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Multi-focus image fusion based on sparse feature matrix decomposition and morphological filtering

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A B S T R A C T

Multi-focus image fusion aims to fuse multiple images with different focus points into one single image where all pixels appear in-focus. A novel multi-focus image fusion method is presented based on a sparse feature matrix decomposition and morphological filtering. First, the sparse feature matrices of original multi-focus images are extracted by decomposing the multi-focus images. Second, a temporary matrix is obtained by weighting the sparse matrices containing salient features of original images. Third, the bright and dark regions are extracted by morphologically filtering the temporary matrix. Finally, the final fusion result is formed by importing the extracted features into the base image which is established by weighting the source images. Experimental results indicate that the proposed method not only works well in various multi-focus image fusions, but also outperforms some existing methods in both subjective and objective qualities.

1. Introduction

Due to the restricting depth-of-focus of optical lenses [1], it is difficult to get an image of all relevant objects in focus. Multi-focus image fusion is an efficient technique to generate an all-in-focus clear image by combining two or more images of the same scene into one composite image. The main principle [2] in multi-focus image fusion is to integrate all the important visual information of original images into the fused synthetic image without any artifacts introduced.

Various approaches have been proposed in recent years. Generally speaking, these methods consist of two categories, the transform domain and spatial domain based fusion methods [3].

In the transform domain based methods, multi-scale geometric analysis (MGA) is a widely considered tool. Those MGA approaches include discrete wavelet transform (DWT) [4], discrete cosine transform (DCT) [5], non-subsampling contourlet transform (NSCT) [6], shearlet transform (ST) [7], non-subsampled shearlet transform (NSST) [8], etc. The basic idea of all those methods is to decompose the source images into a multi-scale domain, then fuse the transform coefficients according to a certain fusion rule, finally construct the fused images via the corresponding inverse transform. Setting an appropriate fusion rule is the most important step. Because the traditional coefficient selection scheme performing the maximum operation on the high-pass coefficients and mean operation on the low-pass coefficients damages the contrast of the fused image, some fusion rules employing focus measures [9] or pulse-coupled neural network (PCNN) [2] in the coefficients selection were presented to transmit as much information of source images as possible to the fused images. These methods, taking advantage of local and neighboring characteristics, achieved better performance. But these algorithms based on the multi-scale decomposition are still sensitive to image misregistration and time-consuming [9,10]. Meanwhile, the incorrect coefficient selection is inevitable because of the complexity of image contents.

In the past few years, the fusion methods based on compressive sensing [11] and sparse representation [12] have attracted many researchers' attention. Despite of the advantage over reducing the processed data size, there is still not a satisfactory fusion rule in compressive domain due to the lack of spatial information of compressed measurements. Besides, the over-complete dictionary learning takes much time and the atom selection in dictionary construction is a difficult issue [13].

The spatial domain based algorithms with the low computational cost and simplicity to operate have been broadly investigated in recent years. The spatial domain based algorithms can be classified as three groups: pixel based, block based and region based fusion methods [10]. The spatial methods can maintain more image information compared with transform based methods and consume less time. The pixel based fusion methods, which mainly use single pixels to generate fused images pixel by

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pixel, easily cause undesirable artifacts. The basic principle is to decompose the source images into blocks with fixed block size and select the image block with a larger focus measure in the block based fusion. Some commonly used focus measures were concluded in [9], such as the spatial frequency (SF), sum-modified-Laplacian (SML), energy of Laplacian of the image (EOL), etc. However, a larger block size may contain clear and blur areas simultaneously [9], and the blocking effect usually exists in the fused images even if the block size is adaptive [14]. In the region based fusion, the fusion result is not stable [14] and the boundary location is hard due to the difficulty of the image segmentation. The local variance of the quaternion wavelet transform (QWT) [15,16] phases as a focus measure was proposed to segment the source images, achieving better fusion results. In a word, the block size, region segmentation and focus measure are the main factors in spatial domain based fusion.

In this work, we propose a novel multi-focus image feature extraction and fusion method based on a sparse feature matrix decomposition. A multi-focus image which is a high dimensional data is projected on a low dimension space via the sparse feature matrix decomposition. The sparse matrix component, including salient features such as edges and contours, can be used for image fusion. The proposed method is a feature space transform based fusion algorithm, which can reduce data storage size because the source images are projected onto a single-scale sparse space. The most significant contributions of our work lie in two aspects. First, we employ a novel sparse feature matrix decomposition method for multi-focus images. Second, an efficient pixel-wise fusion rule is proposed based on the extracted sparse feature matrices.

The rest of the paper is organized as follows. Section 2 provides a detailed description about sparse feature matrix decomposition used for multi-focus image fusion and presents the fusion rule. Experimental results and discussions are presented to evaluate the performance of the proposed method in Section 3. Finally, conclusions are drawn in Section 4.

