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Multifocus image fusion based on robust principal component analysis

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ABSTRACT

Multifocus image fusion has emerged as a major topic in computer vision and image processing community since the optical lenses for most widely used imaging devices, such as auto-focus cameras, have a limiting focus range. Only objects at one particular depth will be truly in focus while out-of-focus objects will become blurry. The ability to create a single image where all scene areas appear sharp is desired not only in digital photography but also in various vision-related applications. We propose a novel image fusion scheme for combining two or multiple images with different focus points to generate an all-infocus image. We formulate the problem of fusing multifocus images as choosing the most significant features from a sparse matrix obtained by a newly developed robust principal component analysis (RPCA) decomposition method to form a composite feature space. The local sparse features that represent salient information of the input images (i.e. sharp regions) are integrated to construct the resulting fused image. Experimental results have demonstrated that it is consistently superior to the other existing state-of-theart fusion methods in terms of visual and quantitative evaluations.

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1. Introduction and motivation

Due to the limited depth of field in commonly used optical lenses, only objects within a certain range of distances from the imaging devices will be captured and recorded sharply whereas objects at other distances will be blurred (or defocused) (Tian and Chen, 2012). This is undesired for accurately interpreting and analyzing images, such as images acquired from surveillance (Haghighat et al., 2011) or optical microscopic systems (Vivanco et al., 2009). Image fusion technique provides a promising way to solve this problem by combining two or multiple images of the same scene that are taken with diverse focuses into a single image in which all the objects within the image are in focus (Ludusan and Lavialle, 2012). Multifocus image fusion has been proven to be an effective way to extend the depth of defocused images (Hong et al., 2007). It has been used in a wide variety of applications like computer vision (; Hong et al., 2007; Tian et al., 2011), remote sensing (Bai et al., 2011), digital imaging (Zhang and Blum, 1999; Aslantas and Kurban, 2010), and microscopic imaging (Hariharan et al., 2007; Malik and Choi, 2009).

The existing fusion methods, based on Stathaki's definitions (Stathaki, 2008), can be mainly categorized into two groups: spatial domain and transform domain techniques. In spatial domain, fusion rules are directly applied to image pixels or image regions. The fused

image can be constructed as a linear combination of input images, where the useful information is transferred to the fusion result by means of a weighting function (Tian et al., 2011; Zhang and Ge, 2009). For instance, Li et al. (2001) devised a scheme that fused multifocus images by dividing the source images into blocks and combining them based on the spatial frequency (SF). In the past few years, they have published more sophisticated fusion techniques at different levels of complexity (Li and Wang, 2008; Li et al., 2002). Miao and Wang (2005) proposed a fusion method using the ratio of blurred and original image intensities. Wen et al. (2007) produced a sharp target gradient field via minimizing the gradient difference and intensity difference with respect to the objective gradient field and intensity constraints. Huang and Jing (2007) compared several clarity measures defined in the spatial domain, such as variance, energy of image gradient, spatial frequency, and evaluated their capability to distinguish clear image blocks from blurred image blocks. The major advantages of spatial domain based fusion methods are the simplicity to implement and low computational complexity. Moreover, the final fused image contains original information from input images. However, such methods are often subject to noise interference and blocking artifacts since the selection criteria are computed based on single or neighboring pixels (Lewis et al., 2007; Wan and Achim, 2009). The presence of image noise could significantly degrade image quality by adding spurious and extraneous information, thus resulting in ambiguous selection in determining focused versus defocused pixels or regions (Malik and Choi, 2008). Various noise filters can be employed to tackle this

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problem, but they also remove the sharpness information in addition to the noise (Shim et al., 2011). In transform domain, image fusion algorithms are implemented in a non-image domain via a certain transform technique, such as discrete cosine transform (Haghighat et al., 2011), pyramid transforms (Wang and Chang, 2011), multiscale geometric transforms (Zhao et al., 2010), and wavelets (Li et al., 2010). A multiresolution transform has been widely adopted to perform image fusion tasks (Zhao et al., 2010; Tian and Chen, 2010; Li et al., 2010). The idea is to decompose the source images into multiresolution representations, and integrate the decompositions to form a composite fusion space according to certain fusion rules. The fused image is finally constructed by applying an inverse multiresolution transformation.

