Transactions on Computational and Scientific Methods | Vo. 4, No. 1, 2024
ISSN: 2998-8780
https://pspress.org/index.php/tcsm
Pinnacle Science Press

Enhanced Image Fusion Using Shearlet Transform and Pulse-Coupled Neural Networks

Megan Thomas[1], Yuzhe Liu[2]

[1]University of Utah, Megantt.94@gmail.com

[2]University of Utah, Liu.yuzhe1993@gmail.com

Abstract: Traditional multi-scale image fusion techniques often struggle to maintain translation invariance during the multi-directional and multi-scale decomposition of images. While the non-downsampled contourlet transform (NSCT) exhibits multi-scale, multi-directional, and translation-invariant properties, it is limited by directional constraints. This paper introduces a novel image fusion framework based on the non-subsampled shearlet transform (NSST) domain. This framework effectively preserves image energy and detail while addressing the directional limitations in image decomposition. The proposed method employs NSST for decomposing the source images and utilizes a pulse coupled neural network (PCNN) model to differentiate the absolute values of high-frequency coefficients across various source images. The low-frequency fusion rule is derived from low-level feature perception image quality metrics, such as image local energy and phase consistency. Subsequently, the NSST inverse transform is applied to reconstruct the fused high-frequency and low-frequency components. This approach retains more image Enhanced Image Fusion Using Shearlet Transform and Pulse-Coupled Neural Networksthe proposed fusion framework outperforms existing methods in infrared-visible image fusion.

Keywords: Image Fusion, NSST, PCNN, phase consistency.

1. Introduction

Image fusion integrates complementary information from multiple source images in the same scene to generate a composite image. For an image fusion system, the input source images can be acquired either from different types of imaging sensors or one sensor with different optical parameter settings. So the fused image as output is more suitable for human perception and machine processing than any individual source image. Image fusion techniques have been widely used in computer vision, surveillance, medical imaging, remote sensing, and so on [1].

Pixel-level fusion algorithms are mainly categorized as spatial domain and transform domain- based solutions [1]. Spatial domain-based solutions directly extract useful information from source images for image fusion [1]. As the simplest way, pixel weighted average strategy is always applied to source image pixels. It often blurs the contour and edge information of source images, loses the useful information, and causes low-quality image fusion results. To enhance the visual quality in the fused image, area, and block segmentation based image fusion solutions are proposed [2]. Although the visual performance of the fused image is improved, the corresponding segmentation algorithm is comparatively complex, and not good for real-time processing. In spatial domain-based image fusion algorithms, it is difficult to determine the size and features of sub-block. V. Atlanta proposed a differential evolution solution to determine the size of the split image [2].

Based on quad-tree structure and morphology, I.De proposed a novel image fusion algorithm [3].M.Bagher integrated block segmentation and discrete cosine transform into image fusion [4].

Other image block recognition and selection methods, such as pulse-coupled neural networks (PCNNs), artificial neural networks [5], had been successfully applied to image fusion.

Although most of the existing solutions can obtain high-quality fusion results in certain extents, fused images may still be unsmooth. The pyramid-based image fusion method is widely used in the transform domain method. However, the pyramid-based transform is lack of direction, so it cannot extract detailed image information in a different direction [5].

In recent years, following the continuous research on wavelet analysis and multi-resolution theory, some new wavelet transforms, such as discrete wavelet(DWT) [6], fuzzy wavelet [7], double-tree complex wavelet(DTCWT) [8], and M-band wavelet transform [5], have been introduced into image fusion. However, DWT or DTCWT cannot represent the curve and edge information of the image well[9] [5]. To represent the spatial structures of the image more accurately, some novel multi-scale geometric analysis tools are introduced into image fusion. For example, contourlet transform can capture the intrinsic geometric structure of the image, and maximize the use of geometric characteristics of data, such as line singularities, plane singularities [5]. Since contourlet transform contains the downsampling process, it has no shift- invariant property. Nonsubsampled contourlet transform (NSCT) can represent complex spatial structures in many different directions well [10].

