Multi Focus Image Fusion by Differential Evolution Algorithm

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Abstract: In applications of imaging system one of the major problems is the limited depth of field which disallow to obtain all-in-focus image. However, microscopic and photographic applications desire to have all-in-focus images. One of the most popular ways to obtain all-in-focus images is the multi focus image fusion. In this paper a novel spatial domain multi focus image fusion method is presented. The method, firstly, calculates point spread functions of the source images by using a technique based on differential evolution algorithm. Then the fused image is constructed by using these point spread functions. Furthermore, the proposed method and other well-known methods are compared in terms of quantitative and visual evaluation.

1 INTRODUCTION

Obtaining image of a scene can be described as the projection of 3-Dimensional real world onto 2-Dimensional image plane. At the end of this process, it is desirable to have all objects that lying at varying distances (planes) in the scene, appear to be focused. However, in practice, cameras that are used in optical imaging systems are not pinhole devices but consist of convex lenses. A convex lens can precisely focus at only one plane of the scene simultaneously. Therefore, a point object that located in any other plane is imaged as a disk rather than a point. However, if the disk, known as the blur circle, is sufficiently small, it is indistinguishable from a point, so that a zone of acceptable sharpness occurs between two planes on either side of the plane of focus. This zone is named as the depth of field (DoF). Limited DoF disallows the imaging systems to obtain all-in-focus images.

One of the most popular ways to extend the depth of field of an imaging system and to obtain all-in-focus images is the multi-focus image fusion that aims gathering information from different focal planes and fusing them into a single image where entire objects in the scene appear in focus.

Recently, a huge number of multi-focus image fusion methods have been proposed. These methods can be divided into two main groups: transform based and spatial domain based methods. In former methods, firstly, a transform is applied on the source images to get transform coefficients. Then, fusion process is executed on these coefficients and at last fused image is acquired by applying inverse transform. The most commonly used transform based methods can be given as Laplacian Pyramid (LP) (Burt and Kolczynski, 1993), Discrete Wavelet Transform (DWT) (Pajares and de la Cruz, 2004) and Discrete Cosine Transform (DCT) (Haghighat et al., 2011). The major disadvantage of these kinds of methods is that applying a transform before the fusion stage modifies the original pixel values and the fusion process is executed on the modified transform coefficients. This may result in with unanticipated brightness and color distortions on the fused images (Li et al., 2013).

On the contrary, the spatial domain based methods obtain the fused images by directly fusing the source images due to their spatial features. In the spatial domain based methods, sharp regions or pixels are explored to establish the fused image by transferring these regions or pixels. In the region based methods the source images are initially segmented into regions by an appropriate algorithm. Then, the regions are compared to detect the sharpest regions. In the pixel based methods, fused images are generated by detecting the sharpest pixels. The most known spatial domain methods are the combination of the sharper blocks by spatial frequency (Li et al., 2001), combination sharper blocks by using Differential Evolution algorithm (Aslantas and Kurban, 2010), region segmentation and spatial frequency based method (Li and Yang, 2008).

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In this paper, a novel spatial domain based multi-focus image fusion method is proposed. The source images of the multi-focus image sets consist of both blurred and focused objects. It is known that the blurred image of an object can be defined as the convolution of the focused image of the same object with a point spread function. From this point of view, the blurred and the focused pixels of the source images can be detected by using estimated point spread functions of the source images. For this purpose, a novel method that uses Differential Evolution algorithm to estimate the PSF's of the blurred parts of the source images is used in this paper. The main reason of choosing DE is the powerful global optimization ability of the algorithm. Moreover, compared with other evolutionary optimization methods, DE has some advantages as being more simple and straightforward to implement and having fewer parameters and space complexity (Das and Suganthan, 2011). The proposed method is composed of the following steps: firstly, the point spread functions are calculated over the source images by using Differential Evolution algorithm. Then, the focused pixels of the source images are detected by using estimated point spread functions. Finally, the detected focused pixels are transferred to establish the fused image.