Wavelet transform, among the multiresolution based fusion schemes, has become popular in image processing field as it provides a natural partition of the image spectrum into multiscale and oriented subbands (Wan and Achim, 2009). Yang (2011) developed a discrete wavelet transform (DWT) based fusion approach by applying different fusion strategies to high and low frequency coefficients, respectively. Tian and Chen (2012) studied the spreading of the wavelet coefficients distribution and evaluated its potential use as an image sharpness measure via a Laplacian mixture model (LMM). Li and Wang (2008) introduced a fusion method by combining wavelet and curvelet transform. They have reported that the combination yielded better fusion results than using the individual transform alone. The transform-based fusion methods have demonstrated many advantages, including improved contrast, better signal-to-noise ratio, and increased fusion quality (Li and Wang, 2008). However, they are usually complicated and time-consuming to implement (Wang et al., 2010).

In this paper, we propose a novel image fusion scheme which is truly different from the above approaches. Our method utilizes a newly introduced technique referred to as robust principal component analysis (RPCA), in which the data matrix is a superposition of a low-rank component and a sparse component (Candès et al., 2011). In theory, under certain assumptions, it is feasible to recover both low-rank and sparse components exactly by solving the principal component pursuit (Lin et al., 2009). There are many important applications can be naturally modeled using this methodology, such as video surveillance (Candès et al., 2011), face reconstruction (Torre and Black, 2001), bioinformatics (Wan et al., 2011), and web search (Candès et al., 2011). In (Torre and Black, 2003), the robust principal component analysis has been proven to be an effective way to construct low-dimensional linear-subspace representations from high dimensional data such as images. The objective of the work is to investigate its potential application in the multifocus image fusion. We establish a multifocus image fusion framework based on the discriminative sparse features that are computed from the sparse matrix. The problem of fusing multifocus images is converted to the problem of selecting the most salient sparse features from the source images to form a composite feature space. The blocking artifacts are eliminated by using a sliding window technique to smooth the transitions between the image blocks. The sparse matrix is computed through an augmented Lagrange multiplier (ALM) method (Lin et al., 2009), a fast version of implementation for recovering low-rank matrices. Being implemented in this fashion, the new methodology is not only robust to noise interference by choosing the most significant sparse features, but also flexible to integrate different fusion strategies in the sparse domain.

The paper is organized as follows. Section 2 provides a problem statement including a generic multi-focus image fusion method and the RPCA-based fusion scheme. The detailed methodology based on the RPCA model is presented in Section 3. Experimental results for comparing the new image fusion method to three existing conventional approaches are demonstrated in Section 4. Finally, conclusions are given in Section 5.

2. RPCA-based fusion method

We first give a brief description regarding the formulations of a generic multi-focus image fusion method and the RPCA-based fusion scheme in this section.

2.1. Generic multifocus image fusion

Multi-focus image fusion involves combining a set of images that are taken from a same scene but with different focuses for creating a single sharp image. Assume that two input images are given, where image $I_A \in \mathbb{R}^{H \times W}$ ($H \times W$ are the dimensions of the image) has focus on one object or region, and image $I_B \in \mathbb{R}^{H \times W}$ focuses on another object or region. The resultant fused image F_{AB} is generated by

$$F_{AB} = \varphi(\tau(I_A), \tau(I_B)) \tag{1}$$

where τ denotes the different domains, such as spatial or multiresolution domain, in which image fusion will perform, and φ is a decision method or fusion criterion to identify focused regions within each source image and eventually combine these objects or regions in focus into an integrated image F_{AB} .

2.2. The RPCA-based fusion scheme

In general, defocused objects or regions in the image appear very blur while objects located within the focus range are clearly captured. Therefore, the problem of fusing multifocus images can be treated as separating clear parts from blur parts of the images. To solve the problem, one straightforward method is to segment the source images into various regions and a region-based fusion rule is adopted to distinguish the sharp regions from the blurry regions, such as Li and Yang's method (Li and Wang, 2008). However, the fusion performance can be highly affected by the accuracy of the segmentation method used. A recently emerged RPCA technique tends to decompose the input data matrix into a low-rank principal matrix and a sparse matrix (Candès et al., 2011). The sparse matrix represents dissimilar information from the principal components which can be useful to build a robust fusion scheme to accurately discriminate the focused regions from the defocused regions. Hence, the salient information from the source images can be described by the extracted features from the sparse matrix.

