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Multi-modality image fusion combining sparse representation with guidance filtering

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Abstract and Figures

Multi-modality image fusion technique is essential for target description. The complementary information can not only compensate the limitations of each image effectively, but also enhance visual effect to human eyes. To preserve structure information and perform detailed information of each source multi-modality image, a novel fusion framework with two-scale image reconstruction is proposed. In the proposal, an improved guided image filtering (GIF)-based weighted average via Gabor energy is put forward for the fusion of base layers contained large scale structure information, and a sparse representation-based separable dictionary learning is recommended to capture small scale detailed information of detail layers. Finally, according to the texture enhancement fusion rule, the fused base and detail layers are integrated to obtain the fusion image. Experimental results demonstrate that the proposed method exhibits significant performance than the basic GIF algorithm, and also outperforms the existing state-of-the-art methods in terms of better edge texture clarity. Moreover, the fusion results show abundant information and better visual effect.

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The schematic diagram of the… Multi-modality image databas… The effect of moving step si… Objective performance of… Image pairs of WBAMI datase…

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METHODOLOGIES AND APPLICATION

Multi-modality image fusion combining sparse representation with guidance filtering

Qiu Hu[1,2] · Shaohai Hu[1,2] · Fengzhen Zhang[3]

Published online: 14 February 2021

Abstract

Multi-modality image fusion technique is essential for target description. The complementary information can not compensate the limitations of each image effectively, but also enhance visual effect to human eyes. To preserve struc information and perform detailed information of each source multi-modality image, a novel fusion framework with scale image reconstruction is proposed. In the proposal, an improved guided image filtering (GIF)-based weighted ave via Gabor energy is put forward for the fusion of base layers contained large scale structure information, and a sp representation-based separable dictionary learning is recommended to capture small scale detailed information of d layers. Finally, according to the texture enhancement fusion rule, the fused base and detail layers are integrated to ob the fusion image. Experimental results demonstrate that the proposed method exhibits significant performance thar basic GIF algorithm, and also outperforms the existing state-of-the-art methods in terms of better edge texture cla Moreover, the fusion results show abundant information and better visual effect.

Keywords Image fusion · Multi-modality image · Sparse representation · Guidance filtering · Gabor energy

1 Introduction

The rapid growth of novel imaging sensors and the availability of large number of imaging modalities have emphasized the field of image fusion (Hermessi et al. 2018), and especially the area multi-modality image fusion has attracted much more attention due to the increasing demands of clinical applications and surveillance purposes (Goshtasby and Nikolov 2007). The goal of multi-modality image fusion is to integrate all comprehensive information of the same scene into a single fused image with no artifacts and inconsistencies production. Through image fusion, diverse modalities of images, such as medi infrared–visible images and multi-focus images, employed for the visual enhancement of human machine perception (Li et al. 2016). For instance, the fı medical image is helpful for diseases diagnosis and red the storage cost in clinical application (Dou et al. 20 The fused infrared–visible image can predicate the lc ization of dangerous objects with respect to the backgrc in the surveillance area (Toet and Franken 2003).

A large number of multi-modality image fusion metl have been proposed in literature. Among these meth multi-scale image fusion and sparse representation (S based image fusion are very successful methods. T focus on different data representations, e.g., multi-s coefficients or sparse coefficients. Multi-scale coeffici can be obtained through multiple multi-scale transfor tions, such as the stationary wavelet transform (SWT) et al. 2002), dual-tree complex wavelet transf (DTCWT) (Lewis et al. 2004), and the newly develc curvelet transform (Nencini et al. 2007) and the non sampled contourlet transform (NSCT) (Li and Yang 20 Though multi-scale coefficients can reasonably repre important information of an image, each transform ha own merits and limitations corresponding to contex

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... Furthermore, several other image decomposition methods are also employed in image fusion techniques. For instance, sparse representation (SR) [17][18][19] [20] [21] can be effectively represented as a linear combination of a few basic elements from a given dictionary. Two-scale image decomposition [22] separates an image into two main components: a base layer representing the low-frequency content and a detail layer capturing the high-frequency content. ...

... The NSCT and NSST-based methods often cause distortion in the color of the synthesized image [49,50] and take a large amount of time to decompose input images. SR-based algorithms have limitations in producing composite images with unclear details and even color distortion [17][18][19] [20] [21]24]. The second limitation is that the synthesis methods for the high-frequency component are not efficient. ...

... This window is shifted throughout the H matrix to determine the local energy of all other coefficients. The mathematical formula for the local energy LEði; jÞ is illustrated in Eq. (20). ...