This paper is structured as follows. The proposed image fusion algorithm is described in section 2. Experimental results are given in section 3. Finally, section 4 concludes the paper.

2 IMAGE FUSION BY DIFFERENTIAL EVOLUTION

In this section, first, general architecture of the differential evolution optimization algorithm is presented. Then the proposed multi-focus image fusion method is explained.

2.1 Differential Evolution Algorithm

Differential Evolution (DE) is a simple yet powerful population based, stochastic optimization algorithm that first introduced by Storn and Price (Storn and Price, 1997). DE is also a member of evolutionary algorithms. As an evolutionary algorithm DE uses mechanisms inspired by biological evolution, such as reproduction, mutation, recombination and selection. However, it differs from classical evolutionary algorithms in producing new generation of possible solutions by using a greedy selection scheme. DE often displays better results than other evolutionary algorithms. The strength of DE is that it can be easily applied to a wide variety of real valued problems despite noisy, multi-modal, multi-dimensional spaces, which usually make the problems very difficult for optimization.

DE algorithm, firstly, initialize a population of possible solutions. Then, new populations are created by using simple mathematical operators to combine the positions of existing individuals. If the position of a recently produced individual is an improvement, then it is included in the population otherwise the new individual is removed. This process is repeated for each generation until one of the stopping criteria (e.g. maximum generation) is met. The basic steps of DE: initialization of population, mutation, recombination and selection are briefly explained in following section.

Initialization of Population: If the function that wants to be optimized has D real parameters, it can be represented with a D-dimensional vector. DE algorithm initializes population of solution with NP solution vectors. Each parameter vector has the following form:

$$x_{i,G} = [x_{1,i,G}, x_{2,i,G}, \dots, x_{D,i,G}]\ i = 1,2,\dots,NP. \tag{1}$$

If there is no prior knowledge about possible solutions, initial population is produced randomly as following expression:

$$x_{i,G} = x_i^L + rand_i[0,1](x_i^H - x_i^L) \tag{2}$$

where x_i^H and x_i^L are the upper and lower bounds for each parameter, respectively.

Mutation: Mutation operator is applied to each parameter of vectors to expand the search space. For a given target vector $x_{i,G}$, a mutant vector $v_{i,G+1}$ generated by combining randomly selected three vectors of current generation $x_{r1,G}$, $x_{r2,G}$, and $x_{r3,G}$ as follows:

$$v_{i,G+1} = x_{r1,G} + F(x_{r2,G} - x_{r3,G}) \tag{3}$$

where i, $r1$, $r2$ and $r3$ are distinct random integer indices and $F \in [0, 2]$ is mutation factor.

Recombination: DE utilizes recombination operator that incorporates successful solutions from the previous generation in order to increase the diversity of the population. The new vector $u_{i,G+1}$ is formed by using the target vector $x_{i,G}$ and the mutant vector $v_{i,G+1}$:

$$u_{j,i,G+1} = \begin{cases} v_{j,i,G+1} & \text{if } rand_{j,i} \le CR \text{ or } j = I_{rand} \\ x_{j,i,G} & \text{if } rand_{j,i} > CR \text{ or } j = I_{rand} \end{cases} \tag{4}$$

where $j = 1,2,\dots,D$; $rand_{j,i} \in [0, 1]$ is a random number, CR ∈ [0, 1] is called recombination probability and I_{rand} ∈ [1,2,…,D] is randomly selected index that ensures $v_{i,G+1} \neq x_{i,G}$.

Selection: The recently produced vector $u_{i,G+1}$ is compared with the target vector $x_{i,G}$ in order to decide which one is included in next generation of population. The one with the better fitness function value is selected by following expression.

$$x_{i,G+1} = \begin{Bmatrix} u_{i,G+1} & \text{if} f(x_{i,G+1}) \leq f(x_{i,G}) \\ x_{i,G} & otherwise \end{Bmatrix} \quad (5)$$

2.2 Detecting the PSFs of the Source Images Using DE

Digital imaging systems are suffered from limited depth of field and this problem lead to obtain images that consist of both sharp and blurred regions. In order to obtain all-in-focus image of a scene, multi-focus images of it obtained from an identical point of view with different optical parameters can be used. However, the sharp pixels of these images need to be properly determined.