Assume we have an input data matrix $D \in \mathbb{R}^{M \times N}$ (*M* and *N* are matrix dimensions) that can be decomposed as:

$$D = A + E$$
, $rank(A) \ll min(M, N)$ (2)

where *A* is a principal matrix known to be low rank, and *E* is a sparse matrix. Although under general conditions this problem is intractable to solve, recent studies (Wright et al., 2009) have discovered that the principal component pursuit, a convex program, can effectively solve this problem under broad conditions. The sparse matrix *E* can be computed by solving the following convex optimization problem:

$$\min_{A,E} ||A||_{*} + \lambda ||E||_{1} \quad \text{s.t.} \quad A + E = D$$
(3)

where $\|\cdot\|_*$ represents the nuclear norm of a matrix, $\|\cdot\|_1$ is the l_1 norm denoting the sum of the absolute values of matrix entries, and $\lambda > 0$ is a parameter for weighting the contribution of the sparse matrix in the optimization process. In the presented fusion framework, the data matrix D with $M \times N$ dimensions contains an $M \times 1$ (m = H * W) matrix of $N(N \ge 2)$ source images after vectorization. For a fast implementation via an augmented Lagrange multiplier method (Lin et al., 2009), λ is set as $1/\sqrt{M}$. Fig. 3(c-d) and Fig. 4(c-d) show two examples of constructed images obtained from the sparse matrices after performing the RPCA decomposition

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Fig. 1. The schematic diagram of the presented fusion algorithm.

on the source images. The sparse features F_A and F_B are computed from the sparse images S_A and S_B , respectively. The fusion image F_{AB} is obtained by combining the salient sparse features via:

$$F_{AB} = \varphi(\phi(F_A), \phi(F_B)) \tag{4}$$

where ϕ is a feature selection function defined by a saliency measure. The detailed implementation of the developed fusion scheme is described in the following section.

3. Methodology

A schematic diagram of the RPCA-based image fusion algorithm is illustrated in Fig. 1. For a simple case, we only consider the problem of fusing two source images. However, the developed fusion method can be extended straightforwardly to handle more than two images by constructing the data matrix *D* with multiple source images after vectorization as described in Section 2.2. In addition, we assume the source images are pre-registered. Therefore, image registration is not included in the entire framework. The algorithm consists of the following 5 steps:

- Step 1: Transform the 2-dimensional source images $\{I_A, I_B\}, I_A, I_B \in \mathbb{R}^{H \times W}$ to the column vectors V_A and V_B , respectively. V_A and V_B are combined together to formulate a data matrix D. For two grayscale source images, D is given by:
 - $D = \begin{bmatrix} V_A; & V_B \end{bmatrix}$

where $D \in \mathbb{R}^{M \times 2}$ $(M = H \times W)$ is the input matrix for the RPCA model.

As mentioned in Section 2.2, the data matrix D is formulated as a combination of source images after vectorization. Therefore, a color image can be processed as three individual source images to be integrated in a single matrix. For two color images, the data matrix D is defined as:

 $D = [V_A^c; V_B^c], c \in \{R_band, G_band, B_band\}$

where *c* denotes the index of the image color band.

- Step 2: Perform the RPCA decomposition on *D* to obtain a principal matrix $A \in \mathbb{R}^{M \times 2}$ and a sparse matrix $E \in \mathbb{R}^{M \times 2}$. The sparse matrix *E* is computed by a fast version of the ALM method Lin et al., 2009, which has been reported to yield similar results with much less computational complexity. Convert each column of matrix *E* into an $H \times W$ matrix to obtain two matrices E_A and E_B ($E_A, E_B \in \mathbb{R}^{H \times W}$) corresponding to the source images I_A and I_B , respectively.
- Step 3: Divide the matrices E_A and E_B into K small blocks. For each pair of corresponding blocks, the standard deviations $SD_A(k)$ and $SD_B(k), k = 1 \dots K$, are calculated. The standard deviation can be used to characterize the local variations within the block. Large values of standard deviation represent sharp regions in good focus, while small values represent blurry regions. Thus, the block with a larger standard deviation is chosen to construct the fused image F_{AB} . However, this will lead to non-smooth transitions between blocks. In order to reduce the blocking artifacts, a sliding window technique is applied to the matrices E_A and E_B . Let $n_A(i,j)$ and $n_B(i,j)$ store the frequency of pixel location (i, j) being selected when a small window is moved from previous position to the current position on E_A and E_B . If a pixel location (i, j) in E_A has a higher standard deviation when the sliding window covers this position, the corresponding $n_A(i,j)$ is added one. The above process is illustrated in Fig. 2. The same rule is also applied to E_B and $n_B(i,j)$. The sliding window technique allows the pixels that are more likely to belong to the sharp regions are selected in the following step.
- Step 4: For a simple case where there are only two input images, a decision map *W* of the same size of the input images is created to record the feature comparison results according to a selection rule:

$$W(i,j) = \begin{cases} 1 & n_A(i,j) > n_B(i,j) \\ -1 & n_A(i,j) < n_B(i,j) \\ 0 & n_A(i,j) = n_B(i,j) \end{cases}$$
(5)

Step 5: A consistency verification process Li et al., 1995 is subsequently applied to refine the decision map by using a majority filter, where a pixel is more likely to belong to the label which many of its neighbors also belong. A 3×3 majority filter Li et al., 2001; Li et al., 2002 is performed on the decision map *W* to obtain a refined decision map *W*_r. Using a small size kernel of majority filter allows to increase the accuracy of decision by ensuring that a



Fig. 2. The illustration of the sliding window technique. (a) Sparse matrices $[E_A, E_B]$. (b) Frequency matrix n_A . Each cell represents the location of image pixel. The red and green rectangles show the sliding window that moves from previous position to the current position. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

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Fig. 3. Fusion Results using the "Clock" grayscale images. (a-b) The original images. (c-d) The images constructed from the sparse matrix after RPCA decomposition. (e) DWTbased method. (f) LMM-based method Tian and Chen (2012). (g) SF-based method Li et al. (2001). (h) RPCA-based method.

fused pixel does not come from a different source image from most of its neighboring pixels, meanwhile avoids over-smoothing the decision map Bovik, 2005. Thus, the composite image F_{AB} is finally obtained based on W_r as:

$$F_{AB}(i,j) = \begin{cases} I_A(i,j) & W_r(i,j) = 1\\ I_B(i,j) & W_r(i,j) = -1\\ (I_A(i,j) + I_B(i,j))/2 & W_r(i,j) = 0 \end{cases}$$
(6)

In order to validate the performance of the RPCA-based fusion method, we choose a simple and widely used maximum selection (MS) fusion scheme (Wan and Qin, 2011) to fuse the input images in the sparse feature space. Moreover, only one feature of standard deviation is computed on the sparse matrix. The presented framework has the potential to be adopted for eventual use with different fusion rules and multiple features, such as image gradient (De and Chanda, 2006), Gabor filters (Redondo et al., 2009), first-order and second-order statistical features (Li et al., 2012).

4. Experimental studies

The RPCA-based fusion method has been evaluated on various pairs of grayscale and color images, which are publicly available online (Image Fusion Online Resource for Research, 2009). The developed approach has one tunable parameter of the block size S. In the experiments, S is assigned as 35×35 pixels for grayscale images and 38×38 for color images, respectively.

The following three methods are used for comparison studies in the experiments. (1) A simple discrete wavelet transform (DWT) based method that utilizes the maximum selection rule on the high-pass coefficients and mean operation on the low-pass coefficients (Nikolov et al., 2001). The fused image is obtained via an inverse DWT. (2) Tian and Chen (2012) employed the spreading of the wavelet coefficients distribution as an image sharpness measure using a Laplacian mixture model. (3) Li et al. (2001) devised a multifocus image fusion approach using the spatial frequency as a selection criterion. The DWT- and LMM-based methods are developed in the multiresolution domain while the SF based approach is performed in the spatial domain. For both the DWTand LMM-based fusion methods, we have used the authors' original implementations. Due to the lack of original source code, we implemented the SF-based method based on Li et al. (2001). For the sake of fair comparison, we used the parameters that were reported by the authors to yield the best fusion results.

Three image quality evaluation criteria are used to provide objective performance comparison in our work. These three metrics are: (i) mutual information (MI) (MacKay and Theory, 2003), which determines the similarity between two images, (ii) Petrovic's metric $Q^{AB/F}$ (Xydeas and Petrovic, 2000), which measures the edge as well as the orientation information in both source images (denoted as *A* and *B*) and fused image (denoted as *F*), (iii)

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Fig. 4. Fusion Results using the "Pepsi" grayscale images. (a and b) The original images. (c and d) The images constructed from the sparse matrix after RPCA decomposition. (e) DWT-based method. (f) LMM-based method Tian and Chen (2012). (g) SF-based method Li et al. (2001). (h) RPCA-based method.

