Multi-Focus Image Fusion via Coupled Dictionary Training

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Motivation

In many computer vision applications, people often have images of the same scene but obtained from different focus distances, and consequently the fusion techniques among the multi-focus source images are required.

This is an important and difficult problem because:

1. Limited depth of field in optical lenses of conventional cameras;
2. High cost of specialized optic sensors;
3. Traditional methods suffer from undesirable artifacts.

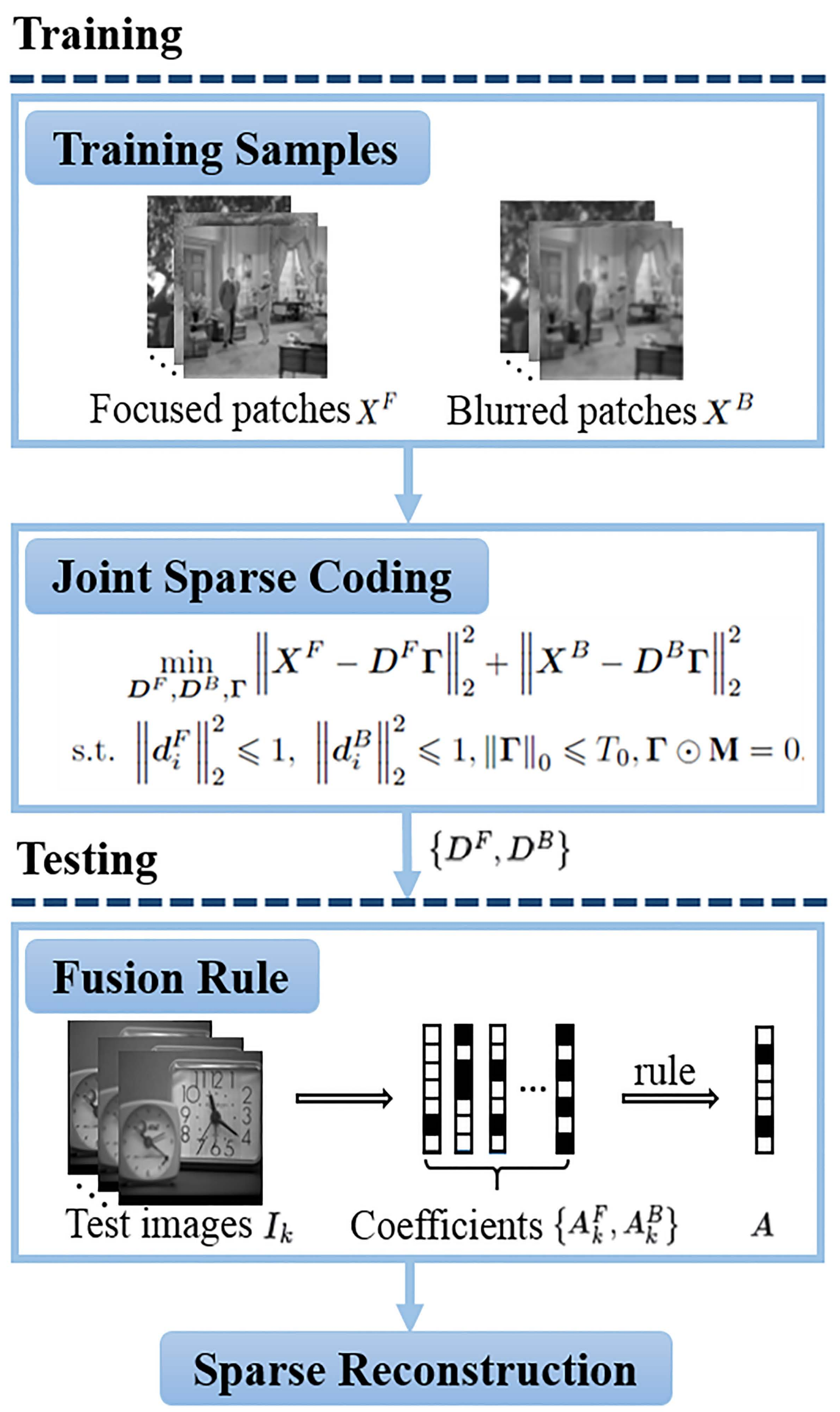
Contribution

A novel algorithm for training the dictionary pairs is proposed so as to fuse multi-focus images. Given the pair of training images, we seek the best possible sparse representations for the focused and blurred categories of images.