The blurred image of an object can be defined as the convolution of the sharp image of the same object with the PSF of the camera (Aslantas and Pham, 2007). If both the sharp and the blurred images of same object are exists then the PSF can be computed by a deconvolution process. Objects at particular distance in the scene are viewed in focus in one of the source images and out of focus in the others. Thus, for all objects, if both of the sharp and the blurred images are exist, the PSF of blurred images can be computed by using them.

To explain the theory of the proposed method, a linear imaging model is used in this paper. Suppose that i_1 is the near focused and i_2 is the far focused image of the same scene. Besides, let f represents the foreground objects and g represents the background objects of the scene.

$$\begin{aligned} i_1 &= f_s + g_b \\ i_2 &= f_b + g_s \end{aligned} \quad (6)$$

where f_s and g_s represent the sharp images and f_b and g_b represent the blurred ones, respectively.

Since the blurred image of an object can be obtained by convolving the sharp image of the same object with the PSF of the camera, Eq. 6 can be written as following:

$$\begin{aligned} i_1 &= f_s + (g_s \otimes h_1) \\ i_2 &= (f_s \otimes h_2) + g_s \end{aligned} \quad (7)$$

where h_1 and h_2 are the PSFs. After examining the several wavelengths and considering the effects of lens aberrations, the point spread function is best described by a 2D Gaussian function (Subbarao et al., 1995).

$$h(x, y) = \frac{1}{2\pi\sigma^2} e^{-\frac{(x^2+y^2)}{2\sigma^2}} \quad (8)$$

where σ is the spread parameter (SP).

In order to determine the optimal PSFs of the source images, the proposed method employs the DE algorithm. The parameters that are searched in optimization process are the SPs of the PSFs of the source images. The steps of detecting the optimal PSFs can be given as follows:

Step 1: Define the parameters of the DE algorithm (*CR*, *F*, *NP*) and the termination criteria.

Step 2: Generate the initial population randomly. Each individual has the parameters as the number of the source images. In our example, each individual consist of two parameters σ_1 and σ_2 that denotes the spread parameters of PSFs of the source images h_1 and h_2, respectively.

Step 3: Evaluate the population by computing the fitness function value of each individuals.

Produce estimated PSFs for the source image by substituting σ_1 and σ_2 in Eq. 8, respectively.

Generate artificially blurred images by convolving the source images with the each other's PSFs. Hence, i_1 is convolved with h_2 and i_2 is convolved with h_1 to produce c_1 and c_2 images, respectively as:

$$\begin{aligned} c_1 &= f_b + g_b \otimes h_2 \\ c_2 &= f_b \otimes h_1 + g_b \end{aligned} \quad (9)$$

Obtain the difference images by subtracting c_2 from i_1 and c_1 from i_2 as:

$$\begin{aligned} d_1 &= f_s - f_b \otimes h_1 \\ d_2 &= g_s - g_b \otimes h_2 \end{aligned} \quad (10)$$

For the ideal PSFs, the dot product of d_1 and d_2 should be equal to zero. In order to obtain the fitness value of the each solution, the following expression is used as the fitness function:

$$\mathrm{f}(\sigma_1, \sigma_2) = \sum \mathrm{d}_1 \,.\, \mathrm{d}_2 \quad (11)$$

Step 4: In order to generate the next generation of population, apply the mutation and recombination operators of DE to current solutions.

Step 5: Repeat the steps 3-4 until a stopping criteria is met.

