MORPHOLOGY BASED IMAGE FUSION DICTIONARY CONSTRUCTION AND REPRESENTATION

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ABSTRACT:
In recent years, multi-focus image fusion has seen a large increase in the use of sparse representation. The creation of an informative dictionary is a crucial step that directly affects how well sparsity-based image fusion works. Different geometric information from the source images is extracted and analyzed in order to obtain sufficient bases for dictionary learning. By using principle component analysis, corresponding subdictionaries are constructed from the classified image bases. One informative dictionary is created by combining all built-in subdictionaries. The compressive sampling matched pursuit algorithm is used to extract the appropriate sparse coefficients for the representation of the source images based on the constructed dictionary. To create the final fused image, the obtained sparse coefficients are first fused by the Max-L1 fusion rule and then inverted. Numerous comparative tests show that the suggested method is competitive with other cutting-edge fusion techniques.

KEYWORDS: **Morphology, Image Fusion, Sparse Representation, Visual information fidelity Entropy.**

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I. INTRODUCTION

For processing various images, cloud computing offers more potent computational resources [1-4]. The blurred objects always show up in the photographs because optical lenses have a limited depth of focus. Getting an entire scene in focus can be challenging [5, 6]. Multi-focus image fusion has received a lot of attention in recent years, and numerous related techniques have been developed and put into practise [5-8]. In multi-focus image fusion, multi-scale transform (MST)-based techniques are frequently employed. Transforms such as wavelet, shearlet, curvelet, and dual tree complex wavelet are described in [9, 10, 11, 12, 13, 14–15], as well as methods for non-subsampled contour transformation (NSCT) [16] are some of the image pixel transformation techniques that are frequently used to represent image features in MST-based methods. Image features are translated into MST bases and coefficients during the transformation process. Two steps make up the MST-based method fusion process. The first is called coefficient fusion, and the second is called fused coefficient transformation.

Since different approaches have different focuses, it is challenging to represent every aspect of source images using just one approach. Sparse representation (SR)-based image fusion has overcome the limitations of MST-based methods in recent years. The fusion process of the SR-based method is comparable to that of the MST-based method. But SR-based methods typically employ trained dictionaries to represent image features in an adaptive manner. Therefore, SR-based methods can more accurately describe the specifics of images to enhance the effects of fused images. The K-means generalised singular value decomposition (KSVD) algorithm is used to combine images based on SR the most frequently [17–19]. A KSVD-based dictionary learning method and a hybrid fusion rule were proposed by Yin et al. [17] for improving the quality of multi-focus image fusion. Additionally, Nejati et al. [18] proposed a KSVD-based multifocus image fusion technique. He improved the KSVD learning procedure to improve the functionality of multi-focus image fusion. A clustering-based dictionary learning method based on image features was proposed by Kim et al. [20]. The performance of the fusion can be enhanced by the trained dictionary's improved descriptions of image features. [21] Zhang introduced a non-negative SR model to enhance image fusion performance. A group dictionary learning approach was put forth by Li et al. [22] to extract various features from various image feature groups. This technique can increase the precision of SR-based fusion and produce better fusion results. Robust principal component analysis was used by Ibrahim et al. [23] to develop a dictionary for the fusion of multi-focus images using SR. Multi-focus image fusion has historically been achieved with the help of previously introduced SRbased methods.

The aforementioned techniques, however, do not take into account the morphological information of image features when learning new words. This study examines the morphological data of the source images to carry out dictionary learning. To improve the accuracy of SR-based dictionary learning, various types of image information are processed in accordance with morphological similarity. The dictionaries are created by sparse coding by extracting geometric information from the source image blocks, such as edges and sharp lines. This paper makes the following two main contributions: (i) To train corresponding dictionaries, morphological data from source images is divided into various image patch groups. More thorough morphological details of the source images are contained in each patch group of classified images. (ii) It suggests using principle component analysis (PCA) to build a concise and informative dictionary. Each image patch group's dimension is reduced using the PCA method, which also produces informative image bases. In addition to ensuring an accurate description of the source images, the trained dictionary's informative feature also lowers the computational cost of SR.