(h)

(g)

structural similarity index (SSIM) (Wang et al., 2004), which quantifies salient information that has been transferred into the fused image, where larger metric values imply better image quality. In order to ensure an objective, unbiased quality assessment, the above measures are used under a third-party implementation, i.e. the MeTriX MuX Visual Quality Assessment Package (Gaubatz, 2011), and Image Fusion Toolkit for Matlab (Image Fusion Online Resource for Research, 2009). Further, the computational complexity of the test methods is evaluated using the Matlab code on an Intel Core2 2.4 GHz machines with a 4 GB RAM.

4.1. Comparison results on grayscale images

Two examples are shown in Fig. 3 and Fig. 4 to fuse two grayscale images focusing on left or right side. The original images with size of 512×512 pixels are displayed in Fig. 4 and Fig. 4(a-b), respectively. The sparse images associated with two original images are illustrated in Fig. 4(a-b), and Fig. 4(c-d). The figures show that the sparse matrix contains salient information that reflects the edges of focused objects while suppresses defocused objects. Thus, the sparse features computed based on the sparse matrix represent important information of objects or regions in the scene that are in good focus.

By inspecting the fusion results, it can be seen that the fusion results obtained from DWT-based method are subject to a severe ringing effect making the entire image blur. The LMM-based method provides a sharp image but exhibits artifacts around edges. For example, in Fig. 3(f), noisy boundaries can be observed on both big and small clocks. The similar artifacts are also shown in Fig. 4(f). The SF-based method yields comparable fused images but suffers blocking artifacts. Fig. 3(g) shows vague edges appearing on the top and bottom of the big clock. The "Pepsi" image in Fig. 4(g) exhibits blurry edges on the table due to an incorrect selection of blocks. Our algorithm achieves superior fusion results by containing all the sharp contents from the source images without introducing artifacts.

The quantitative results in three quality measures are shown in Table 1. Our method gains the highest MI and Q^{AB/F} values compared to other methods, except for the "Pepsi" images when the SF-based method is rated highest using the SSIM measure. In fact, due to the actual definitions of these three metrics, a difference of 0.01 is significant for quality improvement. The running times are shown in Table 1, where one can see that the presented approach yields higher computational cost than the other two methods, due to the matrix decomposition method that requires longer computational time.

4.2. Comparison results on color images

As formulated in Section 3, the color images can be vectorised into three long independent one-dimensional vectors and assembled in a single data matrix. The sparse images can be reconstructed based on these three color channels after applying the RPCA decomposition. Fig. 5 and Fig. 6 demonstrate two examples

Table 1
The objective evaluation and run-time performance for the grayscale images.

Image	Measure	Method					
		DWT	LMM	SF	RPCA		
Clock	MI	7.47	8.07	7.99	8.57		
	Q ^{AB/F}	0.59	0.78	0.77	0.80		
	SSIM	0.86	0.91	0.89	0.91		
	run-time (s)	0.94	22.64	2.50	20.37		
Pepsi	MI	6.81	6.76	7.95	8.65		
	Q ^{AB/F}	0.53	0.71	0.75	0.76		
	SSIM	0.84	0.83	0.86	0.85		
	run-time (s)	1.04	31.32	3.06	26.33		

to combine color images. The input images are resized to be power of 2 to meet the requirement of the LMM-based method.

The first example contains two individuals who were standing about 30 feet apart with extended illumination as shown in Fig. 5(a-b). As the figures show, the DWT-based method suffers a ringing effect that deteriorates the fusion quality. The fused image obtained from the LMM-based method shows clear artifacts around figures and ceiling lights. The SF-based method performs well but exhibits blocking artifacts on the right corner of the fused image and human hair shown on Fig. 5(g). Our method shown in Fig. 5(h) yields the best quality image with respect to visual perception. For example, the ceiling lights on both right and left corners appear sharp, and lines on the top are well connected. Further, the boundaries of both figures are distinct and smooth.