2.3 Fusing the Source Images Using the Optimal PSFs

After estimating optimal PSFs of the source images, the sharp pixels can be detected by using these. To this end, first, the source images are artificially blurred by convolving with the estimated PSFs (h_1 and h_2) to compute the artificially blurred images c_2 and c_1. In c_1 and i_2, f obtained with the same amount of blur. Also, the regions corresponding to g in c_2 and i_1 are blurred equally. By making use of this information, the sharp pixels can be detected.

In order to determine sharp pixels, the difference images are obtaining by substituting optimal PSFs in Eq. 10. By optimal PSFs, f and g are cancelled out in d_1 and d_2, respectively. At last, each pixel of d_1 and d_2 are compared to construct the fused image i_F as:

$$i_F(x,y) = \begin{cases} i_1, & d_1 \geq d_2 \\ i_2, & d_1 < d_2 \end{cases} \tag{11}$$

3 EXPERIMENTAL RESULTS

This section reports the evaluations of the fusion results of the proposed method by quantitatively and visually. In order to evaluate the performance of the proposed method quantitatively, assessing indexes Quality of Edges (QE) (Xydeas and Petrovic, 2000) and Fusion Factor (FF) (Stathaki, 2008) are applied. The results of the proposed method are compared with three other well-known methods: Discrete Wavelet Transform (DWT) (Pajares and de la Cruz, 2004), Discrete Cosine Transform (DCT) (Haghighat et al., 2011) and block based spatial domain (BBSD) (Li et al., 2001). For DWT "sym8" filter and 7 decomposition level are chosen. For BBSD method block size is selected as 16×16 and SF is used as sharpness measure. As a result of many experiments conducted, control parameters of DE is chosen as $CR = 0.6$, $F = 0.6$ and $NP = 16$ for the proposed method.

In the experiments, the multi-focus image sets: "Lab", "Book" and "Watch" are used. The source images of these sets are shown in Fig. 1.

Figure 1: The source images used in the experiments.

The first experiment was performed on the "Lab" source images given in Fig. 1. The fused images and the difference images that obtained by subtracting source images from fused images are shown in Fig. 2. It can be seen on the figure, the fused images of DWT and DCT methods have some artifacts on the head of the man. If the source images of "Lab" image set are examined carefully, it can be seen that head of the man has slightly moved between two images. This condition leads to artifacts in fused images of the DWT and the DCT methods that suffer from shift variance. Although the result of the BBSD method is satisfactory in this area, it produces some artifacts in other regions. Especially, it cannot preserve the form of the clock and introduces some blocking effects. On the other hand, the fused image of the proposed method does not contain major artifacts.

The second experiment was carried out on the "Book" image set that contains detailed textures. The fused and the difference images of the "Book" image set are given in Fig. 3. It can be seen from the figure, the proposed and the DCT methods have a good fusion performance on this image set. On the other hand, the DWT method could not preserve all the high frequency details and this can be seen more clearly in the difference images. Moreover, in spite of producing fewer artifacts than the DWT, the BBSD method produced some artificial edges around the borders of books.

The last experiment was performed on the "Watch" multi-focus image set. Fig. 4 displays the fused and the difference images of the "Watch" image set. If the fused images are examined, intensive distortions on details such as the pin of the watch can be seen in the DWT and DCT methods. Similarly, the BBSD method could not preserve details properly. When the block size cannot fulfill the little details exactly, the BBSD method cannot produce perfect fused images for the image sets that contain too little objects. On contrary, there are no obvious artifacts in the fused image of the proposed method.

Table 1 gives the quantitative results of the methods in terms of the QE and the FF metrics. Bold values in the table indicate the greater values in the corresponding column. It can be seen from the table that the proposed method outperforms the other methods. Only for the "Book" and the "Watch" image sets, the DCT method produced better result than the proposed method in term of FF metric. However, it can be seen that the proposed method has very close result to that. Besides, if the "Watch" fused image of DCT method is examined, blur on the pin of the watch observed. This situation demonstrates that in some cases quality indexes have some significant drawbacks.

Table 1: The quantitative results of the fusion methods.

