Optik 126 (2015) 3920–3923

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Wavelet and guided filter based multifocus fusion for noisy images

Amina Jameel [a], Abdul Ghafoor [a,*], Muhammad Mohsin Riaz [b]

[a] College of Signals, National University of Sciences and Technology (NUST), Pakistan
[b] Centre for Advanced Studies in Telecommunication (CAST), Comsats Islamabad, Pakistan

ARTICLE INFO

Article history:
Received 17 June 2014
Accepted 18 July 2015

Keywords:
Image fusion
Multifocus
Guided filter

ABSTRACT

Wavelet and guided filter based fusion for multifocus images is proposed. Existing guided filter based scheme has limited performance for images having noise. Wavelet based denoising and guided filter based weight maps are proposed to overcome this limitation. Simulation results when analysed visually and quantitatively depict the significance of the suggested scheme.

1. Introduction

Multifocus image fusion process combines images with dissimilar focus settings to obtain an improved image with an increase in depth of field [1]. The cameras currently being used in vision systems have limited depth of field i.e. objects are focused and defocused (blurred) depending upon their distances from the lens. Consequently, all the objects in the captured image are not focused. Therefore, multifocus image fusion technique is required to produce a sharper image (which contains all objects in focus) in biomedical and computer vision etc. applications [1,2].

Multifocus image fusion schemes include spatial domain and multiresolution based approaches. The spatial domain based methods (block and segmentation) directly select regions or blocks in the spatial domain to obtain the fused image [3]. The block based methods produce block effects degrading the fused image quality [2]. The segmentation methods are complicated and time consuming due to the complexity of segmentation algorithm [2]. Multi-scale decomposition based fusion schemes (discrete wavelet wransform, complex wavelet, stationary wavelet transform, contourlet transform, curvelet transform, and non-subsampled contourlet transform (NSCT) etc.) decompose the input images into different levels [1,4,5]. The major advantage of multiresolution based schemes lies in well preservation of the details of different source images. Phamila and Amutha [6] used discrete cosine transform for fusion of multifocus visual images. Huang and Jing [7] used pulse-coupled neural network (PCNN) for multi-focus image fusion. Qu et al. [8] used NSCT in association with PCNN for image fusion. Zhang et al. [9] and Wang et al. [10] recently proposed image fusion algorithms which are also based on PCNN. However, these methods are complex and have not been applied to noisy images.

Recently, guided filter fusion (GFF) scheme [11] was proposed that uses a guided filter to preserve edges hence avoiding blurring effects in the fused image. However, the method provides limited performance for noisy images. Improvement in the weight maps of the GFF scheme were proposed in [12] to fuse magnetic resonance (MR) and computed tomography (CT) images. The method assumes a clear CT image while the MR image was corrupted with rician noise. Since wavelets have been successfully used for image denoising [13], the proposed method is based on wavelet based denoising. The GFF scheme [11] is novel image fusion method based on guided filtering and provides state-of-the-art performance for fusion of noiseless images. In this paper, wavelet based denoising and guided filter based weight maps are proposed to overcome the noise limitation. Simulation results when analysed visually and quantitatively depict the significance of the suggested scheme.

2. Proposed methodology

The main limitation of GFF [11] scheme is its limited performance for noisy images. A redundant translation invariant wavelet transform followed by hard thresholding is used to solve this limitation.

The proposed scheme consists of the following steps: a forward wavelet transform; nonlinear thresholding; multiplication with corresponding weight maps and an inverse wavelet transform. First we discuss the noise removal, then the construction of weight maps is discussed followed by construction of fused image.

* Corresponding author. Tel.: +92 515615233345.
E-mail addresses: amina.phd@students.mcs.edu.pk (A. Jameel), abdulghafoor-mcs@nust.edu.pk (A. Ghafoor), mohsin.riaz@comsats.edu.pk (M.M. Riaz).

http://dx.doi.org/10.1016/j.ijleo.2015.07.173

2.1. Wavelet decomposition and denoising

In practical applications, additive gaussian noise is introduced in image during acquisition process [2]. The noise causes miscalculation of sharpness values, which degrades the performance of image fusion algorithm. The fusion algorithm should not only provide a high quality fused image but it should also be robust and reliable to imperfections (noise).