Major contributions are:

1. Formulation as a multi-focus image fusion problem based on sparsity over a couple of dictionaries;
2. The K-SVD-based coupled dictionary training algorithm;
3. Fusion rule via coupled dictionary training.

Method



– **Coupled dictionary training**

Separate the problem into two sub-problems, namely dictionary update and sparse coding update. Two main steps:

(i) Atoms of the coupled dictionaries $\boldsymbol{D}^F$ and $\boldsymbol{D}^B$ are alternately updated by the sparse representations:

$$\tilde{\boldsymbol{D}}^{F\setminus B} = \arg\min_{\boldsymbol{D}^{F\setminus B}} \left\|(\boldsymbol{X}^{F\setminus B} - \boldsymbol{D}^{F\setminus B}\boldsymbol{\Gamma}^T) \odot \mathbf{M}\right\|_2^2.$$

(ii) Joint sparse coding $\boldsymbol{\Gamma}$ is given by fixing coupled dictionaries:

$$\tilde{\boldsymbol{\Gamma}} = \operatorname{argmin}_{\boldsymbol{\Gamma}} \left\|\boldsymbol{X}^{F\setminus B} - \boldsymbol{D}^{F\setminus B}\boldsymbol{\Gamma}^T\right\|_2^2.$$

– **Image fusion from sparsity**

(i) Collect two sparse representations $\{\boldsymbol{A}_k^F, \boldsymbol{A}_k^B\}$ with respect to the couple of dictionaries $\{\boldsymbol{D}^F, \boldsymbol{D}^B\}$.

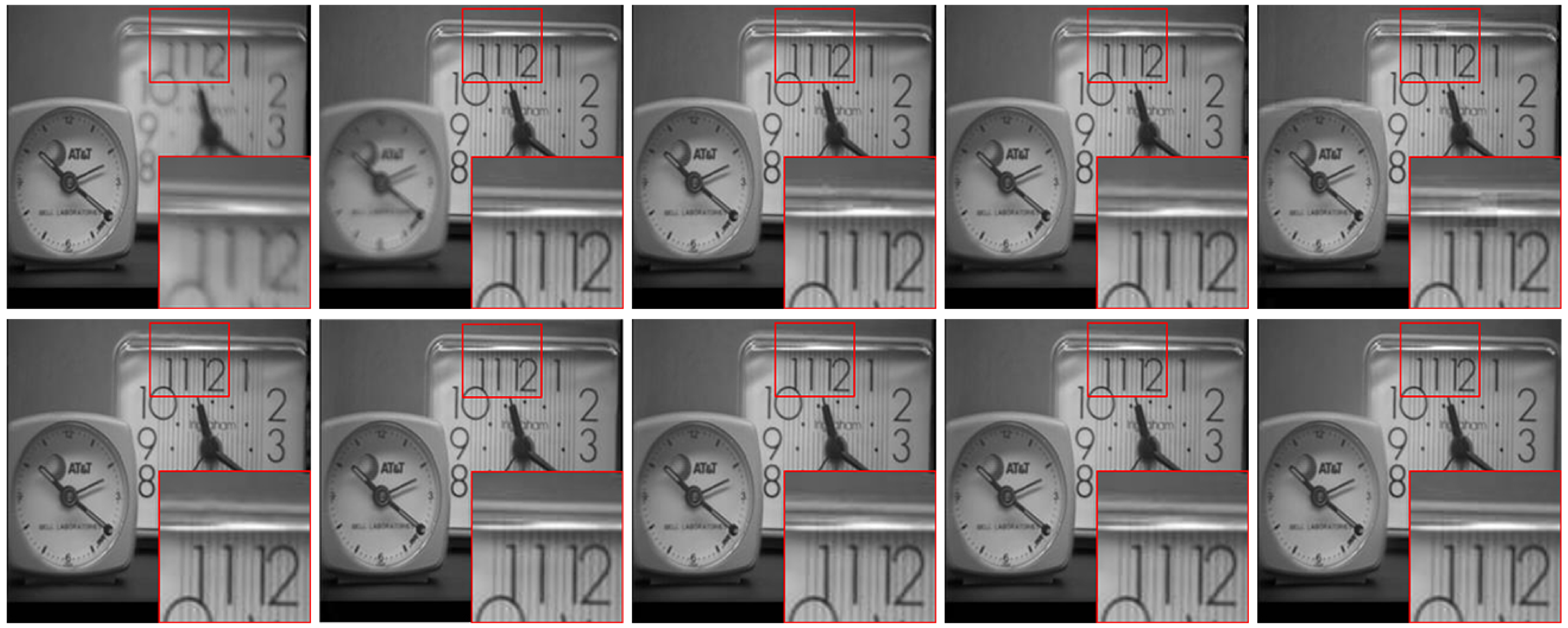
(ii) Define the fusion algorithm based on plain averaging and "choose-max" rule:

$$\boldsymbol{A} \leftarrow \operatorname*{argmax}_{i \neq j} (\boldsymbol{A}_i, \boldsymbol{A}_j);\ \boldsymbol{A}_i, \boldsymbol{A}_j \in \{\boldsymbol{A}_k = \frac{\boldsymbol{A}_k^F + \boldsymbol{A}_k^B}{2}, \forall 1 \leqslant k \leqslant N\}.$$

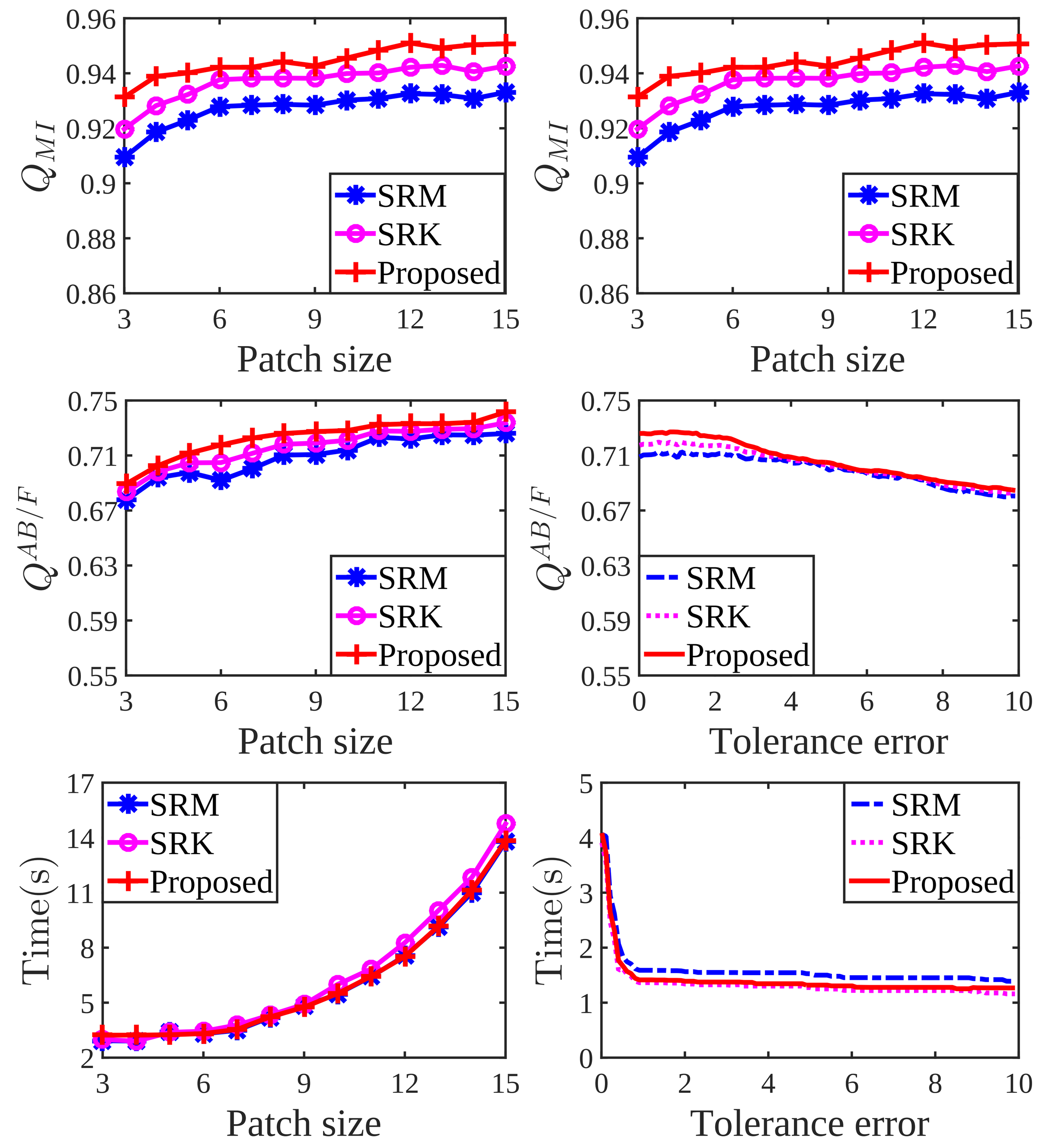
(iii) Generate an all-in-focus image $\boldsymbol{I}_F$ by sparse reconstruction with $\boldsymbol{D}^F$ and $\boldsymbol{A}$:

$$\min_{\boldsymbol{A}} \|\boldsymbol{A}\|_1 \quad \text{s.t. } \boldsymbol{I}_F = \boldsymbol{D}^F\boldsymbol{A}.$$

Results



From left-top to right-bottom: The first source image with focus on the left. The second source image with focus on the right. Fused images obtained by LP [1], MWG [2], DWT [3], NSCT [4], PCA [5], SRM [6], SRK and the proposed method.



Measures	Methods						
	LP	MWG	DWT	NSCT	PCA	SRM	Ours
Q_{MI}	0.9083	0.9045	0.8991	0.9245	0.9381	0.9276	**0.9432**
$Q^{AB/F}$	0.6879	0.7243	0.7013	0.7185	0.6620	0.7214	**0.7451**

Experiments show that the proposed approach well preserves the edge and structural information of source images, and drastically reduces the blocking artifacts and circle blurring.

The values of Q_{MI} and $Q^{AB/F}$ range from 0 to 1, with 1 representing the ideal fusion. The bold values are the best results in the corresponding columns.

Both Q_{MI} and $Q^{AB/F}$ slightly benefit from increasing patch size. When the patch size increases to 9, the running time begins to increase sharply. The tolerance error slightly impacts on $Q^{AB/F}$. When ϵ is larger than 2, Q_{MI} is drastically decreasing.

In multi-focus image fusion, we can see that our proposed method outperforms state-of-the-art methods.

References

[1] P. Burt and E. Adelson, "The laplacian pyramid as a compact image code," *IEEE Trans. Commun.*, 1983.
[2] Z. Zhou, S. Li, and B. Wang, "Multi-scale weighted gradient-based fusion for multi-focus images," *Image Vision Comput.*, 2014.
[3] J. Tian, et al., "Adaptive multi-focus image fusion using a wavelet-based statistical sharpness measure," *Signal Process.*, 2012.
[4] Q. Zhang and B. Guo, "Multifocus image fusion using the nonsubsampled contourlet transform," *Signal Process.*, 2009.
[5] T. Wan, et al., "Multifocus image fusion based on robust principal component analysis," *Pattern Recognit. lett.*, 2013.
[6] B. Yang and S. Li, "Multifocus image fusion and restoration with sparse representation," *IEEE Trans. Instrum. Meas.*, 2010.

Conclusion and Future work

Conclusion:

(i) A novel multi-focus image fusion approach via jointly training the coupled dictionary;
(ii) An effective and accurate fusion rule for estimating these representations.

Future work:

(i) Improve the efficiency of the coupled dictionary training;
(ii) Extend the fusion model to different types of fusion applications.