As second example, the images are focused on right-hand or left-hand side for two books. The text showing on the book becomes blurry because of defocusation. The fusion results are displayed in Fig. 6. Similarly, the DWT-based method exhibits undesirable ringing artifacts round letters that degrade image visually. The SF-based method demonstrates a blurry edge between the two books. The LMM-based method yields a high quality fused image. Our method achieves a consistently good fusion result.

Table 2 lists the quantitative results by using three measures of MI, Q^{AB/F}, and SSIM, which demonstrate that our fusion method achieves best fusion results among all four approaches. We have found that all three metrics generally correlate well with the results of visual analysis. However, it should be noted that edge or structure based metrics (e.g. Q^{AB/F} and SSIM) fuse images containing significant artifacts such as ringing introduced by the transform can sometimes be inadvertently rated high by the metrics but look inferior perceptually.

The computational times are shown in Table 2. Again, our method needs longer running time than the other two methods. This drawback of high computation complexity lies in two aspects: (i) The RPCA requires to compute the singular value decomposition (SVD) of data matrix *D*. The SVD accounts for the majority of the computational load although only partial singular values are calculated in the implementation; (ii) The sliding window technique searches the entire image to compute the frequency matrix, which





Fig. 5. Fusion results using the "Human" color images. (a and b) The original images. (c and d) The images constructed from the sparse matrix after RPCA decomposition. (e) DWT-based method. (f) LMM-based method Tian and Chen (2012). (g) SF-based method Li et al. (2001). (h) RPCA-based method.

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Fig. 6. Fusion results using the "Book" color images. (a and b) The original images. (c and d) The images constructed from the sparse matrix after RPCA decomposition. (e) DWT-based method. (f) LMM-based method Tian and Chen (2012). (g) SF-based method Li et al. (2001). (h) RPCA-based method.

 Table 2

 The objective evaluation and run-time performance for the color images.

Image	Measure	Method				
		DWT	LMM	SF	RPCA	
Human	MI	6.09	8.48	8.84	9.29	
	Q ^{AB/F}	0.57	0.77	0.73	0.81	
	SSIM	0.88	0.89	0.86	0.90	
	run-time (s)	1.67	62.49	4.72	45.26	
Book	MI	7.16	8.48	8.98	9.30	
	Q ^{AB/F}	0.67	0.77	0.76	0.77	
	SSIM	0.87	0.89	0.88	0.90	
	run-time (s)	2.87	65.32	4.06	40.33	

is inefficiently coded using a loop structure in Matlab. For the SVD, accurately predicting the dimension of principal singular space (DPSS) allows a smaller number of singular values to be computed, which could reduce computational cost. Currently, the prediction of DPSS assumes that the rank of *A* is to be monotonically increasing and becomes stable at the true rank. In fact, the ranks of *A* are often oscillating, thus resulting in an inefficient partial SVD (Lin et al., 2009). The accuracy of prediction could be improved via a more intelligent scheme by considering the ratio between successive singular values and the corresponding iterative index. For implementing the sliding window technique, the source image could be divided into several non-overlapped subimages. The

sliding window is applied to each subimage and processed using parallel computing in Matlab to accelerate the computation. We believe these improvements could greatly reduce the computational complexity of our method and speed up the running time.

5. Concluding remarks and future work

In this paper, we have presented a novel image fusion scheme to effectively combine multifocus images into a single all-in-focus image. The RPCA technique is used to decompose the source images into principal and sparse matrices. The important features computed from the sparse matrix are able to represent the salient information from the source images that are acquired from a same scene with different focus points. The experiments were conducted on various pairs of grayscale and color images. The qualitative and quantitative evaluations have demonstrated that the presented RPCA-based fusion scheme achieves consistently superior fusion results compared to a number of state-of-the-art fusion methods in both spatial and wavelet domains. Further, being built in the RPCA decomposition domain, the new fusion scheme is flexible to adopt different types of features that are suitable for a variety of fusion tasks, such as combination of remote sensing images.

Future work will involve optimizing the current fusion framework to reduce the computational complexity and extending the developed method to be applied to noisy images. A recent study (Zhou and Tao, 2011) has showed that the decomposition and T. Wan et al. / Pattern Recognition Letters 34 (2013) 1001-1008

matrix completion tasks can be efficiently solved under noisy case, which is useful for developing an image fusion scheme to handle images that are contaminated by noise. The new method can be applicable to fusing medical images or remote sensing images containing noise that originates in the input device sensor and circuitry, or in the unavoidable shot noise of an ideal photo detector.

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