	Lab		Book		Watch	
	OE	FF	OE	FF	OE	FF
Method	**0.7482**	**9.8998**	**0.7408**	22.5540	**0.7221**	9.3001
DWT	0.6728	7.1553	0.6881	11.4353	06487	5.6153
DCT	0.7446	9.8627	0.7400	**22.9122**	0.7167	**9.3365**
BBSD	0.7478	9.8501	0.7406	22.1375	0.7204	9.2017

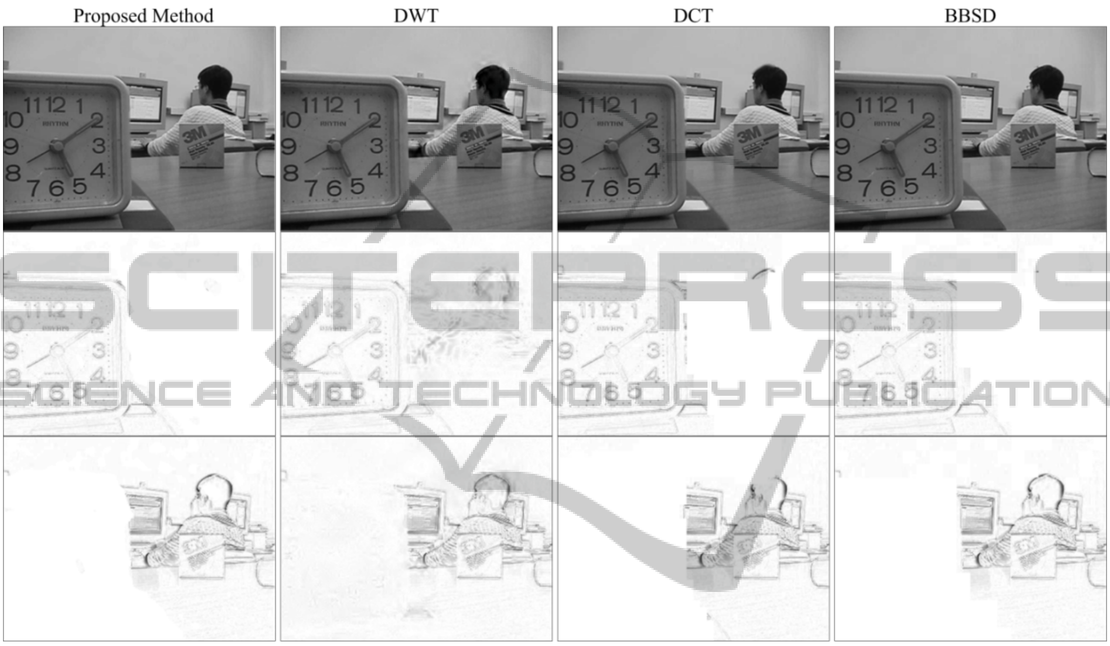

Figure 2: The fused and the difference images of the Lab image set.