II. PROPOSED WORK

2.1 Dictionary learning in image fusion using SR-based image fusion:

Building an overly comprehensive dictionary that is not only reasonably compact in size but also contains the essential details of the source images is crucial for dictionary learning. Popular dictionary learning techniques include KSVD [19], online dictionary learning [24], and stochastic gradient descent [25]. This study uses PCA to improve dictionary learning. To demonstrate the benefits of a PCA-based solution, the learned PCA dictionary is compared to the corresponding KSVD dictionary. Good over-complete dictionaries are crucial for SR-based image fusion.

Unfortunately, it is challenging to find one that is both small and informative. To achieve an over-complete dictionary, Aharon's solution [26] suggested using KSVD to train source image patches and update corresponding dictionaries through SVD operations. During the dictionary learning process, a global and adaptively trained dictionary was used for KSVD to extract image patches. Kim et al. [20] are the authors who first introduced the Dictionary-based clustering solution for image fusion. Based on local structure data, similar patches were clustered from different source images. A small portion of each cluster's components were analysed to create the subdictionary. The learned subdictionaries are combined to create a concise and informative dictionary that effectively describes the structure information of source images.

2.2 Creating a dictionary based on geometric similarity:

To categorize source images, describe texture, edge information, and describe structure, smooth, stochastic, and dominant orientation patches are used in single image superresolution (SISR). From matching image patches, three subdictionaries are learned. For the purpose of creating corresponding compact and informative subdictionaries, the PCA method is used to only extract important information from each cluster. A concise and educational dictionary for image fusion is created by combining all learned sub dictionaries [20]. The suggested two-step geometric solution is shown in Fig. 1. The input source images Ii to Ik are first divided into a number of small image blocks called pin, i [(1, 2,..., k), n [(1, 2,..., w), In each input image, i represents the source image number, n represents the patch number, and w represents the total block number. In order to define patches of dominant orientation, smooth, stochastic, and dominant orientation geometric similarity is used. Then, PCA is used on each group to extract bases that correspond to each group in order to create sub dictionaries. A comprehensive dictionary for instructing the image SR is created by combining all obtained sub dictionaries.

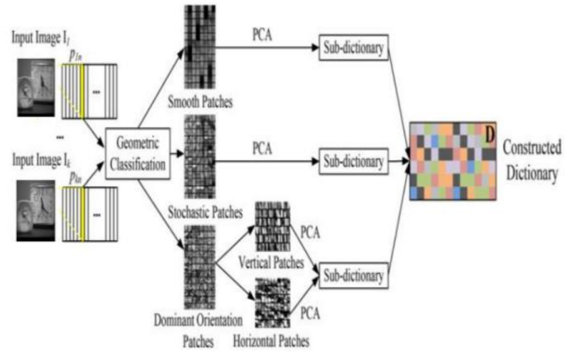

Fig. 1 IMAGE FUSION FRAMEWORK USING MORPHOLOGY

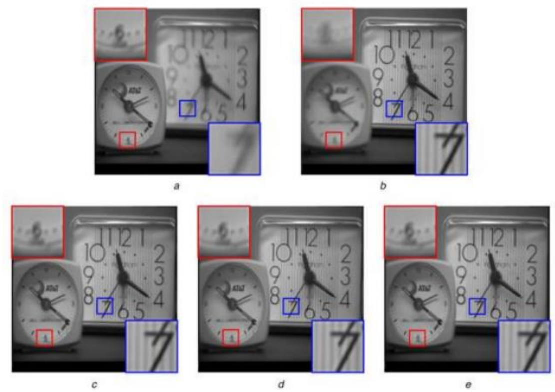

Fig. 2: 'TWO CLOCKS' IMAGE FUSION WITH MULTIPLE FOCUS A)SOURCE IMAGE B) SOURCE IMAGE, C) KSVD-FUSED IMAGE D) JCPD FUSED IMAGE E) PROPOSED METHOD FUSED IMAGE

III. OBJECTIVE EVALUATION METRICS

Four well-known objective evaluations—entropy, mutual information (MI), edge retention QAB/F, and visual information fidelity (VIF)—are used to objectively assess the integrated images. The definitions of these performance metrics are as follows.

3.1 Entropy: The information content of an image is represented by an image's entropy. An image with a higher entropy value is more informative. One image's entropy is defined as,

$$E = -\sum_{l=0}^{L-1} P_l \log_2 P_l \quad \text{...(1)}$$

Where L is the total number of grey levels and Pl is the proportion of gray-valued pixels to all pixels.