This paper proposes a new image fusion framework for the non-subsampled shearlet transform (NSST) domain. The fusion framework can well preserve image energy and detail, and solve the problem of limited direction in image decomposition. This method uses NSST to decompose the source image. The pulse coupled neural network (PCNN) model is used to distinguish the absolute values of high-frequency coefficients in different source images. The low-frequency fusion rule is formulated according to the low-level feature perception image quality such as image local energy and phase consistency. Experiments have shown that the introduction of the PCNN model in image fusion will improve the efficiency of the algorithm and reduce the fusion time. This method can better preserve the energy and detail of the source image. More importantly, the fusion algorithm is based on the transform domain and fully combines the advantages of NSCT, PCNN model, and phase consistency information to better capture the details of the source image. In contrast experiments, 10 sets of infrared-visible images are applied to the fusion performance testing. The experimental results show that the fusion framework is superior to the KIM and MST fusion methods in terms of human visual perception and objective evaluation.

2. Proposed Framework

2.1. Overview

The proposed image fusion framework is shown in Fig.1, which includes four components: image decomposition, high-pass band fusion, low-pass band fusion, and image reconstruction. As shown in Fig.1, source images are decomposed into high and low-frequency bands by applying NSST. Then for high-frequency coefficients, the PCNN model is introduced as the high- frequency coefficient activity metric to realize high-frequency fusion. In the low-frequency fusion, the design is based on the fusion rules of local abrupt changes, local energy and PC features to achieve energy preservation and detail extraction of low-frequency images. Finally, the fused image is obtained by the inverse transform of NSST.

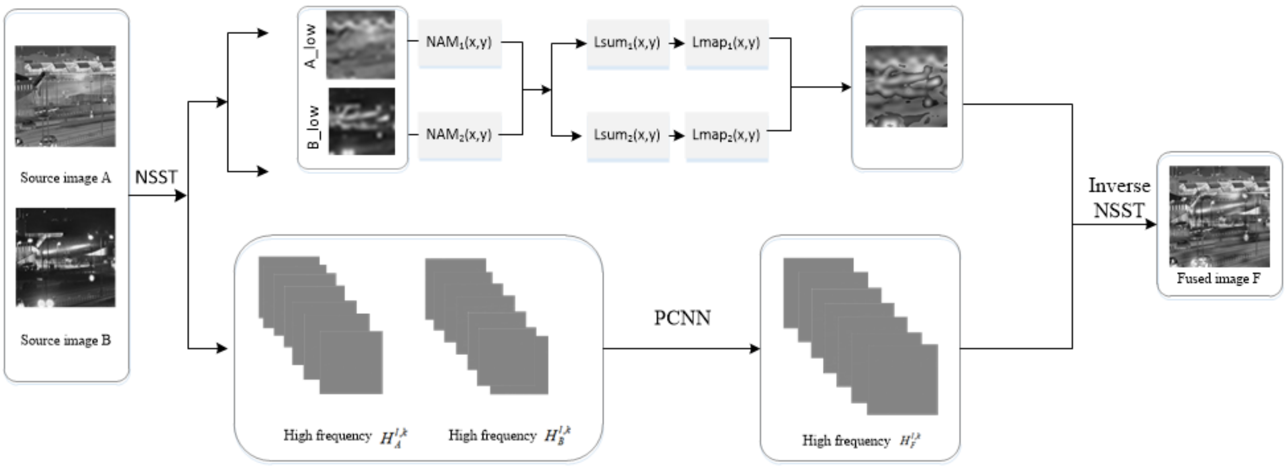

Figure 1. The proposed image fusion framework

2.1.1. Fusion Rule of Low-Frequency Bands

The lowpass subband of NSST filtered images mainly describes the detailed information corresponding to the texture and edge information of source images. Thus the key of highpass subband fusion it to enhance the detailed feature of each source image.