Let F be the fused image obtained by combining noisy input images $\dot{A} = A + N_R$ and $\dot{B} = B + N_R$ of same sizes $M \times N$ (where $m = 1, 2, \ldots, M$ and $n = 1, 2, \ldots, N$). N_R is the the added noise while $\dot{A}$, $\dot{B}$ and A, B represent the noisy and noiseless input images respectively. The sub-sampling at each stage of the transform is omitted to implement a translation invariant wavelet transform. This correspond to the decomposition of the images $\dot{A}$ and $\dot{B}$ into a redundant family of $MN \times (3 \times J + k + 1)$ atoms $\dot{W}_{A,d}$ and $\dot{W}_{B,d}$ respectively where MN is the total number of pixels, J represents the scales of the transform and k is the orientation ($J = 4$, $d = 1, 2, \ldots, 16$ and $k = 1, 2, 3$ in our case). $\dot{W}_{A,1}$ and $\dot{W}_{B,1}$ corresponds to the low scale residual of images $\dot{A}$ and $\dot{B}$ respectively. $\dot{W}_{A,(3\times J+k+1)}$ and $\dot{W}_{B,(3\times J+k+1)}$ have the same size as the original images and correspond to a scale of wavelet coefficient for $k = 1, 2, 3$ (orientation).

Wavelet denoising is used to eliminate the noise present in the image and preserve the characteristics of the signal irrespective of its frequency contents. The small absolute values of wavelet coefficients represent noise [14], while large absolute values more likely carry signal information [14].

For noise removal, coefficients below a certain threshold value are truncated (using soft or hard thresholding). Note that soft thresholding smoothes the details and does not produce sharp edges [14]. In fusion, we require sharp edges. Therefore we have used hard thresholding. The thresholds τ_A and τ_B are,

$$\tau_A = 3\sigma_A \quad \text{and} \quad \tau_B = 3\sigma_B \tag{1}$$

where σ_A and σ_B are noise levels and can be estimated using median absolute deviation [14] or with a learned Markov random field based bayesian framework [15] etc. The denoised coefficients of both the source images are obtained as,

$$W_{A,d} = \Lambda(\dot{W}_{A,d}, \tau_A) \quad \text{and} \quad W_{B,d} = \Lambda(\dot{W}_{B,d}, \tau_B) \tag{2}$$

where Λ is pointwise thresholding operator and $d = 1, 2, \ldots, 16$. $W_{A,d}$, $\dot{W}_{A,d}$ and $W_{B,d}$, $\dot{W}_{B,d}$ are the denoised and noisy coefficients of images $\dot{A}$ and $\dot{B}$ respectively. These coefficients are then multiplied by the weight maps to obtain the fused coefficients.

2.2. Generation of weight maps

The weight maps are obtained from the saliency maps. The saliency images are first obtained by convolving the atoms $W_{A,d}$ and $W_{B,d}$ with a laplacian filter h followed by a gaussian filter g i.e.,

$$S_{A,d} = |W_{A,d} * h| * g \quad \textit{and} \quad S_{B,d} = |W_{B,d} * h| * g \tag{3}$$

where $S_{A,d}$ and $S_{B,d}$ are the saliency maps corresponding to images $\dot{A}$ and $\dot{B}$ respectively. The saliency maps are linked with the detail information of source images. The weight maps $P_{A,d}$ and $P_{B,d}$ are obtained as,

$$P_{A,d} = \xi(S_{A,d}, S_{B,d}) \quad \textit{and} \quad P_{B,d} = \xi(S_{B,d}, S_{A,d}) \tag{4}$$

where $\xi(S_{A,d}, S_{B,d})$ is a function with value 1 for $S_{A,d}(m, n) \geq S_{B,d}(m, n)$, and value 0 for $S_{A,d}(m, n) < S_{B,d}(m, n)$ (similarly for $\xi(S_{B,d}, S_{A,d})$). $S_{A,d}(m, n)$ and $S_{B,d}(m, n)$ are the saliency values for (m, n) pixel in $W_{A,d}$ and $W_{B,d}$ respectively.