3.2 Mutual information: The MI metric calculates the MI of the combined image and the source images. The formal definition of MI for images is,

$$\mathrm{MI} = \sum_{i=1}^{L}\sum_{j=1}^{L} h_{A,F}(i,j)\log_2 \frac{h_{A,F}(i,j)}{h_A(i)h_{F(j)}}, \quad ..(2)$$

Where hA,F (i, j) is the grey histogram of images A and F and L is the number of grey levels. The edge histograms of images A and F are hA(i) and hF(j). MI of the fused image is calculated by equation.

MI(A, B, F) = MI(A, F) + MI(B, F) ....(3)

In this case, MI(A, F) denotes the MI value of the input image A, MI(B, F) denotes the MI value of the input image B, and MI(C, F) denotes the MI value of the input image C.

3.3 Q AB/F : The performance of edge information in a fused image is measured by the gradient-based quality index known as QAB/F.

$$Q^{AB/F} = \frac{\sum_{i,j}(Q^{AF}(i,j)w^A(i,j) + Q^{BF}(i,j)w^B(i,j))}{\sum_{i,j}(w^A(i,j) + w^B(i,j))} \quad ..(4)$$

QAF = QAF g, where The edge strength and orientation preservation values at location (i, j) are QAF 0, QAF g, and QAF 0. Calculating QBF is similar to computing QAF. The importance weights for QAF and QBF are wA(i, j) and wB(i, j), respectively.

3.4 Visual information fidelity: A novel-new metric for measuring the quality of full-reference images is called the VIF. VIF quantifies the MI between the reference image and test image using the human visual system (HVS) model and natural scene statistics. VIF's calculation equation can be found in the following equation (5). Based on the ratio between the distorted test image information and the reference image information, it can be calculated.

$$\mathrm{VIF} = \frac{\sum_{i\in \mathrm{subbands}} I(\overrightarrow{C^{N,i}};\overrightarrow{F^{N,i}})}{\sum_{i\in \mathrm{subbands}} I(\overrightarrow{C^{N,i}};\overrightarrow{E^{N,i}})} \quad ...(5)$$

IV. RESULTS AND DISCUSSIONS

Table 1 displays the average quantitative fusion outcomes of 20 colour multi-focus images using three different techniques. The suggested approach achieves the best results across all four categories of evaluation metrics.

Table 1: 20 COLOUR MULTI-FOCUS IMAGE FUSIONS ARE COMPARED

Parameter	Entropy	QAB/F	MI	VIF
KSVD	5.17	0.76	4.73	0.78
JCPD	5.17	0.77	4.6	0.75
Proposed	5.2	0.8	5.1	0.79

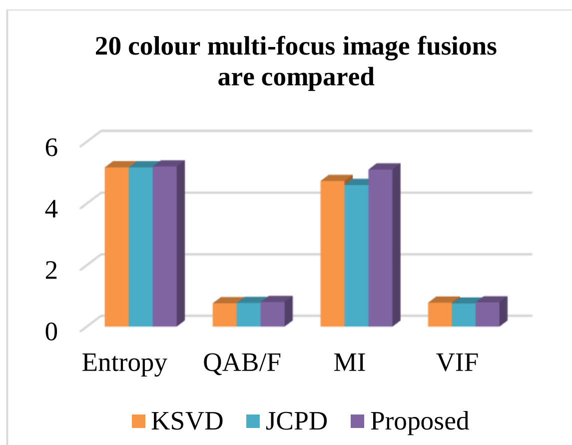

Fig. 3: 20 COLOUR MULTI-FOCUS IMAGE FUSIONS ARE COMPARED

There are two parts to the processing time overall. The first involves creating a dictionary and clustering images, while the second involves sparse coding and coefficient fusion.

The proposed method performs image clustering and dictionary construction significantly better than KSVD and JCDP. On image clustering and dictionary creation, KSVD takes the longest. The proposed solution and JCDP perform sparse coding and coefficient fusion in nearly the same amount of time. Similar to this, KSVD takes more time to complete coefficient fusion and sparse coding, as shown in table 2.