Medical image fusion based on transfer learning techniques and coupled neural P systems

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Dec 2023 · NEURAL COMPUT APPL

Phu-Hung Dinh · Nguyen Long Giang

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... Higher values of XEI indicate greater degree of edge preservation. (vi) Peilla Metric (PM) [1,22, 64] : This quality index is also known as salient quality index, edge-dependent fusion quality index and represents the amount of salient information transferred from source to fused images with minimal or no distortions. Peilla metric considers the magnitude and location of distortion in images while evaluating the fusion algorithm used. ...

... Higher Table 8 Image quality evaluation metrics in selected studies Table 8 continued Reference Metric [29,30,32,44,51,54,71,94,98,130,141,144,145,147,152,154,160,168,171,174,175,178,180,192,193] Normalized Weighted Performance Metric/Xydeas [4,15,18,26,88,101,137,139,140,151,162,166,194] Edge Index /Gradient-based Index/Edge Retention/Xydeas [25,31,42,43, 64, 92,99,108,146,165,182,189,191] and Petrovic Edge Index/Edge-based Similarity Measure [4, 6, 7, 29-32, 56, 57, 68, 93, 97, 110, 111, 114, 122, 129, 144-147, 162, 180] Feature Mutual Information [13,17,27,28,40,44,46,49,51,55,56,74,85,87,88,90,96,102,115,123,125,155,158,169,170,174,183] Average Gradient [42,43,48,76,105,107,138,161,179,184,185,190] [30,33,74,103,106,135,136,148] Mean Value [2,14,95,139,153,157,165,182] Normalized Mutual Information [3, 5, 28, 34, 46, 56, 71, 83, 89, 103, 106, 110, 117-119, 130, 141, 148, 154, 160, 172, 176, 180, 187] Structural Similarity Index Measure [25,26,36,37,47,60,68,70,97,101,123,125,127,156,162,[184][185][186]188] [7, 57,66,116,149,165,179] [51,54,62,65,79,83,87,107,113,185,187,188,190] Information Entropy [14,54,75,82,95,192] Phase Congruency-based Metric [3,10,44,46,67,70,123,134,141,148,156,160,164,176] Peak Signal to Noise Ratio [7,9,36,42,43,47,66,79,128,137,179,190] [8,16,55,87,125,156,160,161,170,176,179] Correlation Coefficient [1,2,6,8,12,15,22,50,63,64,75,90,91,94,98,100,101,116,118,122,147,157,172,181,194] Peilla Metric/Salient Quality Index/Edge-dependent Fusion Quality Index [22,27,28,75,94,95,178,180,192,193] Non-linear Correlation Information Entropy Table 8 continued Reference Metric [2,22,60,94,101,178] Chen and Blum Metric [6,8,29,30,32,51,56,59,86,88,111,114,129,130,142,153,157,167,168,172,175,176,181,187,192,193] Visual Information Fidelity Fusion [26,31,48,57,112,166,182,191] [8,16,27,62,93,133,134,142,152] Mean Structural Similarity Index Measure [34,36,38,46,47,90,103,106,112,170] Tone Mapped image Quality Index [1, 8, 10, 16, 78, 80, 110, 116-119, 124, 127, 131, 133, 150] Fusion Factor [7,9,56,79,89,112,128,138,141,142,164] Root Mean Square Error [17,33,56,75,135,136,142,192] Edge Information [5,8,34,49,67,90,170] Natural Image Quality Evaluator [6, 13, 26-28, 42, 44, 66, 90, 102, 112, 170, 183, 184] Edge Intensity [10, 21, 78, 80, 110, 113, 115-119, 129, 131, 149, 186] Edge Strength [5, 16, 78, 85, 116-119, 124, 131, 133, 161, 163] Fusion Symmetry [34,47,110,139,182,193] Feature Similarity Index [12,40,52,85,97,125] Petrovik Metric Parameter Index ...