In this paper, to make the lowpass subband image more informative, phase congruency (PC) is implemented to enhance the image features. PC is a dimensionless measure that can measure the significance of the image features. In the lowpass subbands, the value of PC is corresponding to the sharpness of the image object. Thus PC is used as the phases of the coefficient with maximal local sharpness. Since image can be regarded as a 2-D signal [huafeng], PC of the image at the location (x,y) can be calculated as eq.1

$$PC(x,y) = \frac{\sum_k E_{\theta_k}(x,y)}{\varepsilon + \sum_n \sum_k A_{n,\theta_k}(x,y)} \tag{1}$$

Design a new activity measure (NAM)that uses PC, LSCM, and LE complement to measure different aspects of information of the image.

$$NAM(x,y) = \left(PC(x,y)\right)^{\alpha_1} \cdot \left(LSCM(x,y)\right)^{\beta_1} \cdot \left(LE(x,y)\right)^{\gamma_1} \tag{2}$$

3. Experiments and Analysis

3.1. Experiment Preparation

10 pairs of infrared-visible images are applied to the fusion performance testing respectively, in contrast, experiments. The resolution of test images is 256×256, 240×320 respectively. Infrared-visible and gray-level multi-focus image pairs were collected by Liu [1] and can be downloaded from quxiaobo.org. All the experiments are programmed in Matlab 2014a on an Intel(R) Core(TM)i7-7700k CPU @ 4.20GHz Desktop with 16.00 GB RAM.

3.1.1. Object Evaluation Metrics

It is not an easy task to quantitatively evaluate the quality of a fused image, as the reference image (ground truth) does not exist in practice. In recent years, many image fusion metrics have been proposed. But none of them can be universally applied to any fusion scenario. It is usually necessary to apply several metrics to make a comprehensive evaluation. In this paper, eight popular metrics are employed to quantitatively evaluate the performance of different fusion methods, which are Q^{TE}, Q^{IE}, $Q^{AB/F}$, Q^{P}, Q^{MI}, Q^{Y}, Q^{CB}, and Q^{VIF}.

3.1. Experimental Result of Infrared-visible Images

Infrared imaging can identify the target well, but it is not sensitive to the change of scene brightness. Visible light imaging can provide better details of the scene where the target is located. Infrared and visible images can be synthesized organically by image fusion technology,which generates new descriptions of scenes or targets. This image fusion technology has been widely used in battlefield evaluation, target recognition and other fields. In the reconnaissance shooting task, the target image is acquired by infrared imaging device and visible light camera. Infrared thermal imaging technology uses thermal radiation technology to convert infrared wavelengths beyond the human eye's observation wavelength into visible information mapped to the image. Visible light camera obtains high resolution, texture and edge information in detail. It is difficult to meet the actual needs of the project by only one type of image. Infrared-visible image fusion technology makes full use of the complementary information of visible and infrared images and space-time correlation to better meet the engineering requirements. We can get high-quality and comprehensive image information by integrating many kinds of image information.

Figure 2 shows examples of infrared and visible images fusion. In Figure 7, (a), (b) are two source images, (c), (d), and (e) are the experimental results of KIM, MST, and our proposed method, respectively. And (f), (g), (h), (i), (j) correspond to local detail magnification maps of (a)-(e). As shown in Figure 7 (h1) and (h2), the image fused by the KIM method has high edge brightness and poor texture details. The fusion image obtained by the MST method is too high in contrast. For example, it weakens some details in (i1). Compared with KIM and MST, the fusion image obtained by our method has better performance in detail clarity and brightness. Through our method of image fusion, high-quality and comprehensive image information can be obtained.