The weight maps are then passed through the guided filter to obtain the refined weight maps ($\Gamma_{A,d}$, $\Gamma_{B,d}$) as,

$$\Gamma_{A,d} = G_{r,\epsilon}(P_{A,d}, W_{A,d}) \quad \textit{and} \quad \Gamma_{B,d} = G_{r,\epsilon}(P_{B,d}, W_{B,d}) \tag{5}$$

where g is the guided filter and r, ϵ are the size of the filter and the extent of blur respectively. The fusion performance is worse when the filter size r is too large or too small for the different atoms. In this paper, the default parameters are set as $r = 7$ and $\epsilon = 10^{-6}$. Since the GFF method does not depend much on the exact parameter choice, these values can obtain good results for most of the images.

2.3. Wavelet reconstruction

The fused coefficients are obtained as,

$$W_{F,d} = W_{A,d}\Gamma_{A,d} + W_{B,d}\Gamma_{B,d} \tag{6}$$

where $d = 1{:}16$ and $W_{F,d}$ are the fused coefficients. Finally, the inverse wavelet transform is applied to reconstruct the fused image F. The hard thresholding of the wavelet coefficients and the different orientation and scale levels of atoms ensures that more information is transferred to the fused image. The incorporation of the wavelet based denoising and its association with GFF take advantage of the characteristics of both and make the proposed method suitable for noisy images.

3. Results and analysis

The proposed technique is verified on several pairs of multifocus source images [16] and it is compared with Haghighat et al. [18], Tian et al. [19], and GFF [11] schemes. For quantitative evaluation, different measures including mutual information measure ζ_{MI}, structural similarity measure ζ_{SSIM}, Xydeas and Petrovic measure ζ_{XP}, Zhao et al. measure ζ_Z, Piella and Heijmans measures

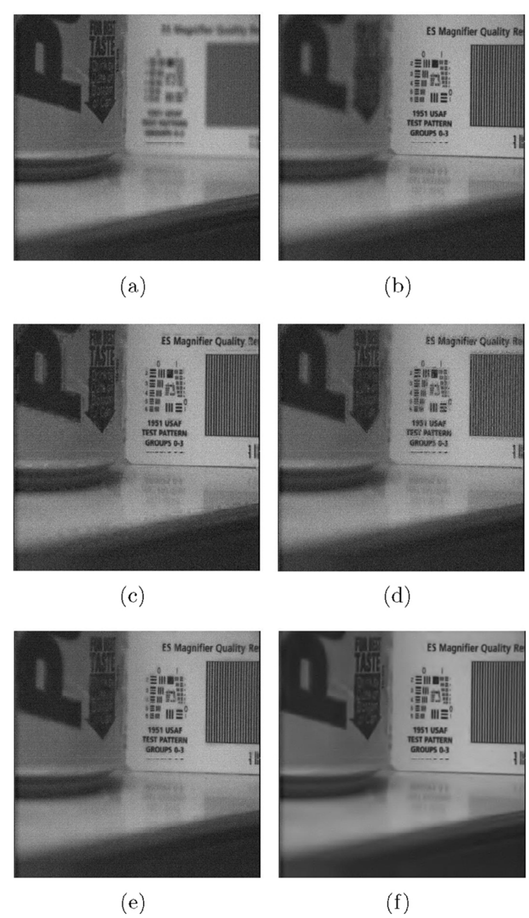

Fig. 1. Example 1: (a) noisy image 1; (b) noisy image 2; (c) Haghighat et al. [18] fused image; (d) Tian et al. [19] fused image; (e) GFF [11] fused image; (f) proposed fused image.