2. The proposed algorithm

It should be noted that it is not the first time that sparse feature matrix decomposition has been applied to multi-focus image fusion. In [17,18], a sparse matrix is calculated via the robust principal component analysis (RPCA), and the fused image is obtained by a decision matrix comparing the local standard deviations of different sparse matrices. In [19], Zhang et al. also utilized the RPCA [20] to generate the sparse matrices, and got the fused image by combining EOL and PCNN to process the sparse matrices. The two methods both achieved good fusion results, demonstrating that sparse feature matrix decomposition is effective and efficient in the multi-focus image fusion. The similarities of the two algorithms are that they both use RPCA to decompose the original images into low-rank and sparse matrices and employ region-based fusion rules to fuse the images. Besides, other region based fusion rules concerning the sparse matrices also have been presented by Zhang et al. in [21–23], which further indicates the potential of sparse matrix decomposition in image fusion. However, we found that RPCA fails to extract enough and indispensable information from source multi-focus images, which is detrimental to subsequent fusion, and the region-based fusion rule easily causes blocking effect and discontinuity in the transition zone. The main difference between our work and previous methods based on sparse feature matrix decomposition are that we use a different decomposition method and new pixel-wise rule. Our decomposition method is able to extract more salient information than RPCA and our pixel-wise fusion rule instead of region-based fusion rule can generate higher-contrast fused images with less running time.

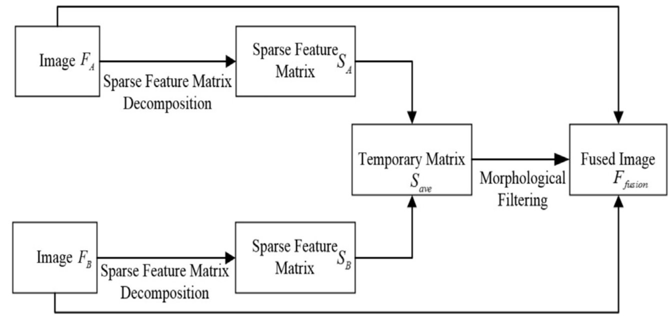

Fig. 1. The block disgram of the presented method.

The block diagram of our method is depicted in Fig. 1. Only two source images are considered in this diagram. However, the proposed method can be easily extended to handle more than two images. Our method mainly consists of the following four steps: sparse feature matrix decomposition, the sparse feature matrices processing, morphological filtering, and image fusion. The method is presented as follows.

2.1. Problem statement

A multi-focus image $F \in R^{M\times N}$ with M rows and N columns can be denoted as

$$F = L + S \tag{1}$$

Each multi-focus image contains the clear and blurry features, corresponding to the sparse matrix S and low-rank matrix L [16]. The sparse feature and low-rank feature image can be calculated by formulating the following expression:

$$\min \|L\|_* + \lambda |S|_1 \quad s.\ t. \quad F = L + S \tag{2}$$

where $\| \ \|_*$ represents the nuclear norm (i.e. the sum of singular values), $\|_1$ stands for the l_1-norm which counts the sum of the absolute values of matrix entries, and $\lambda > 0$ is a regularization parameter balancing the contribution of the sparse matrix. The expression can be solved via the RPCA decomposition, however, the decomposed sparse matrix cannot contain enough salient features (see Fig. 1) due to the globalization of RPCA. A multi-focus image is usually piece-wise smooth, thereby, it is more reasonable to set a local smooth constraint than low-rank constraint. We replace $\|L\|_*$with $\|\nabla L\|_F^2 = \sum_{i,j} [(\nabla_x L)_{i,j}^2 + (\nabla_y L)_{i,j}^2]$ [24], which can describe local features more efficiently. Then, the Eq. (2) can be expressed as

$$\min \|\nabla L\|_F^2 + \lambda |S|_1 \quad s.\ t. \quad F = L + S \tag{3}$$

The augmented Lagrangian function of Eq. (3) is defined as

$$L_\mu(L, S, Y) = \min \|\nabla L\|_F^2 + \lambda |S|_1 + \langle Y, F - L - S\rangle + \frac{\mu}{2}\|F - L - S\|^2 \tag{4}$$

where μ is a positive penalty parameter, Y is the Lagrangian multiplier matrix. Via the alternating direction method (ADM), Eq. (4) can be written in the following iterative formulas:

$$L_{k+1} = \arg\min_L L_\mu(L, S_k, Y_k) \tag{5}$$

$$S_{k+1} = \arg\min_S L_\mu(L_{k+1}, S, Y_k) \tag{6}$$

$$Y_{k+1} = Y_k + \mu(F - L_{k+1} - S_{k+1}) \tag{7}$$

The fast Fourier transform (FFT) is applied to solve L_{k+1}