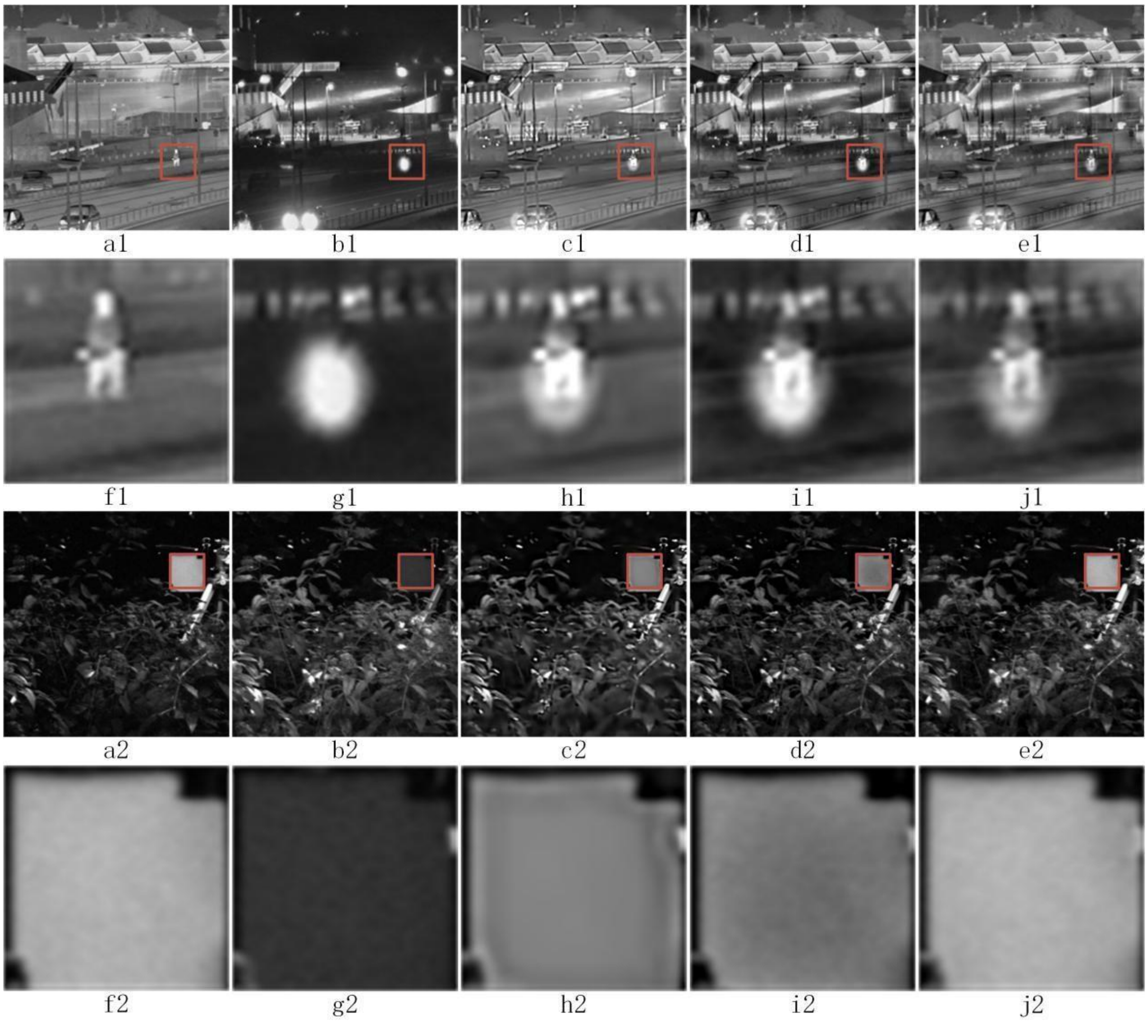

Figure 1. Infrared-visible Image Fusion Experiments

As shown in Table 1, the MST fusion image obtained the best Q^P score. However, the human visual effects and detail preservation capabilities of MST fusion images are not as good as the proposed method. Q^{TE}, Q^{IE}, $Q^{AB/F}$, Q^{MI} Q^{CB}, and Q^{VIF} obtained by our proposed method are the highest. It can be seen that this method has good performance in visual quality and structure preservation, and also has good performance in edge preservation. During the experiment, the testing time of the proposed method is shorter than KIM and MST. Therefore, the fusion framework of our method is better than other methods.

