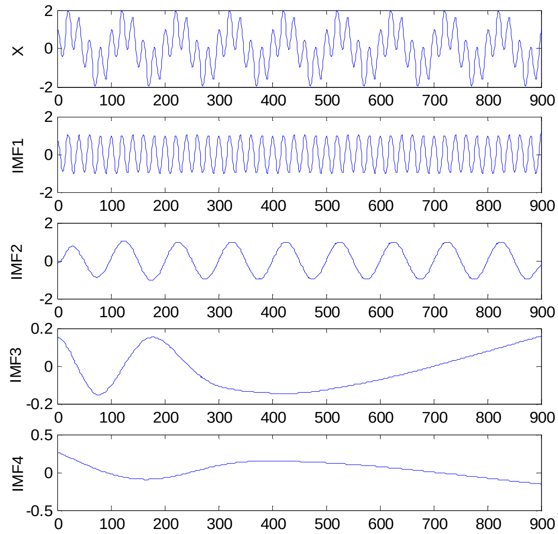

Figure 1: Decomposition of input signal X on intrinstic mode functions (IMFs) using EMD algorithm.

3 Multifocus Image Fusion

It is well known that images with sharp edges contain more information than the blurred images. When capturing image for objects in differences distance, it is not possible to display the picture of one scene in which all areas are sharp, because of the limited depth of the focus. Then, just object in the depth of focus is well focused, while regions in front of and behind depth of focus is blurred. To solve this problem, the camera can be focused on each object respectively and then obtain clear image using image fusion technique. Image fusion technique for two input images A and B uses complex EMD as follows [1]. The rows of each of the images are concatenated so as to construct two vectors (v_1 and v_2) and, using complex EMD, the complex vector $v = v_1 + j \cdot v_2$ is decomposed into M complex IMFs. Sparating the IMFs into their real and imaginary components and reconverting each into their original 2D form gives a set of M scale images of both A and B, denoted by A_i and B_i for $i = 1,2,...,M$ (Fig. 2).

The fused image F is then given by

$$F(x,y) = \sum_{i=1}^{M} \left[\alpha_i(x,y) A_i(x,y) + \beta_i(x,y) B_i(x,y) \right] \tag{2}$$

where (x,y) denotes the spatial location in the image and $\alpha_i(x,y)$ and $\beta_i(x,y)$ are weighted coefficients which satisfy $\alpha_i(x,y) + \beta_i(x,y) = 1$. The values for the coefficients are determined by comparing the local variance for each scale at each location as:

$$\begin{aligned}
\alpha(x,y) &= 0, & if \quad & \operatorname{var}\{A_i(x,y)\} - \operatorname{var}\{B_i(x,y)\} < -\varepsilon \\
\alpha(x,y) &= 0.5, & if \quad & \left|\operatorname{var}\{A_i(x,y)\} - \operatorname{var}\{B_i(x,y)\}\right| < \varepsilon \\
\alpha(x,y) &= 1, & if \quad & \operatorname{var}\{A_i(x,y)\} - \operatorname{var}\{B_i(x,y)\} > \varepsilon
\end{aligned} \tag{3}$$

where $\varepsilon > 0$, and where $\boldsymbol{var}(A_i(x,y))$ denotes the local variance at (x,y) for A_i.

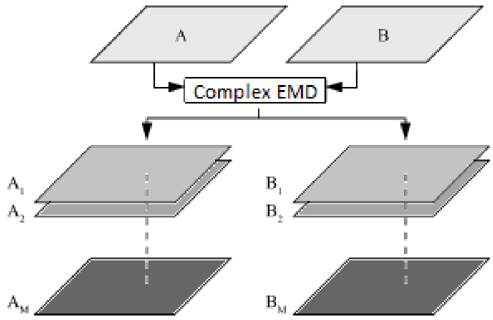

Figure 2: Proposed framework for the simultaneous decomposition of two images by autors.

In this paper, in order to avoid the whole process of decomposition of the input images using complex EMD as proposed in [1], their results obtained at all decomposition levels is analyzed in detail. It was observed that the A_1 and B_1 decomposition levels carry the most information about areas of good image focus, and it could be concluded that the first IMF contains information about the highest frequencies within the signal *X* (Fig. 1). Also, it was concluded that this information can be used to calculate the weights coefficients only on the first decomposition level, under which form a mask for image fusion, without further computation IMFs and weights coefficients at lower decomposition levels. New algorithm would accelerate the image fusion process, because it doesn't require the computation of A_i and B_i and all the weights coefficients, but only A_1 and B_1 and the weigths coefficients on the first level (Fig. 3).