... Higher Table 8 Image quality evaluation metrics in selected studies Table 8 continued Reference Metric [29,30,32,44,51,54,71,94,98,130,141,144,145,147,152,154,160,168,171,174,175,178,180,192,193] Normalized Weighted Performance Metric/Xydeas [4,15,18,26,88,101,137,139,140,151,162,166,194] Edge Index /Gradient-based Index/Edge Retention/Xydeas [25,31,42,43,64,92,99,108,146,165,182,189,191] and Petrovic Edge Index/Edge-based Similarity Measure [4, 6, 7, 29-32, 56, 57, 68, 93, 97, 110, 111, 114, 122, 129, 144-147, 162, 180] Feature Mutual Information [13,17,27,28,40,44,46,49,51,55,56,74,85,87,88,90,96,102,115,123,125,155,158,169,170,174,183] Average Gradient [42,43,48,76,105,107,138,161,179,184,185,190] [30,33,74,103,106,135,136,148] Mean Value [2,14,95,139,153,157,165,182] Normalized Mutual Information [3, 5, 28, 34, 46, 56, 71, 83, 89, 103, 106, 110, 117-119, 130, 141, 148, 154, 160, 172, 176, 180, 187] Structural Similarity Index Measure [25,26,36,37,47,60,68,70,97,101,123,125,127,156,162,[184][185][186]188] [7, 57,66,116,149,165,179] [51,54,62,65,79,83,87,107,113,185,187,188,190] Information Entropy [14,54,75,82,95,192] Phase Congruency-based Metric [3,10,44,46,67,70,123,134,141,148,156,160,164,176] Peak Signal to Noise Ratio [7,9,36,42,43,47,66,79,128,137,179,190] [8,16,55,87,125,156,160,161,170,176,179] Correlation Coefficient [1,2,6,8,12,15,22,50,63, 64, 75,90,91,94,98,100,101,116,118,122,147,157,172,181,194] Peilla Metric/Salient Quality Index/Edge-dependent Fusion Quality Index [22,27,28,75,94,95,178,180,192,193] Non-linear Correlation Information Entropy Table 8 continued Reference Metric [2,22,60,94,101,178] Chen and Blum Metric [6,8,29,30,32,51,56,59,86,88,111,114,129,130,142,153,157,167,168,172,175,176,181,187,192,193] Visual Information Fidelity Fusion [26,31,48,57,112,166,182,191] [8,16,27,62,93,133,134,142,152] Mean Structural Similarity Index Measure [34,36,38,46,47,90,103,106,112,170] Tone Mapped image Quality Index [1, 8, 10, 16, 78, 80, 110, 116-119, 124, 127, 131, 133, 150] Fusion Factor [7,9,56,79,89,112,128,138,141,142,164] Root Mean Square Error [17,33,56,75,135,136,142,192] Edge Information [5,8,34,49,67,90,170] Natural Image Quality Evaluator [6, 13, 26-28, 42, 44, 66, 90, 102, 112, 170, 183, 184] Edge Intensity [10, 21, 78, 80, 110, 113, 115-119, 129, 131, 149, 186] Edge Strength [5, 16, 78, 85, 116-119, 124, 131, 133, 161, 163] Fusion Symmetry [34,47,110,139,182,193] Feature Similarity Index [12,40,52,85,97,125] Petrovik Metric Parameter Index ...

A Systematic Literature Review on Multimodal Medical Image Fusion

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Jul 2023 · MULTIMED TOOLS APPL

Shatabdi Basu · Sunita Singhal · Dilbag Singh

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... Wang et al. [13] have proposed to combine adaptive SR with a Laplacian pyramid (LP) method. Hu et al. [14] used SR and combined it with a guidance filter to synthesize medical images. ...
... Fitness function ( ) is described as Eq. (14). ...

Combining spectral total variation with dynamic threshold neural P systems for medical image fusion

Article

Nov 2022 · BIOMED SIGNAL PROCES

Phu-Hung Dinh

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... There are several methods that are commonly used for image decomposition, including the discrete wavelet transform (DWT), stationary wavelet transform (SWT) [4,5], Laplacian Pyramid (LP) [6][7][8], , and NSST [12][13][14][15][16][17][18]. Other techniques can be employed to decompose images, including sparse representation (SR) [19][20][21][22] [23] [24], spectral total variation (STV) [25,26], two-scale image decomposition [19,27], and hybrid 1 − 0 layer decomposition [28]. During the process of fusing images, special rules are applied to the low and high-frequency coefficients. ...

An efficient approach to medical image fusion based on optimization and transfer learning with VGG19

Article

Jan 2024 · BIOMED SIGNAL PROCES

Cuong Do · Chi Mai Luong · Phu-Hung Dinh · Giang Son Tran

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... In addition, Sparse representation (SR) has also been shown to be effective in decomposing input images in image synthesis algorithms. Some studies can be mentioned as Maqsood and Javed (2020), Shibu and Priyadharsini (2021), Yousif et al. (2022), Li et al. (2021a), Hu et al. (2021) and Barba-J et al. (2022). ...