Table 1. Objective Evaluations of Infrared-Visible Image Fusion Experimentations

	Q^{TE}	Q^{IE}	$Q^{AB/F}$	Q^{P}	MI	Q^{Y}	Q^{CB}	VIFF	time
KIM	0.5343	0.8089	0.6228	0.5805	2.4381	0.7449	0.6386	0.5498	60.246282
MST	0.5528	0.8092	0.7585	0.7795	2.4808	0.8517	0.6407	0.5861	10.785458s
proposed	**0.5871**	**0.8103**	**0.7959**	0.7209	**2.6897**	**0.8991**	**0.6597**	**0.5947**	6.094225s

4. Conclusion

A general image fusion method based on a non-subsampled shearlet transform (NSST) is proposed. The fusion framework combines NSST, pulse coupled neural network (PCNN) and phase congruency (PC) to improve the visual quality of fused images. Specifically, the framework applies NSST to achieve image high and low-frequency decomposition. In the image high-frequency coefficient fusion, the high-frequency fusion is realized by introducing PCNN as the high-frequency coefficient activity metric. It can improve fusion speed. In the low-frequency fusion, the design is based on the fusion rules of local abrupt changes, local energy and PC features to achieve energy preservation and detail extraction of low-frequency images. Finally, the fused image is obtained by the inverse transform of NSST. The experimental results show that the fusion framework is superior to the KIM and MST fusion methods in terms of human visual perception and objective evaluation.

References

[1] Y. Liu, S. Liu, Z. Wang. A General Framework for Image Fusion Based on Multi-scale Transform and Sparse Representation. Information Fusion, vol. 24 (2014), p.147–164.

[2] V. Atlanta, R. Kurban. Fusion of Multi-focus Images Using Differential Evolution Algorithm. Expert Systems with Applications, vol. 37 (2010), p.8861–8870.

[3] I. De, B. Chanda. Multi-focus Image Fusion Using A Morphology-based Focus Measure in A Quad-tree Structure. Information Fusion, vol. 14 (2013), p.136–146.

[4] M.B.A. Haghighat, A. Aghagolzadeh, H. Seyedarabi. A Non-reference Image Fusion Metric Based on Mutual Information of Image Feature. Pergamon Press, vol. 26 (2011), p.744–756.

[5] S. Li, X. Kang, L. Fang, Hu. H. Pixel-level Image Fusion: A Survey of The State of The Art. Information Fusion, vol. 33 (2017), p.100–112.

[6] L.C. Smith, D.L. Turcotte, B.L. Isacks. Stream Flow Characterization and Feature Detection Using A Discrete Wavelet Transform. Hydrological Processes, vol. 12 (2015), p.233–249.

[7] S. Yilmaz, Y. Oysal. Fuzzy Wavelet Neural Network Models for Prediction and Identification of Dynamical Systems. IEEE Transactions on Neural Networks, vol. 21 (2010), p.1599–609.

[8] L. Masmoudi. MRI images Denoising Based in DualTree Complex Wavelet and Bayesian MAP. Ijmer Com 2012.

[9] H. Li, Z. Yu, C. Mao. Fractional Differential and Variational Method for Image Fusion and Super-resolution. Elsevier Science Publishers B. V., vol. 27 (2016), p.138–148.

[10] K.P. Upla, M.V. Joshi, P.P. Gajjar. An Edge Preserving Multiresolution Fusion: Use of Contourlet Transform and MRF Prior. IEEE Transactions on Geoscience & Remote Sensing, vol. 53 (2015), p.3210–3220.

[11] M. Yin, X.N. Liu, Y. Liu, X. Chen. Medical Image Fusion With Parameter-Adaptive Pulse Coupled Neural Network in Nonsubsampled Shearlet Transform Domain. IEEE Transactions on Instrumentation and Measurement, vol. 34 (2018), p. 1–16.

[12] Y. Chen, S.K. Park, Y. Ma, R. Ala. A New Automatic Parameter Setting Method of a Simplified PCNN for Image Segmentation. IEEE Transactions on Neural Networks, vol. 22 (2011), p.880–892.