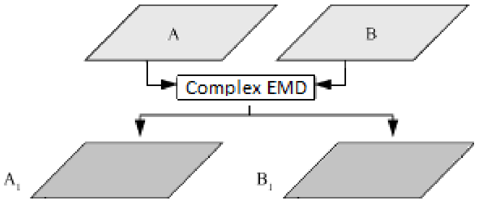

Figure 3: Proposed framework for the simultaneous decomposition of two images.

Pixel variance is calculated using all neighbors contained within the window on spatial location in 2D image matrix, where *N* determines the window size. Because of that, can be expected the window size can influence on corresponding coefficients $\alpha_i(x,y)$ and $\beta_i(x,y)$ in all *M* scale images. This influence is particularly evident at lower images decomposition levels, so we can expect that the proposed algorithm simplification will be robust on these changes then one that uses all decomposition levels for image fusion. Also, the value of the parameter ε affects the determination of weights coefficient. As a result of these deficiencies, fused image in the algorithm proposed in [1] can contain texture that do not exist on any of the input images. This is completely avoided in the proposed image fusion algorithm, because the mask is applied to the orginal, input images, not to the decomposed images, which is another new algorithm advantages.

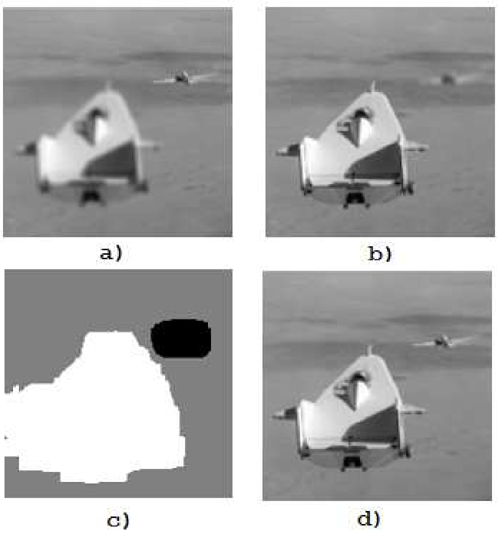

Figure 4: a) and b) Input images with different depth of focus, c) Mask, d) Focused image using proposed algorithm.

When weights coefficients on the 1st decomposition level is calculated, they used for mask creating that contains only 3 pixel values: 0, 0.5, 1 (Fig. 4c)). Pixel value 1 in image mask denoted that algorithm take corresponding pixel from first input image, pixel value 0 denoted that corresponding pixel is from second input image, and value 0.5 denoted that corresponding pixel value on fused image is average value of two input images pixels.

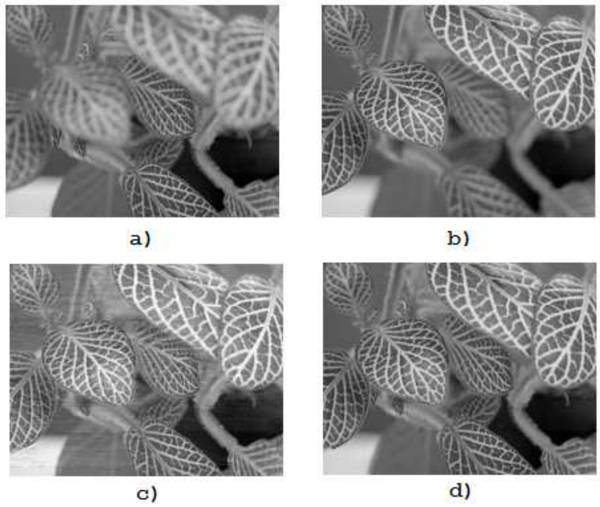

Figure 5: Image fusion - a) First input image, b) Second input image, c) Fused image using algorithm in [1], d) Fused image using proposed algorithm.