Table 2: PROCESSING TIME COMPARISON

Parameter	320 × 240, s	256 × 256, s	520 × 520, s
KSVD	57.7	50.6	1309
JCPD	41.4	34.6	822
Proposed	26.9	21.5	486

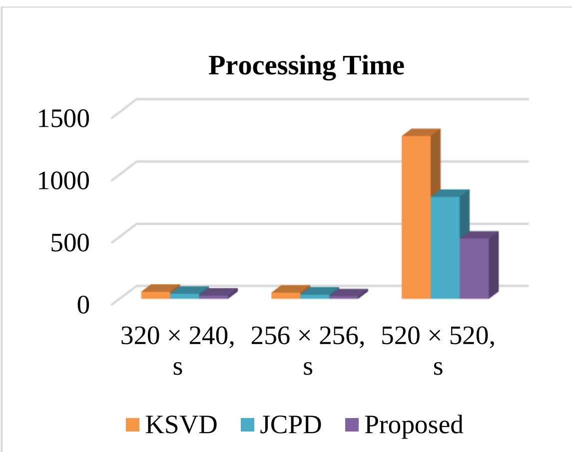

Fig. 4: PROCESSING TIME COMPARISON

V. CONCLUSION

This paper proposes an SR-based image fusion framework based on the geometric information of the image. According to their geometrical similarities, image patches from smooth, stochastic, and dominant orientation source images are analysed and divided into various image patch groups. For each group of image patch images, PCA is applied to extract the key patches for building the corresponding compact and informative subdictionary. A fully trained dictionary is created by combining all obtained subdictionaries. Source image patches are sparsely coded into coefficients based on the trained dictionary. Image block size is adaptively chosen during image processing, as are the best coefficients. The fused image can retain more edge and corner details. In order to fuse the imperfectly coded coefficients, the Max-L1 rule is used. The final fused image is then created by inverting the fused coefficients. In comparative experiments, the proposed solution is compared with the two widely used SR-based methods KSVD and JCPD.

REFERENCES

[1] Wu, W., Tsai, W.T., Jin, C., et al.: 'Test-algebra execution in a cloud environment'. IEEE 8th Int. Symp. on Service Oriented System Engineering, Oxford, UK, 2014, pp. 59–69
[2] Qi, G., Tsai, W.-T., Li, W., et al.: 'A cloud-based triage log analysis and recovery framework', Simul. Modelling Pract. Theory, 2017, 77, pp. 292–316
[3] Tsai, W.T., Qi, G.: 'DICB: dynamic intelligent customizable benign pricing strategy for cloud computing'. IEEE Fifth Int. Conf. on Cloud Computing, Honolulu, HI, USA, 2012, pp. 654–661
[4] Tsai, W.T., Qi, G., Chen, Y.: 'A cost-effective intelligent configuration model in cloud computing'. 32nd Int. Conf. on Distributed Computing Systems Workshops, Macau, China, 2012, pp. 400–408
[5] Li, H., Qiu, H., Yu, Z., et al.: 'Multifocus image fusion via fixed window technique of multiscale images and non-local means filtering', Signal Process., 2017, 138, pp. 71–85
[6] Qi, G., Wang, J., Zhang, Q., et al.: 'An integrated dictionary-learning entropy-based medical image fusion framework', Future Internet, 2017, 9, (4), p. 61
[7] Li, H., Liu, X., Yu, Z., et al.: 'Performance improvement scheme of multifocus image fusion derived by difference images', Signal Process., 2016, 128, pp. 474–493
[8] Li, H., Yu, Z., Mao, C.: 'Fractional differential and variational method for image fusion and

super-resolution', Neurocomputing, 2016, 171, pp. 138–148

[9] Pajares, G., de la Cruz, J.M.: 'A wavelet-based image fusion tutorial', Pattern Recognit., 2004, 37, (9), pp. 1855–1872

[10] Makbol, N.M., Khoo, B.E.: 'Robust blind image watermarking scheme based on redundant discrete wavelet transform and singular value decomposition', AEU – Int. J. Electron. Commun., 2013, 67, (2), pp. 102–112

[11] Luo, X., Zhang, Z., Wu, X.: 'A novel algorithm of remote sensing image fusion based on shift-invariant shearlet transform and regional selection', AEU – Int. J. Electron. Commun., 2016, 70, (2), pp. 186– 197.