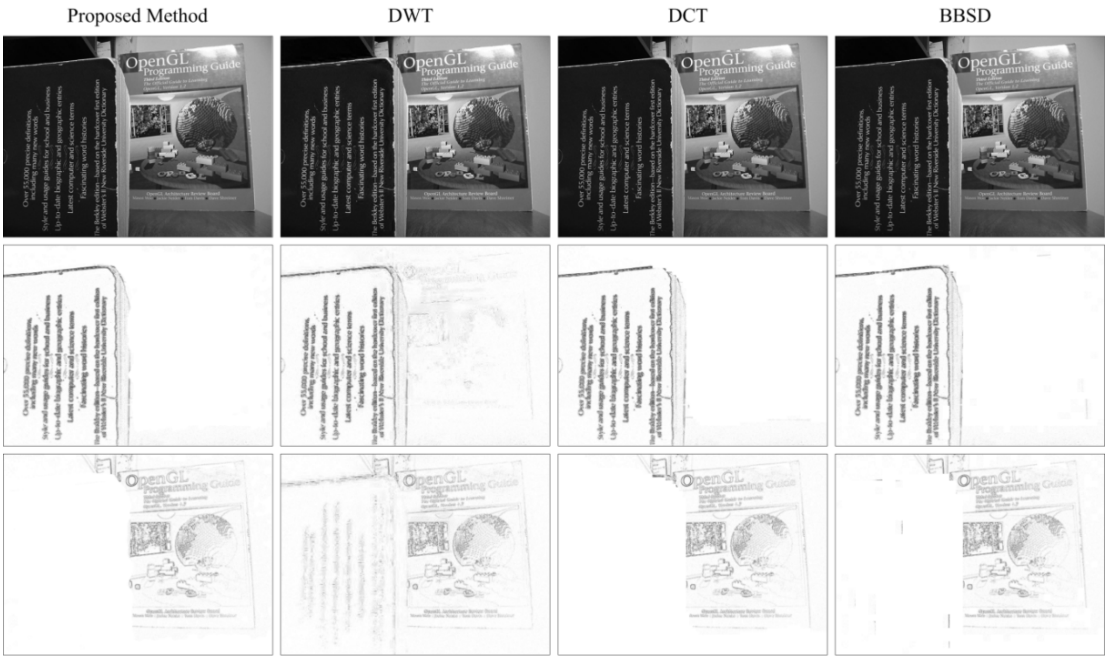

Figure 3: The fused and the difference images of the Book image set.

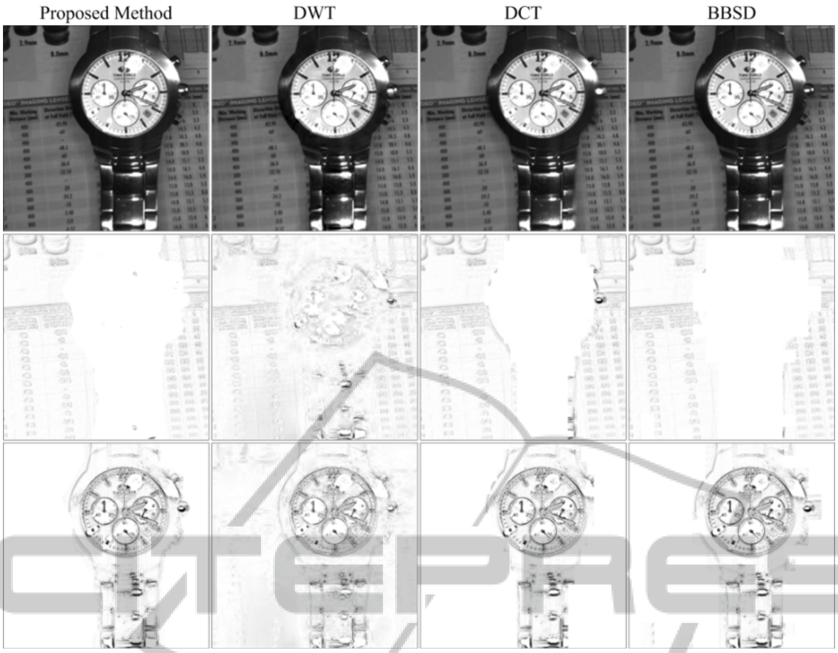

Figure 4: the fused and the difference images of the Watch image set.

4 CONCLUSIONS

In this paper a powerful multi-focus image fusion technique is proposed for extending image's apparent depth of field. The proposed method estimate PSFs of the source images by using DE method, and then each image is artificially blurred by convolving these PSFs. Then, the artificially blurred images are used to determine the sharpest pixels of the source images. Finally, the all-in-focus image of the scene is constructed by gathering the sharpest pixels of the source images. Also experimental results are performed on the multi-focus image sets. These experiments reveal that the proposed method outperforms over the well-known DWT, DCT and BBSD methods in terms of both the quantitative and the visual evaluations.

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