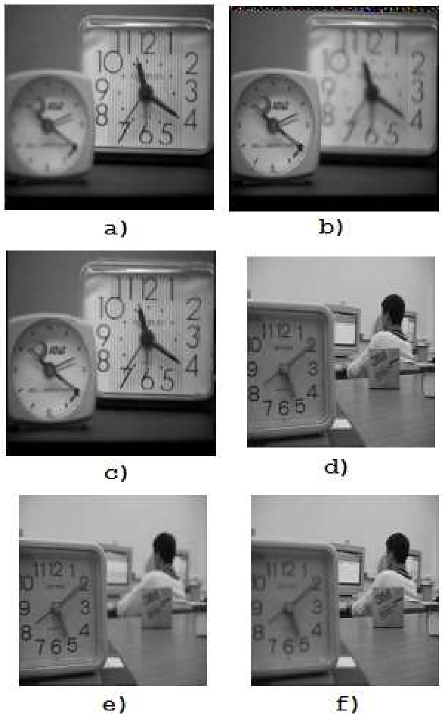

Figure 6: a), b), d), e) Two scene images with different depth of focus, c), f) Fused images using new algorithm.

4 Comparative Analysis

To demonstrate the efficiency of the algorithm, regardless of the scene that is shown in the pictures, the proposed algorithm for image fusion is tested on a group multifocus grayscale and color images of different motives. Image fusion success of all relevant information in one *„all-in-focus“* image is shown in Fig. 4-8. In Fig. 5, we can see the benefits of the new algorithm compared with algorithm proposed by the authors in [1], because its avoided the potential distortion of the fused image, noted as appearance of nonexistent texture. Also, new algorithm is robust on parameters like ε and window size N, while algorithm in [1] isn't. Needing to compute only one level of decomposition (IMF_1) speeds up the process of fusion in proposed algorithm as compared with complex algorithm in [1]. Thus, for example, picture of watches with different depth of focus shown in Fig. 6b), the ratio of speeds initial and the modified algorithm is 4.9. This suggests that the new algorithm performed faster than the first one for 4.9 times, and approximately the same ratio of fusion speed other images from the database we can expect.

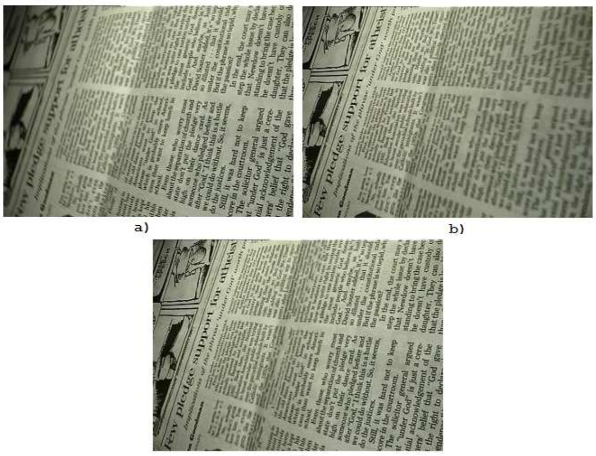

Figure 7: a) and b) Newspaper with different depth of focus, c) Fused imge of newspeper with proposed algorithm.

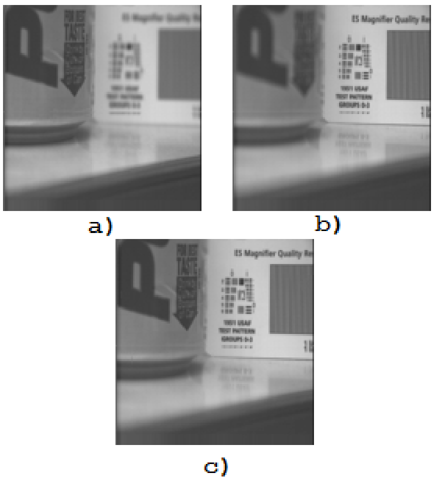

Figure 8: a) and b) Input images with different depth of focus, c) Fused imge with proposed algorithm.

5 Conslusion

In this paper a new algorithm for image fusion based on complex Empirical Mode Decomposition in order to create *„all-in-focus“* image is proposed. Adventages of proposed algorithm is shown on set of images, and results is compared with results of algorithms that also use complex EMD for image fusion. With the new algorithm the possibility of a nonexistent texture in fused image is avoided, while it didn't case in first algorithm. Also, the new algorithm is performed faster than the first one, because calculations all decomposition levels of images isn't required, and image mask is created based on only first decomposition level. Which parts of the original images will be used to form a focused image is decided based on the mask.

Literature

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