A novel approach using structure tensor for medical image fusion

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Sep 2022 · MULTIDIM SYST SIGN P

Phu-Hung Dinh

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... Neural network (Qu et al. 2008;Yin et al. 2018;Kaur and Singh 2021)/deep learning (Li et al. 2018a;Ren et al. 2020Ren et al. , 2021Luo et al. 2021) is widely used in computer vision and image fusion with its powerful imitation ability, but it is still challenging to design suitable neural network and adjust corresponding parameters. Although single method or theory can achieve better performance, the hybrid model Hu et al. 2021; Wang et al. 2021;Li et al. 2021b) combines their advantages to enhance quality of fused images. ...

Image fusion using online convolutional sparse coding

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Chengfang Zhang · Ziyou Zhang · Ziliang Feng

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... Li et al. [36] have proposed combining Sparse representation with a segment graph filter. Hu et al. [37] have introduced an approach base on guidance filtering and Sparse representation. ...

Combining Gabor energy with equilibrium optimizer algorithm for multi-modality medical image fusion

Article

May 2021 · BIOMED SIGNAL PROCES

Phu-Hung Dinh

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Article

Image reconstruction algorithm based on group sparse coefficient estimation

December 2015

S. Liu · G. Wu · L. Xu · [...] · J. Cao

Sparse representation based image prior information model has been widely used in image reconstruction. Aiming at the key problems of dictionary selection and coefficient estimation in sparse representation, this paper proposes the image reconstruction method based on sparse representation combined with nonlocal self-similarity. Firstly, the patch matching based on Euclidean distance is used to ... [Show full abstract]

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Article

A new approach of multi-modal medical image fusion using intuitionistic fuzzy set

August 2022 · Biomedical Signal Processing and Control

Dhanalakshmi Palanisami · Nandhini Mohan · K. G. Lavanya

The main aim of this paper is to blend the multi-modality images into a single image to acquire superior information and obtain excellent visual quality without any artifacts and vagueness. First, the source images are decomposed into base and detail layers by making use of the Gaussian filter. The detail layers are merged using spatial frequency to preserve the edge details and clarity of an ... [Show full abstract]

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Chapter

Research on Multi-spectral and Panchromatic Image Fusion

January 2012 · Communications in Computer and Information Science

Siyu Lai · Juan Wang

A Non-negative Matrix Factorization (NMF) based multi-spectral and panchromatic images fusion algorithm is proposed. The low-resolution multi-spectral image and high-resolution panchromatic image are seen as the sources in NMF decomposition process. In which, the feature basis, contains overall characteristics of source image, is obtained using NMF decomposition. Then, perform histogram matching ... [Show full abstract]

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Article

Multi-modality medical image fusion based on separable dictionary learning and Gabor filtering

April 2020 · Signal Processing Image Communication

Qiu Hu · Shaohai Hu · Fengzhen Zhang

Sparse representation (SR) has been widely used in image fusion in recent years. However, source image, segmented into vectors, reduces correlation and structural information of texture with conventional SR methods, and extracting texture with the sliding window technology is more likely to cause spatial inconsistency in flat regions of multi-modality medical fusion image. To solve these ... [Show full abstract]

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MRI Image Fusion Based on Optimized Dictionary Learning and Binary Map Refining in Gradient Domain

June 2022 · Multimedia Tools and Applications

Qiu Hu · Shaohai Hu · Xiaole Ma · [...] · Jing Fang

The insufficient ability of edge feature extraction and high complexity limit the ability of sparse representation to obtain better medical image fusion performance. In this letter, we propose a novel multimodal medical image fusion method with optimized dictionary learning and binary map refining. The optimized dictionary learning uses loop iterations between separable FISTA and manifold-based ... [Show full abstract]

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An Image Decomposition Fusion Method for Medical Images

July 2020 · Mathematical Problems in Engineering

Lihong Chang · Wan Ma · Yu Jin · Li Xu

A fusion method based on the cartoon+texture decomposition method and convolution sparse representation theory is proposed for medical images. It can be divided into three steps: firstly, the cartoon and texture parts are obtained using the improved cartoon-texture decomposition method. Secondly, the fusion rules of energy protection and feature extraction are used in the cartoon part, while the ... [Show full abstract]

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A novel region-based multimodal image fusion technique using improved dictionary learning

December 2019 · International Journal of Imaging Systems and Technology

Bikash Meher · Sanjay Agrawal · Rutuparna Panda · [...] · Ajith Abraham

Recently, the sparse representation (SR) based algorithms have gained much attention from the researchers in the area of image fusion (IF). The building of a compact discriminative dictionary plays a vital role in the sparse-based IF techniques. In this context, an efficient multimodal IF method based on improved dictionary learning is investigated. The key contributions of this paper are: (a) An ... [Show full abstract]

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