[12] Liu, X., Zhou, Y., Wang, J.: 'Image fusion based on shearlet transform and regional features', AEU – Int. J. Electron. Commun., 2014, 68, (6), pp. 471–477

[13] Sulochana, S., Vidhya, R., Manonmani, R.: 'Optical image fusion using support value transform (SVT) and curvelets', Optik – Int. J. Light Electron Optics, 2015, 126, (18), pp. 1672–1675

[14] Yu, B., Jia, B., Ding, L., et al.: 'Hybrid dual-tree complex wavelet transform and support vector machine for digital multi-focus image fusion', Neurocomputing, 2016, 182, pp. 1–9

[15] Seal, A., Bhattacharjee, D., Nasipuri, M.: 'Human face recognition using random forest based fusion of à-trous wavelet transform coefficients from thermal and visible images', AEU – Int. J. Electron. Commun., 2016, 70, (8), pp. 1041–1049

[16] QU, X.-B., Yan, J.-W., Xiao, H.-Z., et al.: 'Image fusion algorithm based on spatial frequency-motivated pulse coupled neural networks in nonsubsampled contourlet transform domain', Acta Autom. Sin., 2008, 34, (12), pp. 1508–1514

[17] Yin, H., Li, Y., Chai, Y., et al.: 'A novel sparse-representation-based multi-focus image fusion approach', Neurocomputing, 2016, 216, pp. 216–229.

[18] Nejati, M., Samavi, S., Shirani, S.: 'Multi-focus image fusion using dictionary-based sparse representation', Inf. Fusion, 2015, 25, pp. 72– 84

[19] Zhu, Z., Qi, G., Chai, Y., et al.: 'A novel visible-infrared image fusion framework for smart city', Int. J. Simul. Process Model., 2018, 13, (2), pp. 144–155.

[20] Kim, M., Han, D.K., Ko, H.: 'Joint patch clustering-based dictionary learning for multimodal image fusion', Inf. Fusion, 2016, 27, pp. 198– 214

[21] Guo, M., Zhang, H., Li, J., et al.: 'An online coupled dictionary learning approach for remote sensing image fusion', IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens., 2014, 7, (4), pp. 1284–1294.

[22] Li, S., Yin, H., Fang, L.: 'Group-sparse representation with dictionary learning for medical image denoising and fusion', IEEE Trans. Biomed. Eng., 2012, 59, (12), pp. 3450–3459.

[23] Ibrahim, R., Alirezaie, J., Babyn, P.: 'Pixel level jointed sparse representation with RPCA image fusion algorithm'. 38th Int. Conf. on Telecommunications and Signal Processing (TSP), Prague, Czech Republic, 2015, pp. 592–595.

[24] Qi, G., Zhu, Z., Erqinhu, K., et al.: 'Fault-diagnosis for reciprocating compressors using big data and machine learning', Simul. Modelling Pract. Theory, 2018, 80, pp. 104–127.

[25] Zhu, Z., Sun, J., Qi, G., et al.: 'Frequency regulation of power systems with self-triggered control under the consideration of communication costs', Appl. Sci., 2017, 7, (7), p. 688.

[26] Aharon, M., Elad, M., Bruckstein, A.: 'k-SVD: an algorithm for designing overcomplete dictionaries for sparse representation', IEEE Trans. Signal Process., 2006, 54, (11), pp. 4311–4322.

[27] Yang, S., Wang, M., Chen, Y., et al.: 'Single-image super-resolution reconstruction via learned geometric dictionaries and clustered sparse coding', IEEE Trans. Image Process., 2012, 21, (9), pp. 4016–4028.

[28] Gawari, Nisha, and S. Lalitha. "Comparative analysis of PCA, DCT & DWT based image fusion techniques." Int J Emerg Res Manag Technol 3.5 (2014): 54-61.

[29] Lalitha Y. S Shashidhar Sonnad, Multistage Decision Level Image Fusion Technique for WorldView-2 Images, International Journal of Imaging and Robotics,[Formerly known as the “International Journal of Imaging"], 2020.

[30] Honnutagi, Pooja, V. D. Mytri, and Y. S. Lalitha. "Fusion-Based Underwater Image Enhancement by Weight Map Techniques." Recent Developments in Machine Learning and Data Analytics (2019): 32